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The Influence of State Policy and Proximity to Medical Services on Health Outcomes

Jing LI
Singapore Management University, lijing@smu.edu.sg

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Abstract: This paper examines two factors that help to explain geographic variation in health outcomes. The first factor concerns proximity to medical services. The second factor is state-specific health care policy that may impede access to nearby medical services. Four key findings are obtained. First, the effect of local doctors on reducing mortality rates of various diseases in a county attenuates with distance. Second, at approximately the same distance, in-state doctors contribute more to lowering mortality rates in the primary county than do out-of-state doctors. Third, the lesser impact of nearby out-of-state doctors is further reduced when the primary state adopts more stringent policies that restrict entry of out-of-state physicians. Fourth, the impact of nearby doctors is found to be stronger in more urbanized areas. This is consistent with agglomeration economies being effective in contributing, at least in part, to the productivity of treating patients.

Keywords: Agglomeration, Health care, State border

1. Introduction

Mortality rates for heart disease, cancer, and stroke differ dramatically across locations in the United States. As shown in Fig. 1a, Fig. 1b and Fig. 1c, mortality rates associated with these diseases are generally the highest in certain eastern rural states, such as West Virginia, Alabama, Mississippi, and the lowest in states like Utah, Arizona, and New Mexico. Traditional explanations for geographic variation in health outcomes have mainly focused on the impact of health care expenditures and environmental factors.[1] This paper extends the literature by examining the effect of proximity to medical professionals on local population health outcomes and the degree to which state physician licensing policies reduce the impact of out-of-state physicians. A better understanding of these factors is important for improving national health since restricted access to medical services is one of the leading causes for poor health outcomes in lightly developed areas.[2]

[1] Previous studies examining the impact of health care expenditures find inconsistent evidence. Studies using available cross-sectional datasets show almost complete absence of a positive relationship between expenditures and the quality of care (Fisher et al., 2003a, Fisher et al., 2003b, Baicker and Chandra, 2004 and Fisher et al., 2009). In contrast, instrumental variables and panel data evidence suggest that higher spending is associated with significantly lower mortality (McClellae et al., 1994, Cutler, 2007, Chandra and Staiger, 2007 and Doyle, 2011).
[2] See, for example, Casey et al. (2001), and Coughlin et al. (2002).

Fig. 1a. State variation in mortality rates (per 100,000 residents) for heart disease.

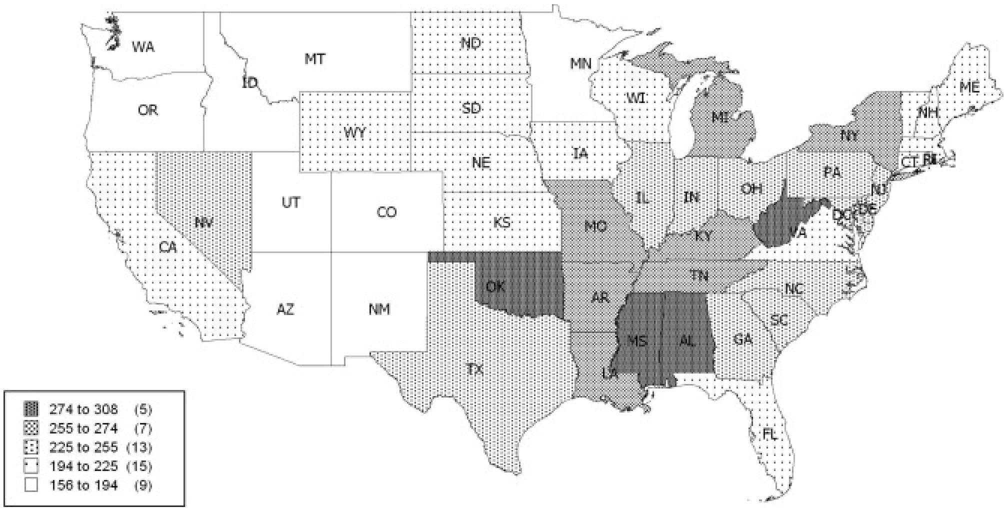


Fig. 1b. State variation in mortality rates (per 100,000 residents) for cancer.

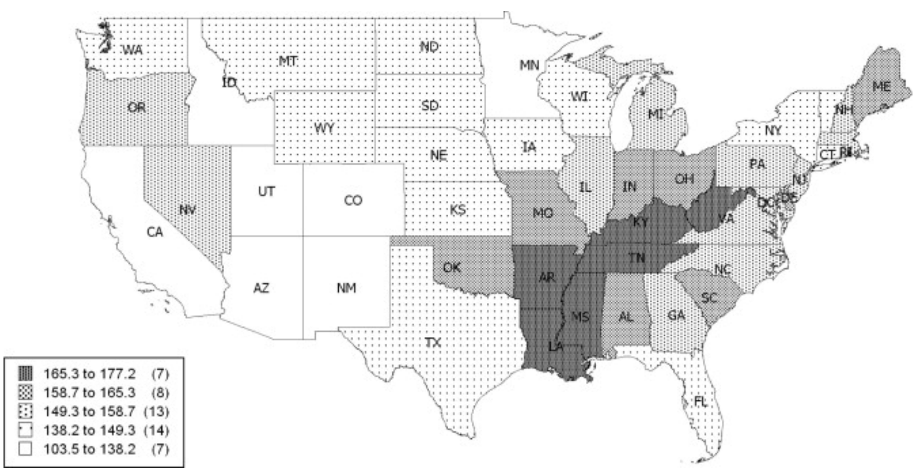
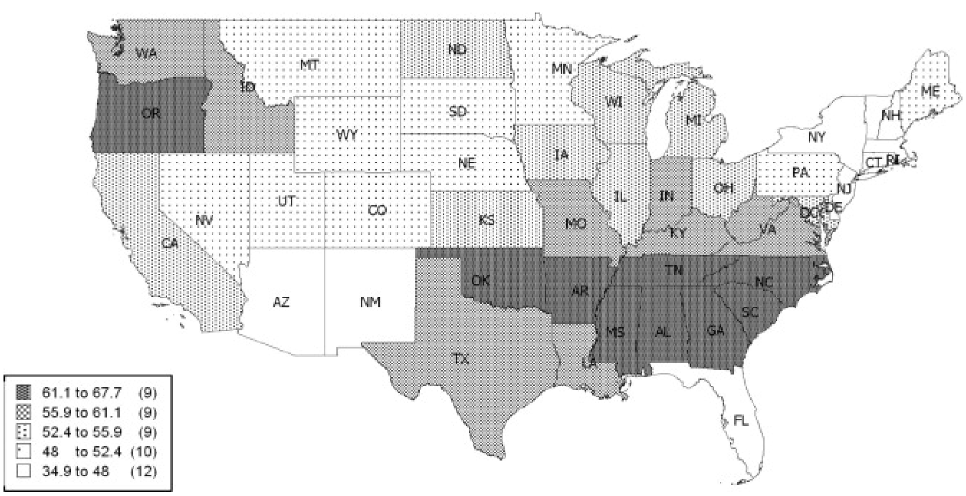


Fig. 1c. State variation in mortality rates (per 100,000 residents) for stroke.



The focus on proximity to medical professionals in explaining local health status is motivated by sharp urban–rural differences in patient outcomes.[3] Using data from the Compressed Mortality File (CMF), Table 1a reports mortality rates from heart disease, cancer, and stroke for areas with different degrees of urbanization. As shown in the table, mortality rates are significantly lower in large cities relative to small cities or remote "non-core" areas. For instance, while the mortality rate for heart disease is as low as 214 per 100,000 residents for large metropolitan areas, it rises up to 248 per 100,000 residents for "non-core" areas. Similar patterns can also be found for cancer and stroke.

Table 1a. Mortality rates (per 100,000 residents) stratified by urbanization level.

Urbanization level[a]	Heart disease	Cancer	Stroke
Large metro[b]	214.1	138.8	46.2
Medium metro[c]	219.0	147.6	52.6
Small metro[d]	225.5	152.1	56.0
Micropolitan[e]	240.4	155.1	56.7
Noncore[f]	247.6	156.9	57.6
F-test of equal mortality rates	154.0	120.2	134.6

a. National Center for Health Statistics (NCHS) has developed an urban–rural classification scheme for U.S. counties and county-equivalents. The classification scheme is based on 2003 Rural–Urban Continuum Codes and 2003 Urban Influence Codes released by Economic Research Service (ERS).
b. Large metro areas contain counties in metro area of at least 1 million residents or more.
c. Medium metro areas contain counties in metro area of 250,000–999,999 population.
d. Small metro areas contain counties in metro area of 50,000–249,999 population.
e. Micropolitan areas contain counties with urban population of 20,000–49,999 (adjacent to metro area).
f. Noncore areas contain counties with urban population of 20,000–49,999 (not adjacent to metro area) and counties with population below 20,000.

One possible explanation of this phenomenon is that larger metropolitan areas provide residents with better access to medical services. This is suggested by Table 1b, which shows that medical services, as measured by the number of doctors per capita, are highly concentrated in large cities. For instance, more than 100 cardiologists per ten million residents are present in large metropolitan areas, but only 28 are present per ten million residents in lightly developed "non-core" areas. This, together with Table 1a, further suggests that better access to medical professionals likely contributes to lower mortality rates from heart disease, cancer and stroke.

[3] In the United States, residents in rural areas generally have poorer health than those in more urbanized areas. See, for example, Eberhardt and Pamuk, 2004 and Eberhardt and Ingram, 2001, and Ricketts (1999).

Table 1b. Number of doctors per 100,000 residents stratified by urbanization level.

