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Essays on Agglomeration, Access To Medical Services, And the Real Estate Market

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Abstract

This dissertation comprises three papers that study how external economies of scale help to explain geographic variation in access to medical services as well as potential implications on the real estate market. Specifically, the first two papers examine whether an increased concentration of the hospital service industry promotes productivity in treating patients and if so, what are the specific channels through which agglomeration economies might take place in the health care industry. The third paper explores how the productivity variation is reflected in the real estate market.

Chapter 2 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. Three 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 amplified when the primary state adopts more stringent policies that restrict entry of out-of-state physicians. This evidence is consistent with labor market pooling as one of the specific channels through which agglomeration economies affect productivity.

Chapter 3 addresses two related questions that help to explain geographic variation in access to medical services. The first question examines the existence of agglomeration economies in the hospital service industry. The second considers whether the sharing of intermediate inputs contributes to spillovers from spatial concentration of hospital services. Three key findings are obtained. First, hospitals in more concentrated areas are more likely to

outsource intermediate services to specialized intermediate service suppliers. This suggests that agglomeration economies exist in the hospital service industry and are generated in part through the sharing of intermediate inputs. Second, the presence of nearby small hospitals increases the tendency to outsource, consistent with a "Chinitz" effect identified elsewhere in the literature. Third, the agglomeration effect attenuates geographically.

Chapter 4 replicates and extends a paper by Holly, Pesaran, and Yamagata (2010). Their paper uses a panel of 49 states over the period of 1975 to 2003 to show that state-level real housing prices are driven by economic fundamentals, such as real per capita disposable income, as well as by common shocks, such as changes in interest rates, oil prices, and technological change. They apply the common correlated effects (CCE) estimator of Pesaran (2006) which takes into account spatial interactions that reflect both geographical proximity and unobserved common factors. This chapter replicates their results using a panel of 384 Metropolitan Statistical Areas (MSAs) observed over the period of 1975 to 2010. Our replication shows that their results are fairly robust to the more geographically refined cross-section units, and to the updated period of study.

ESSAYS ON AGGLOMERATION, ACCESS TO MEDICAL SERVICES, AND THE REAL ESTATE MARKET

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Chapter 1 Introduction

Medical services are highly concentrated in a small number of areas throughout the United States. According to statistics published by the Dartmouth Atlas of Health Care, the number of physicians ranges from 116.0 per one hundred thousand residents in McAllen, Texas, to 319.8 per one hundred thousand residents in White Plains, New York. Further, patient outcomes also vary significantly across locations. For instance, while the age-sex-race adjusted mortality rate stands as low as 25 per 1000 population in Reinbeck, Iowa, it rises up to 203 per 1000 residents in Chalmette, Louisiana. In fact, numerous studies have provided evidence on geographic variation in the health care industry (see, for example, the Dartmouth Atlas of Health Care) as well as its potential consequences on patient outcomes (Fisher et al., 2003a, 2003b; Baicker and Chandra, 2004; Fisher et al. 2009, etc). However, much less efforts have been devoted to exploring possible factors that may contribute to this phenomenon. Undoubtedly, a better understanding of this question is important since restricted access to medical services is presumably one of the leading causes of poor health outcomes in lightly developed areas. This dissertation helps to explain geographic variation in the hospital service industry from the perspective of external economies of scale. Specifically, it argues that an increased concentration of the health care industry promotes productivity in treating patients, and the increase in productivity further attracts medical services to agglomerate in select locations.

Chapter 2 explores whether concentrations of medical professionals help to improve doctor productivity, as captured by reduced mortality rates from heart disease, cancer, and stroke. This is in line with the agglomeration literature, which has provided evidence that productivity is often enhanced when companies operate in concentrated locations (Quigley, 1998; Rosenthal and Strange, 2004; Glaeser and Gottlieb, 2009). Numerous studies have provided evidence in the manufacturing sector. Similar spillover effects in the health care industry have been explored in a few recent studies. These studies find significant localization effects: when the scale of the local health care industry is large, the 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 Pall, 2008).

This chapter, in particular, examines two specific features of agglomeration economies in the hospital service industry, in addition to the existence of the localization effect. The first feature is potential geographic attenuation of the impact of local medical resources. In other words, this chapter looks at the degree to which proximity to medical services affects local patient outcomes and how quickly the impact of nearby doctors attenuates with geographic distance. This is achieved by examining the impact of key features of the local medical industry in two concentric rings that extend out to fifty miles from the geographic centroid of a primary county. Findings suggest that the medical environment in the inner ring has a notably stronger effect on nearby population health outcomes, as is consistent with the geographic attention of the impact of nearby doctors.

The second feature is the possible presence of state border effects that may impede the entry of out-of-state doctors to practice in-state and therefore reduce the impact of out-of-state doctors on nearby patient outcomes. The identification of the state border effect is then achieved by comparing the influence of doctors just on either side of a state border, controlling for distance. Results indicate that the impact of out-of-state doctors is smaller than that of the in-state doctors. Moreover, the lesser impact of out-of-state doctors is further lessened for states with more stringent licensing policies that restrict the entry of out-of-state physicians. Based on the evidence, I argue that the in-state versus out-of-state difference is attributable, at least in part, to state-specific medical licensing regulations that impede the ability of physicians to practice across state lines and thereby reduce the impact of out-of-state doctors on nearby patient outcomes.

Chapter 3 further explores whether the increase in productivity in agglomerated areas arise from the ability of sharing valuable intermediate medical input providers. This is achieved by examining whether hospitals in more agglomerated locations are more likely to outsource for intermediate medical services, such as clinical lab services, blood bank services, etc. These questions are important because they help to shed light on whether external economies of scale help to explain geographic variation in access to medical services and if so, whether intermediate input sharing is one of the channels through which it might take place. Controlling for possible sample selection, I find, as expected, that hospitals in more concentrated locations are more likely to outsource for intermediate medical services as opposed to providing these services in-house. From this, I argue that agglomeration economies exist in the hospital service industry and are generated in part through the sharing of intermediate inputs.