Urbanization level[a]	Doctors	Cardiologists	Oncologists	Neurologists
Large metro[b]	40.63	1.01	0.68	0.19
Medium metro[c]	33.93	0.84	0.50	0.18
Small metro[d]	32.43	0.84	0.53	0.19
Micropolitan[e]	12.81	0.23	0.14	0.05
Noncore[f]	20.86	0.28	0.19	0.07
F-test of equal medical capacity	85.86	110.86	84.11	65.39

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A second factor that may also help to explain lower mortality rates in large cities is that doctors may be more productive in urban areas populated with large numbers of medical professionals. This would be consistent with literature on agglomeration economies, which has provided evidence that productivity is often enhanced when companies operate in agglomerated locations.[4] The increase in productivity is thought to arise from a combination of learning from nearby workers and firms (i.e., knowledge spillovers), sharing of valuable intermediate input providers (i.e., input sharing), and/or opportunities to draw upon skilled pools of nearby labor (i.e., labor market pooling).[5]

Both explanations suggest that the impact of doctors on local patient outcomes will diminish with distance. High travel costs associated with long distances impede access to nearby medical services. Potential spillover effects that may enhance physician productivities in treating patients also tend to attenuate with distance, as suggested in the literature.[6]

The first goal of this paper is to examine the extent to which proximity to medical services affects local patient outcomes and how quickly the impact of nearby doctors attenuates with geographic distance. To this end, I examine the impact of key features of the local medical industry (e.g., the number of physicians) in two concentric rings that extend out to fifty miles from the geographic centroid of a

[4] This idea is introduced in Marshall (1920) and surveyed extensively in later literature (Quigley, 1998, Rosenthal and Strange, 2004 and Glaeser and Gottlieb, 2009).
[5] See, for instance, Glaeser and Maré (2001), and Moretti (2004) for evidence of knowledge spillovers, Holmes, 1999 and Ellison et al., 2010, and Li (2013) for evidence of input sharing, and Rosenthal and Strange (2001), and Costa and Kahn (2000) for evidence of labor market pooling.
[6] See, Rosenthal and Strange, 2003, Rosenthal and Strange, 2005, Rosenthal and Strange, 2008 and Andersson et al., 2009, and Arzaghi and Henderson (2008).

primary county.[7] As will become apparent, the medical environment in the inner ring has a notably stronger effect on nearby population health outcomes.

A second goal of the paper is to identify the possible presence of state border effects that may impede the ability of physicians to practice across state lines and thereby reduce the impact of out-of-state physicians on nearby patient outcomes. Such effects may arise because of state-specific medical licensing regulations and related policies that govern reciprocity of physician licensing across state boundaries.[8] By comparing the influence of doctors just on either side of a state border, I show that the impact of out-of-state doctors on nearby patient outcomes is smaller than that of in-state doctors. The in-state versus out-of-state difference is attributable, at least in part, to state physician licensing laws: results indicate that the lesser impact of out-of-state doctors is further reduced for states with more stringent licensing policies.

As an alternative approach, I also experiment with measures of the per capita number of physicians in a state and the number of physicians per square mile in a state as indicators of the statewide medical policy environment. These measures are motivated by reports that rural states are more proactive in trying to attract medical professionals to their locations.[9] Evidence from this alternative approach is similar to when a direct measure of the policy environment is used in the model specification.

Findings in this paper contribute to two distinct but important literatures. The first is the health economics literature. By examining the influence of state medical licensing policy and proximity to medical services on local patient outcomes, I offer a new perspective on geographic variation in health outcomes. Evidence of state border effects also points to inefficiencies in the health care system and, in this sense, yields important policy implications for state reciprocity agreements. This is particularly important in the context of rising health care expenditures.[10]

This paper also contributes to the literature on the presence of agglomeration economies in the hospital service industry. Numerous studies have provided evidence that productivity is often enhanced when companies operate in concentrated areas, but only a few of these studies have considered the health care industry.[11] This paper further enriches the literature by showing that the impact of nearby doctors is stronger in more urbanized areas. I argue that this evidence is consistent with the idea that concentrations of medical services improve doctor's productivity of treating patients and, in this sense, supports the presence of hospital productivity spillovers at agglomerated locations.[12]

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[7] As a comparison, the median of county area in the United States is 645.18 square miles, which corresponds to a circle with a 14.33-mile radius; the seventy-fifth percentile is 973.41 square miles, which corresponds to a circle with a 17.61-mile radius.

[8] Data source: State Medical Licensure Requirements and Statistics, American Medical Association. Details of this policy are discussed in Section 2.

[9] Texas, for instance, has invested in expanding residency opportunities beyond the number of medical students in Texas with the aim of attracting more out-of-state medical graduates to Texas. http://www.kevinmd.com/blog/2010/11/addressing-physician-shortage-texas.html.

[10] The rise in health care expenditures over time has been documented in Chernew et al. (2003), and Bodenheimer (2005), for instance.

[11] Baicker and Chandra, 2010 and Cohen and Morrison Paul, 2008, and Li (2013) are among the few that examine productivity gains from agglomeration in the health care industry.

[12] There are two caveats to this argument that should be noted for completeness. The first is that patients with greater health problems may seek treatment in large cities where more medical services are provided. This behavior would predict poor underlying health of the patient pool in medically concentrated areas. As a result, the estimated impact of nearby doctors in big cities could suffer from downward bias. The second caveat concerns doctors' abilities. The idea is that more talented doctors or

The empirical work to follow is based on two datasets at the county level: the Compressed Mortality File (CMF) and the Area Resource File (ARF).[13] Separate regressions are carried out for three types of diseases: heart disease, cancer, and stroke. Mortality rates associated with these diseases at the county level are obtained from the CMF and are used as proxies for health outcomes. A wide set of medical factors are extracted from the ARF and are converted into concentric ring variables and further partial concentric rings based on how the rings are intersected by state lines. This specification improves upon previous studies by including a richer palette of explanatory variables that capture the distribution of local medical services.

I obtain four key results. First, the impact of nearby medical professionals on local population health outcomes attenuates with geographic distance. For example, focusing on doctors residing inside the state, doubling the number of doctors within 25 miles reduces the mortality rate for heart disease in a county by 6.26%. This effect drops to 0.46% for doctors within the 25–50 mile distance band. Similar attenuation patterns can also be found for adjacent out-of-state doctors, as well as for other types of diseases considered in this paper. Second, in-state doctors contribute more to lowering mortality rates in the primary county than do out-of-state doctors. Focusing only on the 25-mile ring, doubling the number of nearby in-state doctors reduces the mortality rate for stroke by 8.82%, which is 3.75 higher in percentage points than the corresponding out-of-state effect. Third, the smaller impact of out-of-state doctors is further reduced if the physician licensing policy adopted by the primary state is more likely to restrict entry of out-of-state physicians. The results are robust when the statewide medical policy environment is further instrumented by per-capita number of doctors and number of doctors per square mile. Fourth, after having stratified the sample by population density, I find that the impact of both in-state doctors and out-of-state doctors are stronger in more urbanized areas. This evidence also suggests that concentrations of medical services may generate spillovers that help to improve the productivity of treating patients.

The rest of the paper is organized as follows. Section 2 discusses state-specific medical licensing policies that restrict out-of-state doctors from practicing in-state. Section 3 presents the empirical framework. Section 4 describes data and variables. Section 5 shows the empirical results, highlighting the impact of proximity to medical services, the influence of state borders, and the role of state-specific licensing policies in the imposition of barriers for out-of-state doctors to practice across state lines. Finally, Section 6 concludes.

2. State-specific medical licensing policies

Each state in the United States has its own board of medicine that licenses and regulates the practice of state physicians. Over time, various licensing boards have developed distinctive laws and regulations to ensure the health, safety and welfare of their citizens. The variation in medical regulations and a lack of universal reciprocity between states impose barriers for physicians who are currently holding an active license in one jurisdiction to practice in another. In particular, a physician who is intent on providing

doctors with higher abilities may sort into large cities (Di Addario, 2011 and Combes et al., 2008). This implies that lower mortality rates in concentrated areas could result from doctors in these areas being more capable of treating patients. This sorting behavior leads to the overestimation of the impact of availability of doctors in concentrated areas. The net impact of these two sorting incentives is unclear.

[13] Details regarding these two data files are provided in Section 4.

patient care in another state is required to go through a complicated application process in order to obtain a fully unrestricted medical license from this state.[14]

The application process is referred to as the licensure endorsement. It is generally based on documentation of successfully completing approved examinations, authentication of required core documents, and completion of any additional requirements assessing the applicant's fitness to practice medicine in the new jurisdiction.[15] The high level of standard requires efforts that are viewed as duplicative and time-consuming. For example, applicants may be asked to participate in extensive interviews or, in other instances, to retake and pass current licensing exams if it has been more than a certain number of years since the applicant passed his or her then-current exam. There can be considerable expenses in terms of time and cost associated with preparing interviews or taking exams, particularly for specialists who have limited the scope of their practice for a certain period of time.

There are sizable variations in specific requirements of endorsement policies from one state to another. Differences are shown in three main aspects: application fees for licensure endorsement, interview requirements and maximum years since passing the board examination.[16] Taking year 2007 as an example and as shown in Table 2, thirty-four states require candidates applying for licensure endorsement to show up for a comprehensive interview; eleven states stipulate that a license can only be endorsed within a certain number of years after the applicant passed his or her most recent medical board examination. Among the eleven states with maximum year constraint, Alabama, Arizona, Louisiana, Minnesota, Mississippi, North Carolina, South Carolina, and Texas require doctors to refresh their exam records if it has been more than 10 years since they initially took the exam. The other three states (Idaho, Oregon, and Maryland) have similar but slightly different requirements regarding when exam records expire for endorsement (5, 7, and 15 years, respectively). State variation in interview requirements and maximum year constraints has been generally consistent over time.

I define a state as having "stringent policies" if it restricts the entry of out-of-state physicians by adopting either the interview requirement or the maximum year constraint. I differentiate neither the different extent of the maximum year constraint nor its influence relative to that of a comprehensive interview.[17] The grouping of the licensing requirements is suggested by empirical evidence, and it also helps to pick up a stronger signal as I expect that the states that adopt either of these requirements are significantly different from the other states that have no requirement at all, in terms of their policy impacts on patient outcomes. Out of forty-nine states in the continental United States, thirty-six are classified as those with

[14] State specific medical licensing rules are alleged to protect the public from unprofessional, improper, incompetent, unlawful, fraudulent, or deceptive practice of medicine (Federation of State Medical Boards). However, the underlying driving force to its existence may also involve domestic doctors lobbying against the entry of out-of-state doctors to gain certain monopoly power. This would be consistent with the famous notion of Regulatory Capture developed by George Stigler in the Economic Theory of Regulation, which argues that political participants may use the regulatory power of the government to shape laws and regulations to advance the commercial or special concerns of an interest group.
[15] State Medical Licensure Requirements and Statistics, American Medical Association.
[16] Maximum years since passing board examination refer to the maximum number of years it takes for an out-of-state doctor's exam record to expire for endorsement application to practice in a particular state.
[17] Physician Licensure: An Update of Trends. American Medical Association. http://www.ama-assn.org/ama/pub/about-ama/our-people/member-groups-sections/young-physicians-section/advocacy-resources/physician-licensure-an-update-trends.page.

more demanding application procedures for licensure endorsement. States with stringent medical licensing policies based on this definition are highlighted in bold in Table 2.

Table 2. State-specific medical licensing policies in 2007.

State	Medical license application fee ($)	Interview requirements[a]	Maximum years since passing board exam[b]	State	Medical license application fee ($)	Interview requirements[a]	Maximum years since passing board exam[b]
Alabama	175	NO	10	Nebraska	202	NO	–
Arizona	500	YES	10	Nevada	600	YES	–
Arkansas	400	NO	–	New Hampshire	250	NO	–
California	1295	NO	–	New Jersey	225	YES	–
Colorado	425	NO	–	New Mexico	400	YES	–
Connecticut	450	NO	–	New York	735	NO	–
Delaware	301	YES	–	North Carolina	350	YES	10
Washington, DC	305	NO	–	North Dakota	200	YES	–
Florida	500	YES	–	Ohio	335	NO	–
Georgia	400	YES	–	Oklahoma	400	YES	–
Idaho	400	YES	5	Oregon	375	YES	7
Illinois	300	YES	–	Pennsylvania	20	NO	–
Indiana	250	YES	–	Rhode Island	570	YES	–
Iowa	505	YES	–	South Carolina	600	YES	10
Kansas	300	YES	–	South Dakota	200	YES	–
Kentucky	300	NO	–	Tennessee	235	YES	–
Louisiana	382	YES	10	Texas	885	YES	10
Maine	450	YES	–	Utah	200	YES	–
Maryland	822	NO	15	Vermont	600	YES	–
Massachusetts	600	YES	–	Virginia	302	YES	–
Michigan	150	NO	–	Washington	425	NO	–
Minnesota	200	YES	10	West Virginia	300	YES	–
Mississippi	600	YES	10	Wisconsin	110	YES	–
Missouri	300	YES	–	Wyoming	600	YES	–
Montana	325	YES	–				

a. Interview requirements refer to the fact that physicians are required to participate in comprehensive interviews in order to obtain another fully unrestricted license from the target state board of medicine.
b. Maximum years since passing the board exam stipulate how long it takes for an out-of-state doctor's exam record to expire for endorsement to practice in the target state.

3. Empirical framework

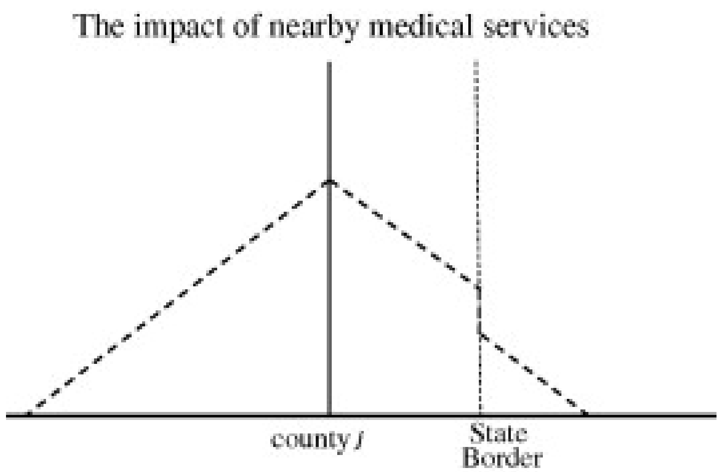
This section describes the empirical framework that motivates the analysis to follow. The modeling approach is built upon the literature on agglomeration economies, which suggests that concentrations of economic activities promote productivity. Numerous studies have provided evidence in the manufacturing sector.[18] Similar spillover effects in the health care industry have been explored in a few recent studies,

[18] To name a few, see Holmes, 1999 and Rosenthal and Strange, 2001, and Ellison et al. (2010).

which find significant localization effects.[19] That is, when the scale of the local health care industry is large, patient outcomes improve (Baicker and Chandra, 2010), and local hospitals are more likely to outsource intermediate medical services (Li, 2013) and run at a lower cost (Cohen and Morrison Paul, 2008).

The existence of agglomeration economies in the hospital service industry further suggests that the impact of concentrations of nearby doctors may attenuate rapidly across geographic space. This is suggested by studies that explore the geographic scope of agglomeration economies.[20] The idea is then captured graphically in Fig. 2, where the horizontal axis denotes locations and the vertical axis represents the magnitude of the impact of doctors located at various distances. The solid line at the center points to the location of the primary county's geographic centroid, and as illustrated by the dashed line, the impact of nearby doctors attenuates gradually with geographic distance. Given that state medical licensing policies likely restrict the entry of out-of-state doctors to practice in-state, the impact of nearby doctors is then expected to drop discretely at state boundaries and continue with its attenuation pattern afterwards.

Fig. 2. Spatial attenuation of the influence of nearby medical professionals and the impact of state borders.



To illustrate the idea of spatial attenuation and the state border effect, I begin by assuming that the county-level health production function follows a Cobb–Douglas functional form. That is,

$$\log(Outcome) = \alpha_1 \log\left(\frac{Doctors}{Beds}\right) + \alpha_2 \log\left(\frac{Nurses}{Beds}\right) + \alpha_3 \log(Beds). \quad \text{equation(3.1)}$$

[19] As established in the literature, agglomeration economies pertain to external economies of scale and are often divided into two types. Those that respect industry boundaries are often referred to as localization economies. Those that extend beyond industry boundaries and focus, instead, on the scale associated with city size are referred to as urbanization economies.

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To capture the geographic attenuation of spillover effects, all the key features of the local medical industry (e.g., number of doctors, nurses and hospital beds) are specified as concentric rings that extend out to fifty miles around the geographic centroid of the primary county.[21] To capture the difference in the extent of spillovers associated with in-state and out-of-state medical services, each concentric ring variable is further divided into the portion belonging to the same state and the portion overlapping the neighboring states. This specification helps to capture state border effects, while also allowing for and controlling for geographic attenuation.

The estimation equation is, thus, specified as follows,

$$\begin{aligned}
\log(Outcome_{is}) = \beta_0 &+ \beta_1 \log\left[\left(\frac{Doctors}{Beds}\right)_{is}^{0-25}\right] + \beta_2 \\
&\times \log\left[\left(\frac{Nurses}{Beds}\right)_{is}^{0-25}\right] + \beta_3 \log(Beds_{is}^{0-25}) + \beta_4 \\
&\times \log\left[\left(\frac{Doctors}{Beds}\right)_{i(-s)}^{0-25}\right] + \beta_5 \\
&\times \log\left[\left(\frac{Nurses}{Beds}\right)_{i(-s)}^{0-25}\right] + \beta_6 \log(Beds_{i(-s)}^{0-25}) + \beta_7 \\
&\times \log\left[\left(\frac{Doctors}{Beds}\right)_{is}^{25-50}\right] + \beta_8 \\
&\times \log\left[\left(\frac{Nurses}{Beds}\right)_{is}^{25-50}\right] + \beta_9 \log(Beds_{is}^{25-50}) \\
&+ \beta_{10} \log\left[\left(\frac{Doctors}{Beds}\right)_{i(-s)}^{25-50}\right] + \beta_{11} \\
&\times \log\left[\left(\frac{Nurses}{Beds}\right)_{i(-s)}^{25-50}\right] + \beta_{12} \log(Beds_{i(-s)}^{25-50}) \\
&+ \boldsymbol{X_{is}}\gamma + \mu_s + \varepsilon_{is}.
\end{aligned} \qquad \text{equation (3.2)}$$

In this expression, the superscript 0–25 indicates that the corresponding variables are defined for the 0–25 mile inner ring and 25–50 represents variables associated with the 25–50 mile outer ring. The subscript is stands for county i in state s, while the subscript $i(-s)$ denotes the portion of the concentric ring formed around the centroid of county i but overlapping the neighboring states. X is a vector of county-level demographic controls. μ captures the state fixed effect. This specification improves upon previous studies by including a richer palette of explanatory variables that capture the distribution of local medical services. It also produces a set of estimates that allow for direct comparison of the impact of doctors at various locations.

[21] To strike a balance between maintaining sufficient power to reliably estimate the model while also retaining as much precision as possible, I specify two distance bands: 0–25 miles and 25–50 miles. This specification is based on the observation that 25 miles are close to the maximum commuting distance for medical practitioners who must be able to travel to the hospital quickly given long work hours and periodic emergencies.

Although tempting, we cannot simply compare the estimates associated with in-state versus out-of-state doctors and attribute the lesser impact of out-of-state doctors to state licensing policies that impede the entry of out-of-state doctors to practice in-state. This is because, in some instances, patients may not be mobile across state lines, especially when their insurance network coincides with state boundaries.[22] It is likely that the impact of out-of-state doctors is smaller because it is more costly for patients to travel across the border and access out-of-state doctors.