Aside from this focus, the chapter also explores the influence of the local industrial organization on the potential for input sharing and related external economies of scale in the hospital service industry. Chinitz (1961) suggested that "large firms are … less of a stimulus to the creation of a community of independent suppliers." Similar arguments have been made by Jacobs (1969), Piore and Sabel (1984), and Saxenian (1994). By focusing on firms' entry decisions, Rosenthal and Strange (2010) found that small firms play an important role in the generation of agglomeration economies. Glaeser, Kerr, and Ponzetto (2010) documented that small firms have a stronger connection with subsequent employment growth than large establishments, which is consistent with Chinitz's view. This chapter also examines this organization-agglomeration relationship but from a different perspective. Specifically, I consider whether the "Chinitz" effect, as captured by the percentage of small hospitals in a county, contributes to local hospitals' decisions to outsource for intermediate services. Evidence suggests that hospitals in areas with a higher percentage of small hospitals are more likely to outsource for intermediate medical services. This implies that small hospitals help to form a more vibrant community, which is more attractive to specialized intermediate input providers and is more likely to encourage vertical disintegration.

Chapter 4 explores the other dimension of the urban/real estate environment. The idea is that, if agglomeration economies help to promote productivity in urbanized areas, the willingness to pay for local real estate properties will increase accordingly. Due to potential spillover effects, housing prices in nearby locations may be highly correlated and contribute to a spatial error component. As an initial effort to explore the spatial component of the housing market, this chapter replicates and extends a recent study by Holly, Pesaran, and Yamagata that was published in the Journal of Econometrics in 2010. Their paper applies the common correlated effects (CCE) estimator of Pesaran (2006) to show that state-level real housing prices are driven by economic fundamentals, such as real per capita disposable income, as well as by common shock, such as changes in interest rates, oil prices, and technological change. This chapter replicates their results using the same method, which takes into account spatial interactions that reflect both geographical proximity and unobserved common factors, but apply the method on a different panel data – a panel of 384 Metropolitan Statistical Areas (MSAs), as oppose to the 49 states as used in their paper, and our panel is observed over the period of 1975 to 2010, instead of 1975 to 2003. Our replication shows that their results are fairly robust to the more geographically refined cross-section units, and to the updated period of study.

Chapter 2 The Influence of State Policy and Proximity to Medical Services on Health Outcomes

2.1 Introduction

Mortality rates for heart disease, cancer, and stroke differ dramatically across locations in the United States. As shown in Figures 2-1, 2-2 and 2-3, 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 chapter 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]

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 2-1 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

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[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, 2003b; Baicker and Chandra, 2004; Fisher et al. 2009). In contrast, instrumental variables and panel data evidence suggest that higher spending is associated with significantly lower mortality (McClellan, McNeil, and Newhouse, 1994; Cutler, 2007; Chandra and Staiger, 2007; Doyle, 2011).
[2] See, for example, Casey, et al (2001), and Coughlin, et al (2002).
[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), Eberhardt and Ingram (2001), and Ricketts (1999).

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.

One possible explanation of this phenomenon is that larger metropolitan areas provide residents with better access to medical services. This is suggested by Table 2-2, 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 2-1, further suggests that better access to medical professionals likely contributes to lower mortality rates from heart disease, cancer and stroke.

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

[4] This idea is introduced in Marshall (1920) and surveyed extensively in later literature (Quigley, 1998; Rosenthal and Strange, 2004; Glaeser and Gottlieb, 2009).
[5] See, for instance, Glaeser and Maré (2001), and Moretti (2004) for evidence of knowledge spillovers, Holmes (1999), Ellison, Glaeser, and Kerr (2010), and Li (2012) for evidence of input sharing, and Rosenthal and Strange (2001), and Costa and Kahn (2000) for evidence of labor market pooling.

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 chapter 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 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 amplified 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

[6] See, Rosenthal and Strange (2003, 2005, 2008), Andersson, Quigley, and Wilhelmsson (2009), and Arzaghi and Henderson (2008).
[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 will be provided in Section 2.2.

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.

My findings in this chapter 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 chapter also contributes to literature on the presence and nature of agglomeration economies. The evidence of a state border effect helps to identify the underlying micro-foundations of agglomeration economies, and more precisely in this case, the role of labor market pooling. Identification of this micro-foundation has proven especially challenging in the agglomeration literature.[11] The strategy adopted here is to show that out-of-state physicians have a smaller positive impact on nearby patient outcomes, controlling for distance. I argue that this is consistent with the idea that access to pools of skilled labor enhances productivity and, hence, supports labor market pooling as an important microfoundation and driver of agglomeration economies.[12]

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[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, Hirth, and Cutler (2003), and Bodenheimer (2005), for instance.

[11] See Rosenthal and Strange (2004).

[12] The idea is that, when companies face idiosyncratic market shocks, having access to a large labor market pool enhances productivity by being able to adjust the number of workers at a lower cost. Similarly, when hospitals experience temporal increase in demand for doctors, the presence of nearby medical professionals helps to increase productivity in treating patients by providing immediate pools of labor to draw upon.

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 three 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, a ten percent increase in doctors within 25 miles reduces the mortality rate for heart disease in a county by 0.626 percent. This effect drops to 0.046 percent 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 chapter. 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, a ten percent increase in doctors inside the state reduces the mortality rate for stroke by 0.882 percent, which is 0.375 higher in percentage points than the corresponding out-of-state effect. Third, the smaller impact of out-of-state doctors is further amplified 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. The evidence also suggests that access to pools of skilled labor

[13] Details regarding these two data files are provided in Section 2.4.

enhances productivity, which is consistent with labor market pooling as one of the specific channels through which agglomeration economies affect productivity.

The rest of the paper is organized as follows. Section 2.2 discusses state-specific medical licensing policies that restrict out-of-state doctors from practicing in-state. Section 2.3 presents the empirical framework. Section 2.4 describes data and variables. Section 2.5 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 2.6 concludes.

2.2 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 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. The level of standard requires efforts that are viewed as duplicative and time-consuming. For example, applicants may be asked to participate

[14] Details can be found in State Medical Licensure Requirements and Statistics, American Medical Association.

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 the 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 board examination.[15] Taking year 2007 as an example and as shown in Table 2-3, 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/her most recent medical board examination. Among the eleven states with maximum years 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 years constraints is relatively consistent over time.