The identification of the state border effect also relies on the assumption that the specified concentric rings are sufficient to capture the attenuation gradient. In other words, the impact of doctors associated with each distance band is assumed to be fairly homogenous. However, if the attenuation of spillover effects is more spatially continuous, the difference between □β_1 source and β_4 should be better interpreted as a mix of the attenuation and the state border effect. This is because the in-state 25-mile partial ring captures medical inputs that are distributed closer to the centroid of the primary county, while the corresponding out-of-state measure tends to capture inputs distributed further away.

These issues are addressed by further exploring exogenous variation in stringency of state medical licensing policies, as discussed in detail in Section 2. Specifically, a dummy variable indicating whether a state adopts more stringent licensing policies is interacted with out-of-state doctor measures. If state borders impede access to nearby medical services due to state-specific licensing laws, the lesser impact of out-of-state doctors will be further reduced for states with more stringent policies, which will then be captured by the coefficient of the interaction term. The identification assumption is that the adoption of more stringent licensing policies is not correlated with unobserved factors, such as restrictions on patient inter-state travel, which may also contribute to the border effect. Based on this assumption, I identify whether the state border effect exists and if so, whether it is attributable, at least in part, to state medical licensing regulations that restrict the entry of out-of-state doctors to practice in-state.

4. Data and variables

The empirical analysis is based on two primary data sources. The first is the Compressed Mortality File (CMF), from which I obtain county-level mortality rates for the three most life-threatening diseases: heart disease, cancer, and stroke.[23] Mortality rates associated with each type of disease in a county are calculated as the number of deaths from the disease between 1999 and 2007 divided by the standard population reported in 2000 decennial census.[24] Heart disease is defined by the ICD-10 codes ranging from GR113-055 to GR113-068, cancer is from GR113-020 to GR113-036, and stroke is defined by GR113-070.[25]

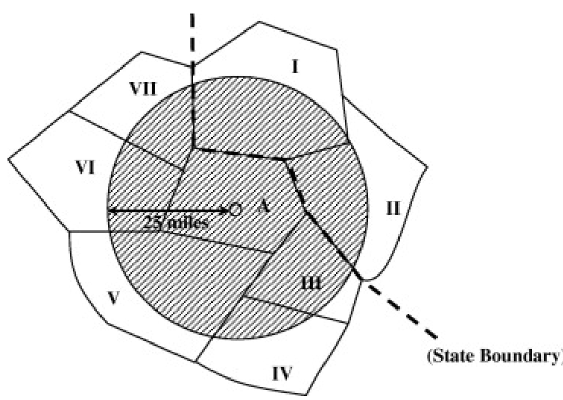
[22] For example, Medicaid insurance policies are administered by the state government and, therefore, tend to include only state licensed physicians within the insurance network.
[23] The ranking for causes of death can be found at http://www.cdc.gov/nchs/fastats/lcod.htm.
[24] Compressed Mortality File 1999–2007 can be accessed through CDC WONDER On-line Database: http://wonder.cdc.gov/cmf-icd10.htm. The data file is compiled by the Centers for Disease Control and Prevention, National Center for Health Statistics.
[25] The International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) is a coding of diseases, signs and symptoms, abnormal findings, complaints, social circumstances and external causes of injury or diseases, as classified by the World Health Organization (WHO).

The second data source is the Area Resource File (ARF), which is published by the Health Resources and Services Administration (HRSA). This file provides the numbers of doctors, nurses and hospital beds at the county level. For measures of doctor capacity, I focus particularly on the numbers of cardiologists, oncologists, and neurologists corresponding to heart disease, cancer and stroke considered in this paper. This helps to capture the impact of the most relevant medical professionals. These variables, together with the numbers of nurses and hospital beds, are further converted into partial concentric ring variables using Geographic Information System (GIS) software (MapInfo and MapBasic, in this instance).

Several steps are taken to form the concentric ring variables. First, circles of radius 25 and 50 miles are drawn around the geographic centroid of each county. Second, treating doctors (nurses, or hospital beds) within a given county as uniformly distributed throughout the area, the number of doctors (nurses, or hospital beds) contained in a given created circle is calculated by constructing a proportional sum of the measure associated with each portion of the county intersected by the given circle. Third, doctors (nurses, or hospital beds) in adjacent circles are differentiated to obtain the corresponding measure within the corresponding concentric ring. Finally, the number of doctors (nurses, or hospital beds) within a given concentric ring is further decomposed into the portion that belongs to the primary state and the portion overlapping the neighboring states.

The construction of the proportional sum measure is better presented in Fig. 3. For example, for county A, a 25-mile circle around its centroid intersects seven neighboring counties. Assuming doctors (nurses, or hospital beds) in each county are uniformly distributed throughout the area, the measure associated with the shaded portion of each county can be calculated by simply applying the area weight of the portion. In this way, the number of doctors (nurses, or hospital beds) within the circle is calculated as the sum of the doctors (nurses, or hospital beds) belonging to each shaded portion of the counties (including A itself) that overlap the circle.

Fig. 3. Number of doctors (nurses, hospital beds) within a given circle calculated using proportional sum method.



To further control for environmental factors that may also influence patient outcomes, I extract a set of standard demographic variables from the ARF. These include the percentage of uninsured population, the percentage of residents greater than 65 years old, per capita income, the percentage of people in poverty, the percentage of Black inhabitants, the percentage of Asian inhabitants, the percentage of Hispanic inhabitants, and the percentage of people with lower than high school education. In addition, in all of the models that I adopt later, state fixed effects are included to capture unobserved differences across states that may also help to explain patient outcomes, such as weather and diet.

Table 3 provides summary statistics of the variables that enter the estimation equation. As shown in the table, the average mortality rate for heart disease is 0.29%, highest among all three. The average mortality rates for cancer and stroke are 0.18% and 0.07%, respectively. These three diseases are listed as the most life threatening diseases, according to the statistics published by the Center for Disease Control and Prevention. This is also the reason that I focus on these diseases for my analysis. At the same time, means and standard deviations are also reported for medical professionals, nurses, and hospital beds in each county, as well as in partial concentric rings measured separately for the in-state portion and the out-of-state portion.[26] Summary statistics for county-level demographic attributes are provided towards the end of the table.

Table 3. Summary statistics.[a]

	Mean	Std. dev.
Mortality rate of heart disease (%)	0.29	0.09
Mortality rate of cancer (%)	0.18	0.04
Mortality rate of stroke (%)	0.07	0.03
Cardiologists	7.00	30.06
Cardiologists_0–25_in-state	21.98	74.35
Cardiologists_0–25_out-of-state	5.82	43.87
Cardiologists_25–50_in-state	42.07	76.25
Cardiologists_25–50_out-of-state	19.41	81.96
Oncologists	1.40	5.84
Oncologists_0–25_in-state	5.06	12.24
Oncologists_0–25_out-of-state	1.81	6.70
Oncologists_25–50_in-state	9.34	14.10
Oncologists_25–50_out-of-state	4.27	13.26
Neurologists	4.55	21.06
Neurologists_0–25_in-state	14.81	53.19
Neurologists_0–25_out-of-state	4.25	32.57
Neurologists_25–50_in-state	27.40	51.57
Neurologists_25–50_out-of-state	13.03	57.40
Nurses	418.30	1516.97
Nurses_0–25_in-state	1209.57	3147.51
Nurses_0–25_out-of-state	233.93	1815.55
Nurses_25–50_in-state	2559.82	3602.38
Nurses_25–50_out-of-state	976.16	3440.44
Hospital beds	311.06	1014.34
Hospital beds_0–25_in-state	896.74	2204.19
Hospital beds_0–25_out-of-state	173.84	1336.77
Hospital beds_25–50_in-state	1902.94	2442.34
Hospital beds_25–50_out-of-state	724.89	2447.77
% Black	8.84	14.57
% Asian	1.06	1.95
% Hispanic	6.21	12.05
% of uninsured	20.68	6.69
% of >65 years old	15.71	4.17
Per capita income	30347.01	8127.01
% in poverty	15.12	6.24
% of <high school	9.11	5.25
% of unemployed	4.85	1.69

a. Sample contains 3108 counties in total.

[26] Medical input variables are inflated by one in order to avoid zeros that render invalidity when constructing the key regressors in log terms.

5. Results

5.1. How quickly does the impact of doctors attenuate?

This section discusses the impact of proximity to medical services on local patient outcomes. Table 4a shows results when mortality rates are used directly as proxies for patient outcomes (log mortality rates as dependent variables). Table 4b reports estimates when patient outcomes are represented as an exponential function of the quality indicators (mortality rates as dependent variables). As a further robustness check, I also estimate the log–linear specification and report the results in Table 4c. The following discussion will focus on Table 4a, but similar results can also be found in Table 4b and Table 4c.

Table 4a. Attenuation and state border effects.[a] Dependent variable: Log Mortality Rates of various diseases (%) (*t* statistics are reported in parentheses using robust standard errors).

	Heart disease		Cancer		Stroke	
	(a)	(b)	(c)	(d)	(e)	(f)
Log (specialists per bed)_0–25_in-state	−0.0660***	−0.0626***	−0.0533***	−0.0524***	−0.0882***	−0.0892***
	(−8.11)	(−7.32)	(−5.73)	(−5.76)	(−8.25)	(−7.46)
Log (specialists per bed)_0–25_out-of-state	−0.0110	−0.0056	−0.0094	−0.0040	−0.0507***	−0.0396***
	(−1.42)	(−0.71)	(−1.29)	(−0.54)	(−4.79)	(−3.67)
Log (specialists per bed)_25–50_in-state	–	−0.0046	–	−0.0004	–	0.0065
	–	(−0.47)	–	(−0.06)	–	(0.51)
Log (specialists per bed)_25–50_out-of-state	–	−0.0029	–	−0.0053	–	−0.0214***
	–	(−0.50)	–	(−1.05)	–	(−2.65)
Log (nurses per bed)_0–25_in-state	−0.0519***	−0.0402**	−0.0155	−0.0157	−0.0167	−0.0042
	(−3.55)	(−2.58)	(−1.18)	(−1.25)	(−0.87)	(−0.21)
Log (nurses per bed)_0–25_out-of-state	−0.0337**	−0.0245	−0.0065	−0.0057	−0.0227	−0.0150
	(−2.41)	(−1.64)	(−0.64)	(−0.52)	(−1.08)	(−0.65)
Log (nurses per bed)_25–50_in-state	–	−0.0306	–	0.0006	–	−0.0469
	–	(−1.41)	–	(0.03)	–	(−1.54)
Log (nurses per bed)_25–50_out-of-state	–	−0.0213	–	0.0015	–	0.0083
	–	(−1.34)	–	(0.11)	–	(0.37)
Log (hospital beds)_0–25_in-state	−0.0051	−0.0025	−0.0171***	−0.0155***	−0.0168**	−0.0178**
	(−1.05)	(−0.46)	(−3.62)	(−3.13)	(−2.39)	(−2.31)
Log (hospital beds)_0–25_out-of-state	−0.0051	−0.0061	−0.0064	−0.0042	−0.0441***	−0.0347***
	(−0.86)	(−1.03)	(−0.99)	(−0.65)	(−5.22)	(−4.05)
Log (hospital beds)_25–50_in-state	–	−0.0020	–	−0.0025	–	0.0053
	–	(−0.36)	–	(−0.56)	–	(0.71)
Log (hospital beds)_25–50_out-of-state	–	0.0044	–	−0.0012	–	−0.0134**
	–	(1.03)	–	(−0.27)	–	(−2.08)
State fixed effects	49	49	49	49	49	49
Observations	3108	3108	3108	3108	3105	3105
R-squared	0.705	0.707	0.721	0.722	0.518	0.520

$^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

a. Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of >65 years old, per capita income, % in poverty, % of <high school, and unemployment rate (%).

Table 4b. Attenuation and state border effects (linear–log model).a Dependent variable: Mortality Rates of various diseases (%) (t statistics are reported in parentheses using robust standard errors).

	Heart disease		Cancer		Stroke	
	(a)	(b)	(c)	(d)	(e)	(f)
Log (specialists per bed)_0–25_in-state	−0.0174***	−0.0150***	−0.0083***	−0.0077***	−0.0059***	−0.0059***
	(−8.57)	(−6.92)	(−7.31)	(−6.60)	(−9.27)	(−8.02)
Log (specialists per bed)_0–25_out-of-state	−0.0042**	−0.0028	−0.0020*	−0.0013	−0.0029***	−0.0020***
	(−2.15)	(−1.39)	(−1.88)	(−1.13)	(−4.63)	(−3.15)
Log (specialists per bed)_25–50_in-state	–	−0.0061**	–	−0.0014	–	0.0002
	–	(−2.35)	–	(−1.28)	–	(0.25)
Log (specialists per bed)_25–50_out-of-state	–	−0.0011	–	−0.0010	–	−0.0015***
	–	(−0.70)	–	(−1.26)	–	(−2.70)
Log (nurses per bed)_0–25_in-state	−0.0118***	−0.0108***	−0.0023	−0.0029	−0.0009	0.0002
	(−3.04)	(−2.70)	(−1.25)	(−1.55)	(−0.74)	(0.13)
Log (nurses per bed)_0–25_out-of-state	−0.0108***	−0.0077*	−0.0011	−0.0012	−0.0028*	−0.0019
	(−2.72)	(−1.78)	(−0.66)	(−0.64)	(−1.76)	(−1.05)
Log (nurses per bed)_25–50_in-state	–	0.0000	–	0.0019	–	−0.0039*
	–	(0.00)	–	(0.76)	–	(−1.92)
Log (nurses per bed)_25–50_out-of-state	–	−0.0071	–	0.0007	–	−0.0004
	–	(−1.59)	–	(0.34)	–	(−0.27)
Log (hospital beds)_0–25_in-state	−0.0030***	−0.0021	−0.0031***	−0.0027***	−0.0018***	−0.0019***
	(−2.68)	(−1.63)	(−4.70)	(−3.81)	(−4.32)	(−4.14)
Log (hospital beds)_0–25_out-of-state	−0.0022	−0.0023	−0.0015	−0.0011	−0.0024***	−0.0018***
	(−1.52)	(−1.52)	(−1.62)	(−1.17)	(−5.12)	(−3.58)
Log (hospital beds)_25–50_in-state	–	−0.0005	–	−0.0007	–	0.0006
	–	(−0.34)	–	(−1.08)	–	(1.26)
Log (hospital beds)_25–50_out-of-state	–	0.0007	–	−0.0005	–	−0.0009*
	–	(0.62)	–	(−0.70)	–	(−1.93)
State fixed effects	49	49	49	49	49	49
Observations	3108	3108	3108	3108	3105	3105
R-squared	0.684	0.687	0.743	0.744	0.478	0.481

$^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

a. Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of >65 years old, per capita income, % in poverty, % of <high school, and unemployment rate (%).

In Table 4a, estimates are reported separately for heart disease, cancer, and stroke. For each type of disease, I first run OLS regressions with only 25-mile ring controls. I then add 25–50 mile rings to capture possible attenuation effects. The estimated coefficient associated with the closer distance band is both higher in magnitude and more significant. Focusing only on the in-state portion and taking heart disease as an example, the estimated elasticity of cardiologists within 25 miles is 0.0626 (the absolute value of the estimated coefficient in 1st row, column (b)). This effect is much stronger than cardiologists present in the 25–50 mile concentric ring (0.0046 in 3rd row, column (b)). For other types of diseases, the estimated elasticities of the 25-mile ring measures are generally of higher magnitude than those corresponding to the 25–50 mile concentric rings. Similar patterns can also be found for other medical inputs.[27]

[27] The impact of out-of-state hospital beds on mortality rates from stroke is stronger than the corresponding in-state effect. This may or may not have something to do with the fact that people suffering from stroke require urgent treatment.

Table 4c. Attenuation and state border effects (log–linear model).[a] Dependent variable: Log Mortality Rates of various diseases (%) (t statistics are reported in parentheses using robust standard errors).

	Heart disease		Cancer		Stroke	
	(a)	(b)	(c)	(d)	(e)	(f)
Specialists per bed_0–25_in-state	−1.6288***	−1.5189***	−3.4461***	−3.5769***	−2.4649***	−2.6840***
	(−2.89)	(−2.64)	(−3.29)	(−3.22)	(−3.11)	(−3.03)
Specialists per bed_0–25_out-of-state	−0.0250***	−0.0049	−0.0105*	−0.0019	−0.0073	0.0012
	(−2.99)	(−0.51)	(−1.72)	(−0.29)	(−0.61)	(0.09)
Specialists per bed_25–50_in-state	–	−0.1959	–	−2.0184	–	−1.6412*
	–	(−0.29)	–	(−1.15)	–	(−1.80)
Specialists per bed_25–50_out-of-state	–	−0.0371***	–	−0.0171**	–	−0.0298**
	–	(−3.54)	–	(−2.10)	–	(−2.07)
Nurses per bed_0–25_in-state	−0.0866***	−0.0733***	−0.0276**	−0.0263**	−0.0489**	−0.0351
	(−5.46)	(−4.29)	(−2.21)	(−2.05)	(−2.40)	(−1.60)
Nurses per bed_0–25_out-of-state	−0.0422***	−0.0376***	−0.0091	−0.0099	−0.0485***	−0.0381*
	(−3.39)	(−2.78)	(−0.97)	(−1.00)	(−2.63)	(−1.96)
Nurses per bed_25–50_in-state	–	−0.0444**	–	−0.0114	–	−0.0560**
	–	(−2.14)	–	(−0.75)	–	(−2.00)
Nurses per bed_25–50_out-of-state	–	−0.0058	–	0.0070	–	−0.0048
	–	(−0.43)	–	(0.70)	–	(−0.27)
Hospital beds_0–25_in-state	−5.09e−06**	−5.62e−06**	−3.16e−06*	−2.18e−06	−1.68e−05***	−1.39e−05***
	(−2.21)	(−2.38)	(−2.01)	(−1.34)	(−6.32)	(−5.20)
Hospital beds_0–25_out-of-state	1.47e−06	1.30e−06	1.33e−06	7.61e−07	−8.23e−08	−1.77e−06
	(0.65)	(0.58)	(0.81)	(0.50)	(0.03)	(−0.62)
Hospital beds_25–50_in-state	–	−1.70e−06	–	−2.65e−06	–	−4.85e−06*
	–	(−0.74)	–	(−1.83)	–	(−1.69)
Hospital beds_25–50_out-of-state	–	−1.16e−06	–	−1.90e−06	–	−9.03e−06***
	–	(−0.58)	–	(−1.42)	–	(−3.57)
State fixed effects	49	49	49	49	49	49
Observations	3108	3108	3108	3108	3105	3105
R-squared	0.696	0.698	0.714	0.715	0.506	0.510

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

a. Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of >65 years old, per capita income, % in poverty, % of <high school, and unemployment rate (%).

Generally speaking, evidence reported in Table 4a, Table 4b and Table 4c is consistent with spatial attenuation of the influence of medical services on nearby patient outcomes. Medical professionals within 25 miles have a notably higher effect on the primary county's health status, whereas the effects of doctors and nurses beyond this range are not significant in terms of reducing the primary county's mortality rates for heart disease, cancer, and stroke.