I define a state as having "stringent policies" if it restricts entry of out-of-state physicians by adopting either the interview requirement or the maximum years constraint. I differentiate neither the different extent of maximum years constraint nor its influence compared to that of a

[15] 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.

comprehensive interview.[16] Out of forty-nine states in the continental United States, thirty-six are classified as those with more demanding application procedures for licensure endorsement.[17]

2.3 Empirical Framework

This section describes the framework that motivates the empirical analysis to follow. The modeling approach is built upon the literature on agglomeration economies. Numerous studies have provided evidence that external economies of scale enhance productivity in the manufacturing sector.[18] The existence of similar spillover effects in the health care industry has been explored in a few recent studies. These studies find significant localization effects: when the scale of 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, 2012) and run at a lower cost (Cohen and Pall, 2008).[19]

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

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

To capture the geographic attenuation of spillover effects, all the key features of 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.[20] To

[16] 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
[17] States with stringent medical licensing policies based on this definition are highlighted in bold in Table 3-3.
[18] To name a few, see Holmes (1999), Rosenthal and Strange (2001), and Ellison, Glaeser, and Kerr (2010).
[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.
[20] 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 to 25 miles and 25 to 50 miles. This specification is based on the assumption that 25

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 geographic attenuation.[21]

The estimation equation is, thus, specified as follows,

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

In this expression, the superscript $0-25$ indicates that the corresponding variables are defined for the 25-mile ring and $25-50$ represents variables associated with the 25-50 mile concentric 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. $\boldsymbol{X}$ is a vector of county-level demographic controls. μ captures the state fixed effect.

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.

[21] The above idea is captured graphically in Figure 2-4. The horizontal axis denotes locations. The centered solid line points to the location of the primary county's geographic centroid. The vertical axis represents the magnitude of the spillover effect from doctors located at various distances from the centroid of the primary county. As illustrated by the dashed line, the impact of nearby doctors is expected to attenuate gradually with distance, drop discretely at state boundaries, and continue with its attenuation pattern afterwards.

The identification of state border effects 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 $\hat{\beta}_1$ and $\hat{\beta}_4$ 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.

I address this issue by exploring exogenous variation in stringency of state medical licensing policies, as discussed extensively 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 should be amplified for states with more stringent policies, which will be captured by the coefficient of the interaction term. The identification assumption is that the adoption of more stringent endorsement policies is not correlated with unobserved factors that may also influence health outcomes.

2.4 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. [22] Mortality rates associated with each type of disease in a county are calculated as the number of deaths from the disease between 1999

[22] The ranking for causes of death can be found at http://www.cdc.gov/nchs/fastats/lcod.htm.

and 2007 divided by the standard population reported in 2000 decennial census.[23] Heart disease is defined by the ICD-10 codes ranging from GR113-055 to GR113-068, cancer is defined as GR113-020 to GR113-036, and stroke is defined by GR113-070.[24]

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 chapter. 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.[25] 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

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[23] 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.

[24] 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).

[25] The construction of the proportional sum measure is better presented in Figure 2-5. For example, for county A, a 25-mile circle around its centroid intersects seven neighboring counties. 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 counties (including A itself) that overlap the circle, assuming doctors (nurses, or hospital beds) are uniformly distributed throughout the area.

decomposed into the portion that belongs to the primary state and the portion overlapping the neighboring states.

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.

Table 2-4 provides summary statistics of each variable that enters the estimation equation. 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. Means and standard deviations are also reported for doctors per bed, nurses per bed, and hospital beds as partial concentric rings measured separately for the in-state portion and the out-of-state portion.[26]

2.5 Results

2.5.1 How quickly does the impact of doctors attenuate?

This section reports estimates on the degree to which proximity to medical services affects patient outcomes. Table 2-5 shows results when mortality rates are used directly as proxies for patient outcomes (log mortality rates as dependent variables), while Table 2-6 reports estimates when patient outcomes are represented as an exponential function of the quality indicators (mortality rates as dependent variables). The following discussion will focus on Table 2-5, but similar results can also be found in Table 2-6.

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

In Table 2-5, estimates are reported separately for heart disease, cancer, and stroke. For each type of disease, I first run OLS regressions with only 25-mile rings for the medical establishment 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, 2nd column). This effect is much stronger than cardiologists present in the 25-50 mile concentric ring (0.0046 in 3rd row, 2nd column). Similar patterns also show up for the estimated elasticities associated with nurse measures.[27] 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.[28]

Generally speaking, the evidence reported in Table 2-5 and Table 2-6 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.

2.5.2 Is there a state border effect?

In addition to spatial attenuation, estimates reported in Table 2-5 and Table 2-6 also help to explain whether state borders impede access to nearby medical services. As shown in both tables, the in-state doctor effect is generally of higher magnitude and more significant compared to the corresponding out-of-state doctor effect. This is especially so when focusing on the 25-

[27] The estimated positive impact of nurses on population health outcomes is consistent with findings in Gruber and Kleiner (2012) which show that nurse strikes tend to impose a negative influence on patient outcomes in New York State.

[28] I am cautious about comparing estimated elasticities associated with the out-of-state portion of each concentric ring variable since the identification solely relies on a small portion of the sample. Partly for this reason, the out-of-state portion estimates tend to be insignificant.

mile distance band. For instance, in Table 2-5, the estimated elasticities associated with in-state and out-of-state neurologists within 25 miles are 0.0892 and 0.0396, respectively, and are both significantly identified (1st and 2nd rows, 6th column). The magnitude of the estimated coefficient for the in-state portion is 0.0496 higher than that for 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.[29]

Although evidence presented in both tables is generally consistent and robust, I am still cautious with interpretation of the state border effect. As discussed earlier, to argue that the in-state versus out-of-state difference is due to the influence of state borders, I implicitly assume that the attenuation gradient is properly controlled for. If the attenuation tends to be more spatially continuous, in-state doctors are considered as distributed closer to the centroid of the primary county. In this way, the difference in the in-state versus out-of-state estimates associated with each distance band should be better treated as a mix of both the attenuation effect and the state border effect.

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 amplified for states with stricter policies. This is accomplished by interacting a dummy variable for states adopting stricter licensing policies with controls for the number of out-of-state doctor per bed within 25 miles.[30] As shown in the first three columns of Table 2-9, the estimated coefficient associated with the interaction term for the three types of

[29] The evidence for neurologists within 25-50 miles distance band seems counter-intuitive. For now, I don't have a good explanation of it.

[30] Only 25-mile rings are included in this specification since the effects of various medical inputs beyond this range are generally insignificant as demonstrated in Table 2-5 and Table 2-6.

diseases is generally positive and significant.[31] 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. These findings provide further evidence for the impact of state borders.