5.2. Is there a state border effect?

In addition to spatial attenuation, estimates reported in Table 4a, Table 4b and Table 4c also help to explain whether state borders impede access to nearby medical services. As shown in these tables, the in-state doctor effect is generally of higher magnitude and more significant than the corresponding out-of-state doctor effect. This is especially so when focusing on the 25-mile distance band. For instance, in Table 4a, the estimated elasticities associated with in-state and out-of-state cardiologists within 25 miles are 0.0660 and 0.0110, respectively (1st and 2nd rows, column (a)). The magnitude of the estimated coefficient for the in-state portion is 0.0550 higher than that of the out-of-state portion. This pattern is generally consistent for all three types of diseases and is robust to how the health outcome is measured, although in some instances the out-of-state elasticities tend to be imprecisely estimated.[28]

Although the evidence for in-state versus out-of-state difference is generally consistent and robust, one should still be cautious with interpretation of the state border effect. As discussed earlier, to argue that the lesser impact of out-of-state doctors is due to the influence of state borders or state-specific licensing laws, I implicitly assume that the attenuation gradient is properly controlled for and potential patient immobility across state lines will not contribute to the border effect. If, however, the attenuation pattern tends to be more spatially continuous and patients tend to be restricted to access in-state doctors alone due to the writing of their insurance policy, the in-state versus out-of-state difference should be better treated as a mix of both the attenuation effect and patient immobility across state lines.

In order to identify the state border effect in a more convincing way, I exploit exogenous variation in stringency of state-specific medical licensing policies to examine whether the lesser impact of out-of-state doctors is further reduced for states with more stringent policies. This is accomplished by interacting a dummy variable for states adopting stricter licensing policies with controls for out-of-state doctors within 25 miles.[29] As shown in column (a), column (b), and column (c) of Table 5, the estimated coefficients associated with the interaction terms for three types of diseases are generally positive and significant.[30] This suggests that patient outcomes in states with stricter licensing policies are less likely to be affected by the presence of nearby out-of-state doctors. The estimates reported here also help to generate a sense of how strong these policies are in deterring out-of-state doctors in treating in-state patients. Specifically, taking heart disease as an example, doubling the number of in-state cardiologists within 25 miles reduces mortality rates from heart disease by 6.56%. The corresponding impact of out-of-state cardiologists drops to 2.46%. Moreover, for states with more stringent licensing policies, doubling the number of out-of-state cardiologists only helps to reduce heart disease mortality rates of the primary county by 0.98% (−2.46 + 1.48). These findings provide further evidence for the existence of state border effect and how state licensing policies contribute to this effect.

[28] The evidence for neurologists within 25–50 miles distance band seems counter-intuitive. For now, I do not have a good explanation of it.

[29] Only 25-mile rings are included in this specification since the effects of various medical inputs beyond this range are generally insignificant.

[30] Results from alternative specifications are reported in Table A3 and Table A4. Estimates are robust to various model specifications.

Table 5. The effect of state-specific medical licensing policies.[a] Dependent variable: Log Mortality Rate of various diseases (%) (*t* statistics are reported in parentheses using robust standard errors).

	Licensing policy dummy			Doctors per capita dummy			Doctors per square mile dummy		
	Heart disease	Cancer	Stroke	Heart disease	Cancer	Stroke	Heart disease	Cancer	Stroke
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
Log (specialists per bed)_0–25_in-state	−0.0656***	−0.0533***	−0.0881***	−0.0660***	−0.0532***	−0.0882***	−0.0666***	−0.0543***	−0.0899***
	(−8.06)	(−5.73)	(−8.24)	(−8.11)	(−5.73)	(−8.25)	(−8.17)	(−5.81)	(−8.41)
Log (specialists per bed)_0–25_out-of-state	−0.0246***	−0.0150*	−0.0567***	−0.0125	−0.0107	−0.0525***	−0.0135*	−0.0109	−0.0565***
	(−2.73)	(−1.84)	(−4.92)	(−1.59)	(−1.47)	(−4.89)	(−1.70)	(−1.49)	(−5.29)
Log (specialists per bed)_0–25_out-of-state × stringent reciprocity rules	0.0148***	0.0058*	0.0068	–	–	–	–	–	–
	(2.89)	(1.79)	(1.07)	–	–	–	–	–	–
Log (specialists per bed)_0–25_out-of-state × (doctors per capita > median)	–	–	–	0.0060	0.0084***	0.0091*	–	–	–
	–	–	–	(1.46)	(3.49)	(1.73)	–	–	–
Log (specialists per bed)_0–25_out-of-state × (doctors per square mile > median)	–	–	–	–	–	–	0.0090**	0.0106***	0.0187***
	–	–	–	–	–	–	(2.08)	(4.06)	(3.24)
Log (nurses per bed)_0–25_in-state	−0.0517***	−0.0154	−0.0165	−0.0516***	−0.0151	−0.0162	−0.0529***	−0.0171	−0.0189
	(−3.54)	(−1.17)	(−0.86)	(−3.53)	(−1.15)	(−0.85)	(−3.62)	(−1.30)	(−0.99)
Log (nurses per bed)_0–25_out-of-state	−0.0346**	−0.0071	−0.0234	−0.0323**	−0.0040	−0.0208	−0.0312**	−0.0024	−0.0165
	(−2.49)	(−0.69)	(−1.10)	(−2.30)	(−0.39)	(−0.98)	(−2.23)	(−0.23)	(−0.78)
Log (hospital beds)_0–25_in-state	−0.0052	−0.0172***	−0.0169**	−0.0051	−0.0169***	−0.0167**	−0.0052	−0.0176***	−0.0173**
	(−1.07)	(−3.64)	(−2.40)	(−1.04)	(−3.60)	(−2.38)	(−1.08)	(−3.73)	(−2.47)
Log (hospital beds)_0–25_out-of-state	−0.0066	−0.0073	−0.0447***	−0.0042	−0.0041	−0.0423***	−0.0030	−0.0019	−0.0397***
	(−1.12)	(−1.13)	(−5.30)	(−0.70)	(−0.64)	(−5.03)	(−0.50)	(−0.30)	(−4.62)
State fixed effects	49	49	49	49	49	49	49	49	49
Observations	3108	3108	3105	3108	3108	3105	3108	3108	3105
R-squared	0.705	0.722	0.518	0.705	0.722	0.519	0.705	0.722	0.520

$^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

a. Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of >65 years old, per capita income, % in poverty, % of <high school, and unemployment rate (%).

5.3. Robustness checks

As additional robustness checks, I also experiment with two other ways of instrumenting the stringency of the state medical policy environment. The first is to use state-wide per capita number of doctors, and the second is to use the number of doctors per square mile. These instruments are motivated by broad recognition that there are fewer doctors in rural areas and that rural areas tend to be more proactive in trying to attract physicians. In this sense, it is the rural nature of the state, as possibly captured by per capita number of doctors and the number of doctors per square mile, that drives related policies that govern reciprocity of physician licensing across state lines.

Table 6 and Table 7 show state rankings by per capita number of doctors and the number of doctors per square mile. States with doctor capacity above the median are classified as being more likely to restrict entry of out-of-state physicians, whereas the rest are assumed to be less likely to do so. A similar dummy variable for policy stringency is created based on the above description and is interacted with the out-of-state measure of medical professionals. Corresponding results are reported from column (d) to column (i) in Table 5. It is shown that the estimated coefficient for the interaction term also tends to be positive and significant. This evidence suggests that the impact of out-of-state doctors on nearby patient outcomes is higher for rural states that are more proactive in attracting out-of-state physicians. This pattern is observed for all three types of diseases considered in this paper. These findings provide further evidence for the existence of state border effects that are likely attributable to state policies.

Table 6. Rank of states by number of doctors per capita (per 100,000 residents).

Rank	State	Doctors per capita	Rank	State	Doctors per capita
1	Washington, DC	81	26	Delaware	28
2	Massachusetts	51	27	Nebraska	27
3	New York	44	28	North Dakota	27
4	Maryland	43	29	New Mexico	27
5	Vermont	43	30	Missouri	27
6	Connecticut	41	31	Montana	26
7	Rhode Island	41	32	Kentucky	25
8	New Jersey	35	33	West Virginia	25
9	Pennsylvania	34	34	South Carolina	25
10	Minnesota	32	35	Kansas	25
11	Maine	32	36	Indiana	24
12	New Hampshire	31	37	South Dakota	24
13	Oregon	31	38	Arizona	24
14	Illinois	31	39	Alabama	24
15	Washington	30	40	Georgia	23
16	California	30	41	Utah	23
17	Virginia	30	42	Texas	23
18	Ohio	30	43	Arkansas	22
19	Florida	29	44	Iowa	21
20	Louisiana	29	45	Wyoming	21
21	Colorado	29	46	Nevada	21
22	Wisconsin	29	47	Mississippi	20
23	Tennessee	29	48	Oklahoma	19
24	North Carolina	28	49	Idaho	19
25	Michigan	28			

Another robustness check pertains to alternative distance bands that capture the distribution of local medical services. Previous specifications adopt 25 miles as the cutoff distance based on the observation that 25 miles roughly correspond to the maximum commuting distance for doctors. To examine how sensitive the results are to various radiuses, I also experiment with using 20 miles and 30 miles as the cutoff distance in constructing concentric ring measures. I find robust results in both cases. Estimates are reported in Table 8.

Table 7. Rank of states by number of doctors per square mile (SM).