As additional robustness checks, I also experiment with two other ways of instrumenting the stringency of state medical policy environment. The first is to use statewide per capita number of doctors, while 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 captured by per capita number of doctors and doctors per square mile, that is driving related policies that govern reciprocity of physician licensing across state lines.

Table 2-7 and Table 2-8 show the rankings of states by per capita number of doctors and number of doctors per square mile. States with index values 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 as a proxy for policy stringency is created based on the above definition and is interacted with the out-of-state measure of medical professionals. Corresponding results are reported between column 4 and column 9 in Table 2-9. As shown in the table, the estimated coefficients for the interaction term are generally positive and significant. This evidence is consistent with the idea 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. The general pattern is consistent for all three types of diseases considered in this chapter.

The identification of state border effects shows that out-of-state physicians have a less positive impact on nearby patient outcomes. Given that knowledge spillovers are unlikely to be

[31] Estimated results obtained when mortality rates are used as the dependent variables are reported in the Appendix. Estimates are robust to how patient outcomes are measured.

impeded by state boundaries, the smaller impact of out-of-state doctors provides support for the idea that access to pools of skilled labor enhances productivity.[32] As with findings in Rosenthal and Strange (2001) and Ellison, Glaeser, and Kerr (2010), this is consistent with labor market pooling as an important microfoundation of agglomeration economies.

2.6 Conclusion

This chapter 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 ten percent 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 percent, respectively. The impact of doctors further away tends to be insignificant and smaller in magnitude.

A 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 amplified 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.

As a further perspective, the evidence of state border effect suggests that restrictions on access to pools of skilled medical professionals reduce the beneficial effect of doctors on nearby

[32] The policy prohibits long-term medical practice of out-of-state doctors without licensure endorsement, but allows for temporal out-of-state medical consultation. The latter facilitates unrestricted knowledge exchanges. I also experiment with including medical laboratories on either side of the border as proxies for medical inputs, but the signal tends to be weak due to proliferation of highly correlated controls.

patient outcomes. This evidence is consistent with labor market pooling as a specific channel through which spillover effects might occur.

References

Andersson, R., Quigley, J.M., Wilhelmsson, M., 2009. Urbanization, productivity, and innovation: Evidence from investment in higher education. Journal of Urban Economics 66, 2–15.

Arzaghi, M., Henderson, J.V., 2008. Networking off Madison Avenue. The Review of Economic Studies 75, 1011–1038.

Baicker, K., Chandra, A., 2004. Medicare Spending, The Physician Workforce, and Beneficiarie'Quality of Care. Health Affairs w4, 184-197.

Baicker, K., Chandra, A., 2010. Understanding agglomerations in health care. In: Glaeser, E.L. (Ed.), Agglomeration Economics. University of Chicago Press, pp. 211–364.

Bodenheimer, T., 2005. High and rising health care costs. Part 1: seeking an explanation. Annals of Internal Medicine 142, 847–854.

Casey, M.M., Thiede Call, K., Klingner, J.M., 2001. Are rural residents less likely to obtain recommended preventive healthcare services? American Journal of Preventive Medicine 21, 182–188.

Chandra, A., Staiger, D.O., 2007. Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks. Journal of Political Economy 115, 103–140.

Chernew, M.E., Hirth, R.A., Cutler, D.M., 2003. Increased Spending On Health Care: How Much Can The United States Afford? Health Affairs 22, 15–25.

Cohen, J.P., Morrison Paul, C., 2008. Agglomeration and cost economies for Washington state hospital services. Regional Science and Urban Economics 38, 553–564.

Costa, D.L., Kahn, M.E., 2000. Power couples: changes in the locational choice of the college educated, 1940–1990. The Quarterly Journal of Economics 115, 1287–1315.

Coughlin, S.S., Thompson, T.D., Hall, H.I., Logan, P., Uhler, R.J., 2002. Breast and cervical carcinoma screening practices among women in rural and nonrural areas of the United States, 1998-1999. Cancer 94, 2801–2812.

Cutler, D.M., 2007. The lifetime costs and benefits of medical technology. Journal of Health Economics 26, 1081–1100.

Doyle, J.J., Jr., 2011. Returns to Local-Area Health Care Spending: Evidence from Health Shocks to Patients Far From Home. American Economic Journal: Applied Economics 3, 221–243.

Eberhardt, M.S., Pamuk, E.R., 2004. The importance of place of residence: examining health in rural and nonrural areas. American Journal of Public Health 94, 1682–1686.

Eberhardt, M.S., Ingram, D.D., 2001. Urban and Rural Health Chartbook. Hyattsville, MD.

Ellison, G., Glaeser, E.L., Kerr, W.R., 2010. What causes industry agglomeration? evidence from coagglomeration patterns. American Economic Review 100, 1195–1213.

Fisher, E.S., Bynum, J.P., Skinner, J.S., 2009. Slowing the growth of health care costs—lessons from regional variation. New England Journal of Medicine 360, 849–852.

Fisher, E.S., Wennberg, D.E., Stukel, T.A., Gottlieb, D.J., Lucas, F.L., Pinder, E.L., 2003. The implications of regional variations in Medicare spending. Part 1: the content, quality, and accessibility of care. Annals of Internal Medicine 138, 273–287.

Fisher, E.S., Wennberg, D.E., Stukel, T.A., Gottlieb, D.J., Lucas, F.L., 2003. The implications of regional variations in Medicare spending. Part 2: health outcomes and satisfaction with care. Annals of Internal Medicine 138, 288–298.

Glaeser, E.L., Maré, D.C., 2001. Cities and skills. Journal of Labor Economics 19, 316–342.

Glaeser, E.L., Gottlieb, J.D., 2009. The wealth of cities: agglomeration economies and spatial equilibrium in the united states. Journal of Economic Literature 47, 983–1028.

Gruber, J., Kleiner, S.A., 2012. Do strikes kill? evidence from new york state. American Economic Journal: Economic Policy 3, 127–157.

Heffler, S., 2004. Health spending projections through 2013. Health Affairs 4, 79–93.

Holmes, T.J., 1999. Localization of industry and vertical disintegration. Review of Economics and Statistics 81, 314–325.

Li, J., 2012. Intermediate input sharing in the hospital service industry. Syracuse University. Unpublished working paper.

Marshall, A., 1920. Principles of Economics. London: Macmillan.

McClellae, M., McNeil, B., Newhouse, J., 1994. Does more intensive treatment of acute myocardial infarction in the elderly reduce mortality? JAMA 272, 859–866.

Moretti, E., 2004. Workers' education, spillovers, and productivity: evidence from plant-level production functions. American Economic Review 94, 656–690.

Quigley, J.M., 1998. Urban diversity and economic growth. The Journal of Economic Perspectives 12, 127–138.

Ricketts, T., 1999. Rural Health in the United States. Oxford University Press, New York.

Rosenthal, S.S., Strange, W.C., 2001. The determinants of agglomeration. Journal of Urban Economics 50, 191–229.

Rosenthal, S.S., Strange, W.C., 2003. Geography, industrial organization, and agglomeration. Review of Economics and Statistics 85, 377–393.

Rosenthal, S.S., Strange, W.C., 2004. Evidence on the nature and sources of agglomeration economies. Handbook of Regional and Urban Economics 4, 2119–2171.

Rosenthal, S.S., Strange, W.C., 2005. The geography of entrepreneurship in the New York metropolitan area. Federal Reserve Bank of New York Economic Policy Review 11, 29–53.

Rosenthal, S.S., Strange, W.C., 2008. The attenuation of human capital spillovers. Journal of Urban Economics 64, 373–389.

Table 2-1: 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 (Adjacent to Metro) [e]	240.4	155.1	56.7
Noncore [f]	247.6	156.9	57.6

[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.

Table 2-2: 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 (Adjacent to Metro) [e]	12.81	0.23	0.14	0.05
Noncore [f]	20.86	0.28	0.19	0.07

[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.

Table 2-3: 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 D.C.	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 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.

Table 2-4: Summary Statistics

	mean	std. dev.	min	max
Mortality rate of heart disease (%)	0.2886	0.0924	0.0281	0.7649
Mortality rate of cancer (%)	0.1797	0.0444	0.0169	0.3396
Mortality rate of stroke (%)	0.0689	0.0256	0.0035	0.2372
Log (# of cardiologists per bed)_0-25_in-state	-4.0550	0.7690	-6.8373	0.0000
Log (# of cardiologists per bed)_0-25_out-of-state	-1.1538	1.6738	-6.4263	0.7433
Log (# of cardiologists per bed)_25-50_in-state	-4.2377	0.6451	-7.1134	0.0000
Log (# of cardiologists per bed)_25-50_out-of-state	-2.4164	1.9906	-6.2631	0.3980
Log (# of oncologists per bed)_0-25_in-state	-4.8715	0.9245	-7.0113	0.0000
Log (# of oncologists per bed)_0-25_out-of-state	-1.3369	1.9745	-6.6008	0.6262
Log (# of oncologists per bed)_25-50_in-state	-5.3450	0.6191	-7.3046	0.0000
Log (# of oncologists per bed)_25-50_out-of-state	-2.9279	2.4426	-7.1263	0.1919
Log (# of neurologists per bed)_0-25_in-state	-4.3627	0.8218	-6.6455	0.0000
Log (# of neurologists per bed)_0-25_out-of-state	-1.2306	1.7951	-6.4344	0.3118
Log (# of neurologists per bed)_25-50_in-state	-4.6198	0.6480	-6.8180	0.0000
Log (# of neurologists per bed)_25-50_out-of-state	-2.6133	2.1643	-6.6801	0.0000
Log (# of nurses per bed)_0-25_in-state	0.0530	0.4267	-2.7535	1.4299
Log (# of nurses per bed)_0-25_out-of-state	0.0099	0.2709	-1.9194	1.2620
Log (# of nurses per bed)_25-50_in-state	0.1166	0.3424	-1.3950	0.9828
Log (# of nurses per bed)_25-50_out-of-state	0.0321	0.3277	-1.7804	1.4345
Log (# of hospital beds)_0-25_in-state	5.7471	1.5236	0.0000	10.5712
Log (# of hospital beds)_0-25_out-of-state	1.4868	2.2910	0.0000	10.4414
Log (# of hospital beds)_25-50_in-state	6.8705	1.2969	0.0000	10.3956
Log (# of hospital beds)_25-50_out-of-state	3.4818	3.0747	0.0000	10.6523
% Black	8.8421	14.5663	0.0000	86.5000
% Asian	1.0589	1.9529	0.0000	31.6715
% Hispanic	6.2075	12.0488	0.1000	97.5000
% of Uninsured	20.6792	6.6926	7.9000	50.6000
% of > 65 years old	37.3756	3.9667	20.6000	54.3000
Per capita income	30347.01	8127.01	8579.00	132728.00
% in poverty	15.1210	6.2421	2.4000	55.9000
% of < high school	9.1094	5.2538	0.0000	46.3000
Unemployment rate (%)	4.8521	1.6919	1.5000	18.0000

[a] Sample contains 3,108 observations in total.

Table 2-5: Attenuation and State Border Effects [a]

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

	Heart Disease		Cancer		Stroke	
Log (# of 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 (# of 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 (# of specialists per bed)_25-50_in-state	-	-0.0046	-	-0.0004	-	0.0065
	-	(-0.47)	-	(-0.06)	-	(0.51)
Log (# of specialists per bed)_25-50_out-of-state	-	-0.0029	-	-0.0053	-	-0.0214***
	-	(-0.50)	-	(-1.05)	-	(-2.65)
Log (# of 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 (# of 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 (# of nurses per bed)_25-50_in-state	-	-0.0306	-	0.0006	-	-0.0469
	-	(-1.41)	-	(0.03)	-	(-1.54)
Log (# of nurses per bed)_25-50_out-of-state	-	-0.0213	-	0.0015	-	0.0083
	-	(-1.34)	-	(0.11)	-	(0.37)
Log (# of 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 (# of 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 (# of hospital beds)_25-50_in-state	-	-0.0020	-	-0.0025	-	0.0053
	-	(-0.36)	-	(-0.56)	-	(0.71)
Log (# of hospital beds)_25-50_out-of-state	-	0.0044	-	-0.0012	-	-0.0134**
	-	(1.03)	-	(-0.27)	-	(-2.08)
No. of State Fixed Effects	49	49	49	49	49	49
No. of Observations	3,108	3,108	3,108	3,108	3,105	3,105
R-squared	0.705	0.707	0.721	0.722	0.518	0.520