Rank	State	Doctors per SM	Rank	State	Doctors per SM
1	Washington, DC	69.7688	26	Louisiana	0.2413
2	New Jersey	3.4629	27	Missouri	0.2241
3	Massachusetts	3.1080	28	Alabama	0.2091
4	Rhode Island	2.7993	29	Texas	0.2037
5	Connecticut	2.6195	30	Minnesota	0.1933
6	Maryland	1.9689	31	West Virginia	0.1901
7	New York	1.5432	32	Colorado	0.1338
8	Delaware	0.9641	33	Arizona	0.1329
9	Pennsylvania	0.9232	34	Arkansas	0.1190
10	Florida	0.8105	35	Oregon	0.1189
11	Ohio	0.7547	36	Maine	0.1188
12	Illinois	0.6792	37	Mississippi	0.1181
13	California	0.6729	38	Iowa	0.1140
14	Virginia	0.5342	39	Oklahoma	0.0998
15	North Carolina	0.4697	40	Kansas	0.0848
16	New Hampshire	0.4413	41	Utah	0.0720
17	Tennessee	0.4191	42	Nebraska	0.0626
18	Indiana	0.4174	43	Nevada	0.0488
19	Georgia	0.3735	44	New Mexico	0.0432
20	South Carolina	0.3497	45	Idaho	0.0343
21	Michigan	0.2892	46	South Dakota	0.0247
22	Vermont	0.2781	47	North Dakota	0.0242
23	Washington	0.2751	48	Montana	0.0169
24	Kentucky	0.2672	49	Wyoming	0.0115
25	Wisconsin	0.2466			

As shown in Table 8, the evidence of state border effects remains strong. For each type of disease, the estimated coefficients associated with in-state doctor measures are generally of higher magnitude and more significant than that of the out-of-state doctor measures within the same distance band. Moreover, the coefficient associated with the interaction term tends to be positive and significantly identified, which is consistent with findings obtained using 25-mile distance bands adopted earlier. The evidence from these alternative distance band setups, therefore, suggests that the main findings in this paper are fairly robust to how the concentric ring measures are specified.

The final set of robustness checks stratifies the sample by population density. Specifically, I estimate the model separately for the top 900 counties that are most densely populated as well as for the rest of the counties that are in low-density areas. This is based on the idea that agglomeration economies tend to be more pronounced when there are more doctors available in highly concentrated areas. The results reported in Table 9 confirm this expectation. Specifically, focusing on the mortality rates from cancer for instance, the estimated elasticity associated with nearby in-state oncologists in more densely populated areas is 0.1123 (first row, column (b)), whereas the corresponding elasticity associated with oncologists in less densely populated areas reduces to 0.0170 (first row, column (e)). Similar patterns can also be found for heart disease and stroke. This evidence further suggests that there may exist spillovers from spatial concentration of medical services that enhance the productivity of treating patients.

Table 8. The effect of state-specific medical policies.[a] Dependent variable: Log Mortality Rate of various diseases (%) (*t* statistics are reported in parentheses using robust standard errors).

	Use 20 miles as cutoff instead of 25 miles			Use 30 miles as cutoff instead of 25 miles		
	Heart disease	Cancer	Stroke	Heart disease	Cancer	Stroke
	(a)	(b)	(c)	(d)	(e)	(f)
Log (specialists per bed)_0-cutoff_in-state	−0.0681***	−0.0549***	−0.0991***	−0.0611***	−0.0508***	−0.0831***
	(−8.65)	(−5.92)	(−9.45)	(−7.32)	(−5.51)	(−7.68)
Log (specialists per bed)_0-cutoff_out-of-state	−0.0181*	−0.0069	−0.0398***	−0.0270***	−0.0177**	−0.0563***
	(−1.83)	(−0.73)	(−3.00)	(−3.32)	(−2.45)	(−5.42)
Log (specialists per bed)_0-cutoff_out-of-state ×						
Stringent reciprocity rules	0.0170***	0.0046	−0.0013	0.0165***	0.0059**	0.0023
	(3.22)	(1.43)	(−0.19)	(3.51)	(2.01)	(0.40)
Log (nurses per bed)_0-cutoff_in-state	−0.0491***	−0.0194*	−0.0114	−0.0552***	−0.0113	−0.0159
	(−3.81)	(−1.79)	(−0.68)	(−3.36)	(−0.74)	(−0.74)
Log (nurses per bed)_0-cutoff_out-of-state	−0.0409***	−0.0112	−0.0328	−0.0282**	−0.0007	−0.0017
	(−2.95)	(−1.14)	(−1.46)	(−2.01)	(−0.06)	(−0.08)
Log (hospital beds)_0-cutoff _in-state	−0.0089*	−0.0211***	−0.0262***	−0.0007	−0.0124***	−0.0106
	(−1.82)	(−4.03)	(−3.63)	(−0.14)	(−2.74)	(−1.48)
Log (hospital beds)_0-cutoff_out-of-state	0.0002	−0.0011	−0.0379***	−0.0073	−0.0095*	−0.0460***
	(0.03)	(−0.14)	(−3.73)	(−1.43)	(−1.67)	(−6.20)
State fixed effects	49	49	49	49	49	49
Observations	3108	3108	3105	3108	3108	3105
R-squared	0.707	0.723	0.521	0.703	0.721	0.516

* $p < 0.1$. ** $p < 0.05$. *** $p < 0.01$.

a. Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of >65 years old, per capita income, % in poverty, % of <high school, and unemployment rate (%).

Table 9. The effect of state-specific medical policies.[a] Dependent variable: Log Mortality Rate of various diseases (%) (t statistics are reported in parentheses using robust standard errors).

	High population density areas			Low population density areas		
	Heart disease	Cancer	Stroke	Heart disease	Cancer	Stroke
	(a)	(b)	(c)	(d)	(e)	(f)
Log (specialists per bed)_0–25_in-state	−0.0655***	−0.1123***	−0.0991**	−0.0487***	−0.0170***	−0.0420***
	(−2.76)	(−3.02)	(−2.52)	(−5.34)	(−2.63)	(−3.46)
Log (specialists per bed)_0–25_out-of-state	−0.0585	−0.0650	−0.0335	−0.0175**	−0.0017	−0.0336***
	(−1.50)	(−1.00)	(−0.42)	(−2.02)	(−0.22)	(−2.94)
Log (specialists per bed)_0–25_out-of-state × stringent reciprocity rules	0.0236	0.0288**	0.0018	0.0131***	0.0020	0.0023
	(1.59)	(2.02)	(0.09)	(2.75)	(0.82)	(0.39)
Log (nurses per bed)_0–25_in-state	−0.0587**	−0.0043	−0.0098	−0.0499***	−0.0346***	−0.0602**
	(−2.57)	(−0.19)	(−0.32)	(−2.65)	(−2.70)	(−2.45)
Log (nurses per bed)_0–25_out-of-state	−0.0199	0.0001	0.0132	−0.0263*	−0.0058	−0.0254
	(−0.64)	(0.00)	(0.26)	(−1.78)	(−0.63)	(−1.22)
Log (hospital beds)_0–25_in-state	−0.0010	−0.0603**	−0.0124	−0.0085	−0.0099**	−0.0264***
	(−0.06)	(−2.23)	(−0.39)	(−1.52)	(−2.09)	(−3.59)
Log (hospital beds)_0–25_out-of-state	−0.0218	−0.0332	−0.0016	−0.0041	0.0013	−0.0325***
	(−0.69)	(−0.52)	(−0.02)	(−0.70)	(0.20)	(−3.85)
State fixed effects	49	49	49	49	49	49
Observations	900	900	900	2208	2208	2205
R-squared	0.705	0.722	0.518	0.705	0.722	0.519

*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

a. Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of >65 years old, per capita income, % in poverty, % of <high school, and unemployment rate (%).

6. Conclusion

This paper provides evidence that spatial concentration of medical services improves local population health outcomes and the influence tends to attenuate with geographic distance. Estimates suggest that a 10% increase in the number of doctors that are present within 25 miles of the primary county reduces mortality rates from heart disease, cancer, and stroke by 0.660%, 0.533%, and 0.882%, respectively. The effect of doctors further away tends to be statistically insignificant and smaller in magnitude. The impact of nearby doctors is found to be stronger in areas where medical services are more concentrated.

The second result is that state-specific licensing policies that restrict out-of-state doctors from practicing across state boundaries impede patient access to nearby out-of-state physicians and, thereby, reduce the health outcome of residents living in border areas. The smaller impact of out-of-state doctors is further reduced when the primary state adopts more stringent physician licensing policies. Two other ways of capturing the border effect, by drawing on state variation in per capita number of doctors and number of doctors per square mile, yield consistent results. The latter is based on the argument that rural states that face shortages of medical professionals tend to design policies in a way that is more attractive to out-of-state doctors.

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Appendix

Table A1: The Effect of State-Specific Medical Policies (Linear-Log Model) [a]

Dependent Variable: <u>Mortality Rate</u> of Various Diseases (%) (*t* statistics are reported in parentheses using robust standard errors)