[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 2-6: Attenuation and State Border Effects

Dependent Variable: Mortality Rates of Various Diseases (%)

	Heart Disease		Cancer		Stroke	
Log (# of 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 (# of 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 (# of specialists per bed)_25-50_in-state	-	-0.0061**	-	-0.0014	-	0.0002
	-	(-2.35)	-	(-1.28)	-	(0.25)
Log (# of specialists per bed)_25-50_out-of-state	-	-0.0011	-	-0.0010	-	-0.0015***
	-	(-0.70)	-	(-1.26)	-	(-2.70)
Log (# of 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 (# of 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 (# of nurses per bed)_25-50_in-state	-	0.0000	-	0.0019	-	-0.0039*
	-	(0.00)	-	(0.76)	-	(-1.92)
Log (# of nurses per bed)_25-50_out-of-state	-	-0.0071	-	0.0007	-	-0.0004
	-	(-1.59)	-	(0.34)	-	(-0.27)
Log (# of 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 (# of 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 (# of hospital beds)_25-50_in-state	-	-0.0005	-	-0.0007	-	0.0006
	-	(-0.34)	-	(-1.08)	-	(1.26)
Log (# of hospital beds)_25-50_out-of-state	-	0.0007	-	-0.0005	-	-0.0009*
	-	(0.62)	-	(-0.70)	-	(-1.93)
No. of State Fixed Effects	49	49	49	49	49	49
No. of Observations	3,108	3,108	3,108	3,108	3,105	3,105
R-squared	0.684	0.687	0.743	0.744	0.478	0.481

[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 2-7: 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 D. C.	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			

Table 2-8: Rank of States by Number of Doctors per Square Mile (SM)

Rank	State	Doctors per SM	Rank	State	Doctors per SM
1	Washington D. C.	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			

Table 2-9: The Effect of State-Specific Medical Policies

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

	Licensing Policy Dummy			Doctors per Capita Dummy			Doctors per Square Mile Dummy		
	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke
Log (# of 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 (# of 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 (# of specialists per bed)_0-25_out-of-state × Stringent Reciprocity Rules	0.0148***	0.0058*	0.0068	-	-	-	-	-	-
	(2.89)	(1.79)	(1.07)						
Log (# of 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 (# of 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 (# of 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 (# of 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 (# of 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 (# of 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)
No. of State Fixed Effects	49	49	49	49	49	49	49	49	49
No. of Observations	3,108	3,108	3,105	3,108	3,108	3,105	3,108	3,108	3,105
R-squared	0.705	0.722	0.518	0.705	0.722	0.519	0.705	0.722	0.520

[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 2-10: The Effect of State-Specific Medical Policies

Dependent Variable: Mortality Rates of Various Diseases (%)

	Licensing Policy Dummy			Doctors per Capita Dummy			Doctors per Square Mile Dummy		
	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke	Heart Disease	Cancer	Stroke
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)
No. of State Fixed Effects	49	49	49	49	49	49	49	49	49
No. of 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

Figure 2-1: State Variation in Mortality Rates (per 100,000 Residents) for Heart Disease

Figure 2-2: State Variation in Mortality Rates (per 100,000 Residents) for Cancer

Figure 2-3: State Variation in Mortality Rates (per 100,000 Residents) for Stroke

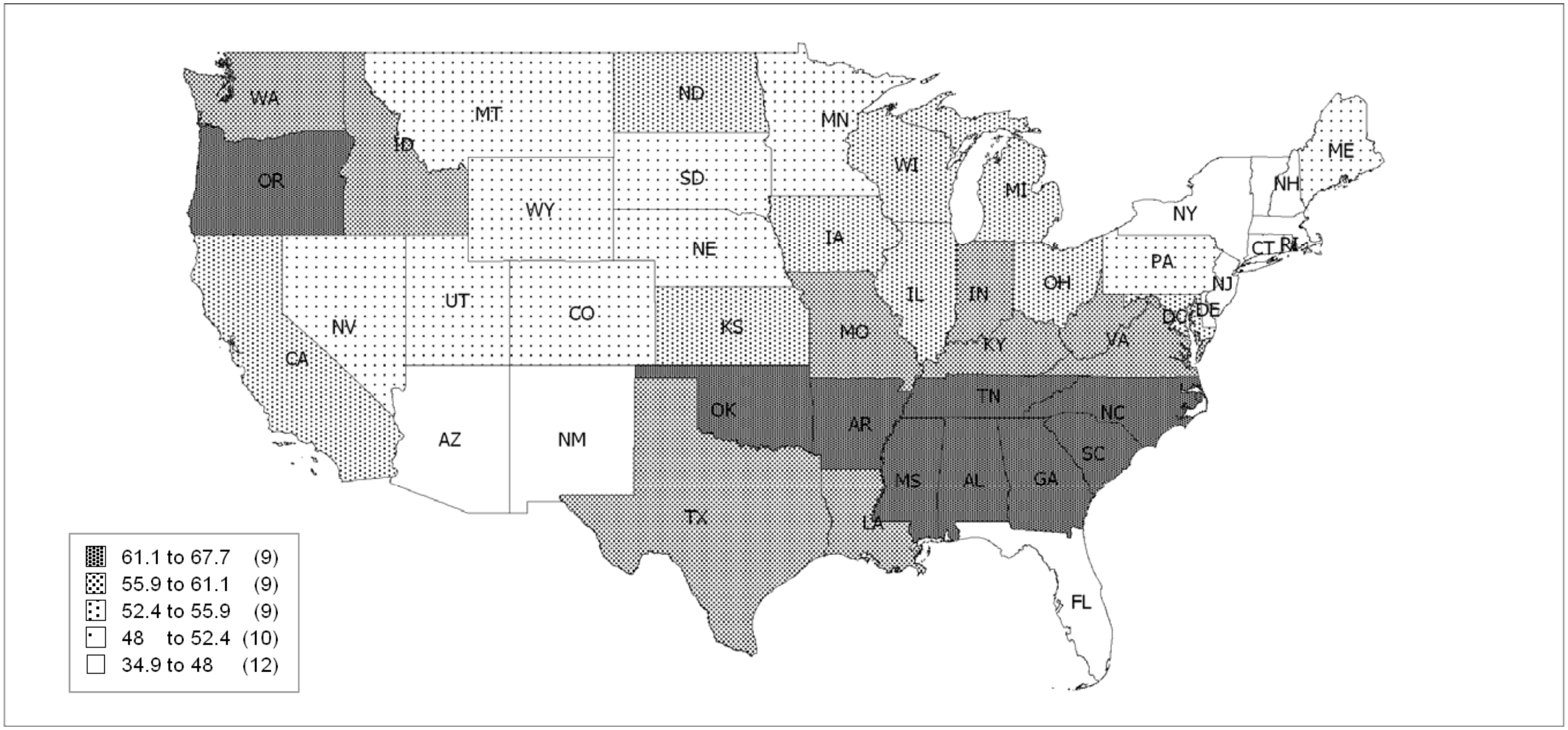


Figure 2-4: Spatial Attenuation of the Influence of Nearby Medical Professionals and the Impact of State Borders

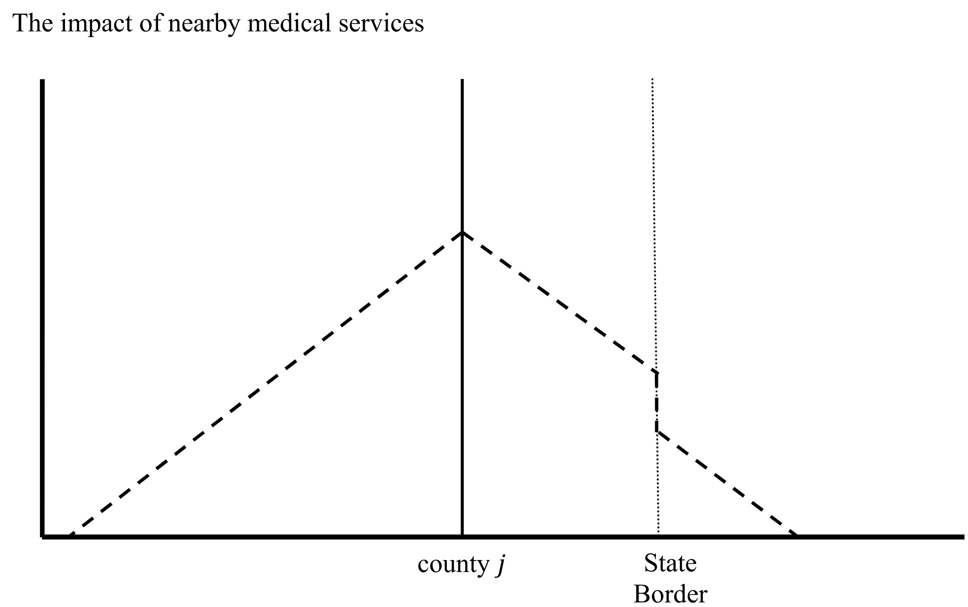
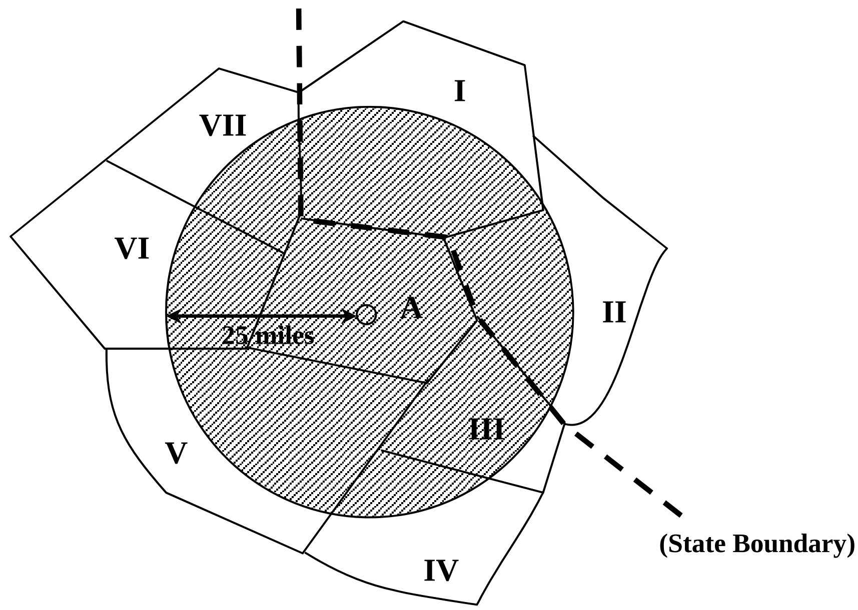


Figure 2-5: Number of Doctors (Nurses, Hospital Beds) within a Given Circle Calculated Using Proportional Sum Method



Chapter 3 Intermediate Input Sharing in the Hospital Service Industry

3.1 Introduction

The distribution of health care resources in the United States displays a high degree of spatial concentration. As shown in Figure 3-1, for instance, a large fraction of hospital beds are located in a small number of counties, including California, the Chicago area, the Northeast coastal area (from Washington D.C. to Boston), and Florida. The tremendous concentration of health care capacity in a small number of locations has received much attention in recent years. However, most efforts have focused on documentation of this phenomenon and less progress has been made in explaining why medical services are spatially concentrated.[33] A better understanding of the phenomenon is important because restricted access to medical services is one of the leading causes for poor health care outcomes in lightly developed areas.[34]

Among those studies that have sought to explain geographic concentration of medical services, many have considered population distribution as a potential driving force. Health care resources are drawn to areas with the largest number of residents demanding medical services. This is, in part, due to high transportation costs associated with delivering these services to patients.[35] However, as indicated by Goodman, et al. (1996) and Goodman (2004), concentration of local population only partly explains geographic variation in hospital services. This is also illustrated by Figure 3-2, which shows that county-level measures of hospital beds per resident still display considerable spatial concentration. The evidence suggests that, in addition to geographic variation in the distribution of population, there exist other mechanisms that may also contribute to spatial concentration of medical services.

[33] The Dartmouth Atlas Project, for example, has devoted a huge amount of resources in past twenty years to documentation of dramatic differences in the spatial distribution of medical care services across the United States. See http://www.dartmouthatlas.org.
[34] See, for example, Casey, et al (2001), and Coughlin, et al (2002).
[35] In this respect, the health care industry can be classified as a "market-oriented" industry. See O'Sullivan (2006) for details.