	Licensing Policy Dummy			Doctors per Capita Dummy			Doctors per Square Mile Dummy		
	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
Log (# of specialists per bed)_0-25_in-state	-0.0173***	-0.0083***	-0.0059***	-0.0174***	-0.0083***	-0.0059***	-0.0176***	-0.0085***	-0.0060***
	(-8.52)	(-7.31)	(-9.26)	(-8.57)	(-7.31)	(-9.26)	(-8.61)	(-7.41)	(-9.38)
Log (# of specialists per bed)_0-25_out-of-state	-0.0083***	-0.0028**	-0.0034***	-0.0046**	-0.0022**	-0.0030***	-0.0048**	-0.0022**	-0.0032***
	(-3.47)	(-2.41)	(-4.95)	(-2.28)	(-2.07)	(-4.70)	(-2.35)	(-2.05)	(-4.94)
Log (# of specialists per bed)_0-25_out-of-state × Stringent Reciprocity Rules	0.0045***	0.0009*	0.0007	-	-	-	-	-	-
	(2.93)	(1.74)	(1.48)	-	-	-	-	-	-
Log (# of specialists per bed)_0-25_out-of-state × (Doctors per capita > median)	-	-	-	0.0015	0.0012***	0.0005	-	-	-
	-	-	-	(1.25)	(3.09)	(1.31)	-	-	-
Log (# of specialists per bed)_0-25_out-of-state × (Doctors per square mile > median)	-	-	-	-	-	-	0.0020	0.0014***	0.0011**
	-	-	-	-	-	-	(1.57)	(3.28)	(2.58)
Log (# of nurses per bed)_0-25_in-state	-0.0118***	-0.0023	-0.0009	-0.0117***	-0.0023	-0.0009	-0.0120***	-0.0026	-0.0011
	(-3.03)	(-1.25)	(-0.72)	(-3.01)	(-1.22)	(-0.72)	(-3.09)	(-1.36)	(-0.84)
Log (# of nurses per bed)_0-25_out-of-state	-0.0110***	-0.0012	-0.0029*	-0.0104***	-0.0008	-0.0027*	-0.0102***	-0.0006	-0.0025
	(-2.80)	(-0.71)	(-1.79)	(-2.63)	(-0.45)	(-1.69)	(-2.58)	(-0.36)	(-1.54)
Log (# of hospital beds)_0-25_in-state	-0.0030***	-0.0031***	-0.0018***	-0.0030***	-0.0031***	-0.0018***	-0.0030***	-0.0032***	-0.0018***
	(-2.71)	(-4.72)	(-4.34)	(-2.68)	(-4.67)	(-4.31)	(-2.71)	(-4.80)	(-4.39)
Log (# of hospital beds)_0-25_out-of-state	-0.0026*	-0.0017*	-0.0025***	-0.0020	-0.0012	-0.0023***	-0.0017	-0.0009	-0.0022***
	(-1.85)	(-1.78)	(-5.27)	(-1.37)	(-1.28)	(-4.89)	(-1.18)	(-1.01)	(-4.50)
State Fixed Effects	49	49	49	49	49	49	49	49	49

Observations	3,108	3,108	3,105	3,108	3,108	3,105	3,108	3,108	3,105
R-squared	0.685	0.743	0.478	0.684	0.744	0.478	0.684	0.744	0.479

[a] Specialists refer to cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. *** p<0.01, ** p<0.05, * p<0.1

Table A2: The Effect of State-Specific Medical Policies (Log-Linear Model) [a]

Dependent Variable: Log Mortality Rate of Various Diseases (%) (*t* statistics are reported in parentheses using robust standard errors)

	Licensing Policy Dummy			Doctors per Capita Dummy			Doctors per Square Mile Dummy		
	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke
	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)	(i)
Specialists per bed_0-25_in-state	-1.6207***	-3.3737***	-2.4554***	-1.6272***	-3.4623***	-2.4810***	-1.6489***	-3.5300***	-2.5447***
	(-2.88)	(-3.19)	(-3.09)	(-2.89)	(-3.30)	(-3.12)	(-2.87)	(-3.38)	(-3.16)
Specialists per bed_0-25_out-of-state	-0.0619***	-0.0332**	-0.0175	-0.0353***	-0.0211***	-0.0228	-0.0443***	-0.0285***	-0.0421**
	(-3.55)	(-2.26)	(-0.76)	(-3.35)	(-2.67)	(-1.44)	(-3.60)	(-3.01)	(-2.41)
Specialists per bed_0-25_out-of-state × Stringent Reciprocity Rules	0.0484**	0.0297*	0.0134	-	-	-	-	-	-
	(2.51)	(1.88)	(0.52)	-	-	-	-	-	-
Specialists per bed_0-25_out-of-state × (Doctors per capita > median)	-	-	-	0.0257	0.0262**	0.0387*	-	-	-
	-	-	-	(1.59)	(2.23)	(1.78)	-	-	-
Specialists per bed_0-25_out-of-state × (Doctors per square mile > median)	-	-	-	-	-	-	0.0384**	0.0355***	0.0692***
	-	-	-	-	-	-	(2.35)	(3.03)	(3.03)
Nurses per bed_0-25_in-state	-0.0864***	-0.0277**	-0.0490**	-0.0863***	-0.0271**	-0.0482**	-0.0883***	-0.0291**	-0.0421**
	(-5.42)	(-2.21)	(-2.40)	(-5.46)	(-2.18)	(-2.37)	(-5.57)	(-2.34)	(-2.41)
Nurses per bed_0-25_out-of-state	-0.0439***	-0.0100	-0.0490***	-0.0397***	-0.0064	-0.0446**	-0.0378***	-0.0049	0.0692***
	(-3.51)	(-1.06)	(-2.65)	(-3.17)	(-0.68)	(-2.42)	(-3.03)	(-0.53)	(3.03)
Hospital beds_0-25_in-state	-4.56e-06**	-3.49e-06**	-1.70e-05***	-5.28e-06**	-2.96e-06*	-1.65e-05***	-5.29e-06**	-2.98e-06*	-1.64e-05***
	(-2.00)	(-2.21)	(-6.38)	(-2.28)	(-1.87)	(-6.20)	(-2.27)	(-1.88)	(-6.13)

Hospital beds_0-25_out-of-state	1.55e-06	1.38e-06	-6.22e-08	1.72e-06	1.59e-06	3.00e-07	2.05e-06	1.88e-06	9.61e-07
	(0.69)	(0.85)	(-0.02)	(0.77)	(1.00)	(0.10)	(0.92)	(1.19)	(0.32)
State Fixed Effects	49	49	49	49	49	49	49	49	49
Observations	3,108	3,108	3,105	3,108	3,108	3,105	3,108	3,108	3,105
R-squared	0.698	0.715	0.506	0.698	0.715	0.506	0.698	0.715	0.507

[a] Specialists refer to cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. *** p<0.01, ** p<0.05, * p<0.1

Table A3: The Effect of State-Specific Medical Policies [a]

Dependent Variable: Log Mortality Rate of Various Diseases (%) (*t* statistics are reported in parentheses using robust standard errors)

	Metro Areas			Non-Metro Areas		
	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke
	(a)	(b)	(c)	(d)	(e)	(f)
Log (specialists per bed)_0-25_in-state	-0.0681***	-0.0472***	-0.0687***	-0.0485***	-0.0284***	-0.0578***
	(-5.20)	(-2.61)	(-3.86)	(-3.94)	(-3.44)	(-3.45)
Log (specialists per bed)_0-25_out-of-state	-0.0478***	-0.0260	-0.0983***	-0.0144	-0.0075	-0.0249*
	(-2.61)	(-1.02)	(-3.41)	(-1.45)	(-0.93)	(-1.95)
Log (specialists per bed)_0-25_out-of-state ×						
Stringent Reciprocity Rules	0.0246***	0.0137**	0.0139	0.0085	0.0007	-0.0072
	(2.99)	(2.00)	(1.23)	(1.47)	(0.25)	(-1.03)
Log (nurses per bed)_0-25_in-state	-0.0382**	-0.0134	0.0065	-0.0438*	-0.0171	-0.0544
	(-2.06)	(-0.70)	(0.27)	(-1.73)	(-1.11)	(-1.60)
Log (nurses per bed)_0-25_out-of-state	-0.0221	-0.0234	0.0205	-0.0427**	0.0062	-0.0598**
	(-1.12)	(-1.49)	(0.62)	(-2.20)	(0.49)	(-2.33)
Log (hospital beds)_0-25_in-state	-0.0020	-0.0034	0.0106	-0.0028	-0.0087*	-0.0052

	(-0.22)	(-0.29)	(0.77)	(-0.47)	(-1.72)	(-0.62)
Log (hospital beds)_0-25_out-of-state	-0.0201	-0.0131	-0.0749***	-0.0023	-0.0035	-0.0275***
	(-1.45)	(-0.56)	(-2.96)	(-0.38)	(-0.54)	(-3.03)
State Fixed Effects	49	49	49	49	49	49
Observations	1,776	1,776	1,776	1,332	1,332	1,329
R-squared	0.703	0.723	0.501	0.702	0.722	0.503

[a] Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of > 65years old, per capita income, % in poverty, % of < high school, and unemployment rate (%). *** p<0.01, ** p<0.05, * p<0.1

Table A4: The Effect of State-Specific Medical Policies [a]

Dependent Variable: Log Mortality Rate of Various Diseases (%)

(t statistics are reported in parentheses using robust standard errors)

	Heart Disease	Cancer	Stroke
	(a)	(b)	(c)
Log (specialists per bed)_0-25_in-state	-0.0654***	-0.0534***	-0.0885***
	(-8.04)	(-5.75)	(-8.26)
Log (specialists per bed)_0-25_out-of-state	-0.0238***	-0.0138*	-0.0518***
	(-2.70)	(-1.73)	(-4.54)
Log(# of doctors per bed)_0-25_out × Maximum Year Constraint	0.0324***	0.0031	-0.0144
	(3.56)	(0.54)	(-1.07)
Log(# of doctors per bed)_0-25_out × Interview Requirement	0.0171***	0.0065**	0.0064
	(3.33)	(2.07)	(0.97)
Log(# of doctors per bed)_0-25_out × Both Requirements	0.0081	0.0025	-0.0069
	(1.31)	(0.66)	(-0.88)
Log (nurses per bed)_0-25_in-state	-0.0526***	-0.0158	-0.0178
	(-3.59)	(-1.20)	(-0.93)
Log (nurses per bed)_0-25_out-of-state	-0.0361***	-0.0071	-0.0224
	(-2.60)	(-0.70)	(-1.06)
Log (hospital beds)_0-25_in-state	-0.0050	-0.0172***	-0.0171**
	(-1.04)	(-3.65)	(-2.43)
Log (hospital beds)_0-25_out-of-state	-0.0058	-0.0067	-0.0438***
	(-0.99)	(-1.03)	(-5.18)
State Fixed Effects	49	49	49
Observations	3,108	3,108	3,105
R-squared	0.706	0.722	0.519

[a] Specialists stand for cardiologists for heart disease, oncologists for cancer, and neurologists for stroke. Other control variables include % Black, % Asian, % Hispanic, % of uninsured, % of > 65years old, per capita income, % in poverty, % of < high school, and unemployment rate (%). *** p<0.01, ** p<0.05, * p<0.1