This chapter draws on previous literature on agglomeration and related spillover effects (e.g. the sharing of intermediate inputs) to highlight two important and related factors, apart from spatial concentration of population, that help to explain geographic variation in access to medical services. The first is whether local agglomeration of medical services fosters spillover effects that enhance the efficiency with which medical services are provided and which, therefore, contribute to spatial concentration in the hospital service industry. Identification of such a relationship is difficult and is achieved here indirectly by considering a second, closely related feature of the medical service industry. Specifically, I estimate and characterize conditions under which hospitals contract out for intermediate inputs when providing certain types of medical services. Some further background will help to put this in perspective.

There is an extensive literature on agglomeration economies, which has provided evidence that productivity is often enhanced when companies operate in agglomerated locations.[36] Rosenthal and Strange (2004) describe various microfoundations of agglomeration economies for which productivity spillovers might occur.[37] One of these microfoundations is that spatial concentration of a particular industry attracts specialized intermediate input producers and encourages intermediate input sharing. I explore the existence of similar spillover effects in the hospital service industry by examining whether the sharing of intermediate medical inputs contributes to spillovers from spatial concentration of medical services. In doing so, I

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[36] See Quigley (1998), Rosenthal and Strange (2004), and Glaeser and Gottlieb (2009) for surveys of this literature. Numerous studies have provided evidence that external economies of scale enhance productivity in the manufacturing sector, but few of these studies have focused on the health care industry. Baicker and Chandra (2010), Cohen and Pall (2008), and Li (2012) are among the few that examine productivity gains from agglomeration in the health care industry.

[37] Marshall (1920) brought up three mechanisms through which agglomeration economies might take place: intermediate input sharing, labor market pooling, and knowledge spillovers. See, for instance, Glaeser and Maré (2001) and Moretti (2004) for evidence of knowledge spillovers, Holmes (1999) and Ellison, and Glaeser, and Kerr (2010) for evidence of input sharing, and Rosenthal and Strange (2001) and Costa and Kahn (2000) for evidence of labor market pooling. There are many other sources of agglomeration that were not discussed in Marshall, including home market effects, urban consumption opportunities, and rent-seeking. See Rosenthal and Strange (2004) for a detailed discussion.

provide evidence that agglomeration economies likely enhance productivity in the hospital service industry, while also identifying one channel through which that might occur.

My findings in this chapter contribute to both the health economics literature and the urban/agglomeration literature. They contribute to the health economics literature by emphasizing a relatively new perspective – external economies of scale – that helps to explain geographic variation in access to medical services. For example, evidence of agglomeration economies in the health care sector suggests that spatial concentration of health care services may generate cost savings, which are likely to be especially important going forward as U. S. hospitals face increasing pressure to become more efficient. This chapter also contributes to the agglomeration literature by providing evidence that intermediate input sharing is more prevalent in agglomerated locations. As with Holmes (1999), such patterns are consistent with the idea that input sharing is an important microfoundation of agglomeration economies. To date, however, few studies have provided evidence of input sharing as a source of agglomeration economies.

The analysis to follow also examines the influence of the local industrial organization on the potential for input sharing and related external economies of scale in the hospital service industry.[38] Chinitz (1961) suggested that "large firms are … less of a stimulus to the creation of a community of independent suppliers." Similar arguments have been made by Jacobs (1969), Piore and Sabel (1984), and Saxenian (1994). By focusing on firms' entry decisions, Rosenthal and Strange (2010) found that small firms play an important role in the generation of agglomeration economies. Glaeser, Kerr, and Ponzetto (2010) documented that small firms have a stronger connection with subsequent employment growth than large establishments, which is

[38] Industrial organization in this context refers to the composition of the local industry: whether the local industry is composed of a large number of small establishments or is dominated by a small number of large establishments.

consistent with Chinitz's view. I also examine this organization-agglomeration relationship but from a different perspective. Specifically, I consider whether the "Chinitz" effect, as captured by the percentage of small hospitals in a county, contributes to local hospitals' decisions to outsource for intermediate services.

Four types of intermediate medical services are examined in the paper: clinical laboratory, blood bank, anatomical laboratory, and CAT scan. Using the 2009 provider of services (POS) file, Table 3-1 reports how the provision of a particular service varies across different counties.[39] Clinical laboratory services are more universally provided compared with other services, but they are still available in just eighty-four percent of the counties in the United States. At the other extreme, CAT scan services are available in only forty-two percent of the counties. This evidence coincides with geographic variation in access to medical services documented above.

As a first step in explaining spatial concentration of medical services, I draw on central place theory and explore further the influence of local concentrations of population.[40] Central place theory suggests that three factors influence an industry's tendency to locate in populated areas: the extent of internal economies of scale, per capita demand for the industry's product, and travel/shipping cost. If the provision of a particular service is associated with low per capita demand and high fixed costs (i.e. deep internal economies of scale), the service will only be provided in heavily populated areas with sufficient numbers of potential customers to take advantage of internal economies of scale by spreading out fixed costs. High transport costs

[39] http://www.cms.gov. The POS file is the primary dataset that this chapter draws on. It provides detailed hospital-level information on how a particular intermediate service is provided, the scale and property of the hospital, etc. This information can be aggregated to the county-level using the existing county identifier.

[40] Central place theory is a key building block of economic geography (King, 1984). It was developed by Christaller (1933) and Lösch (1940) and is used to predict the number, size, and scope of cities in a region. As shown recently by Hsu (2008) and Mori et al. (2008), central place theory also provides a route to explain empirical regularities in city size distribution and industrial locations.

further increase this tendency by limiting the geographic scope of a firm's market area. This implies that the decision to provide a service will depend on proximity to local concentrations of population, the effect of which will attenuate with geographic distance as travel costs to a given hospital increase.[41] I confirm these patterns.

Two technical hurdles must be overcome in order to measure the influence of agglomeration economies and the "Chinitz" effect on the propensity of hospitals to outsource for certain types of medical services. The first concerns the geographic scope of agglomeration economies. This chapter initially assumes that spillover effects from agglomeration do not extend beyond county boundaries. This is convenient given readily available county-level data. However, it is somewhat unsatisfying in that the benefits firms derive from proximity to each other are likely to attenuate with distance.[42] To further capture the spatial extent of spillover effects from agglomeration, local distribution of medical services (e.g., number of hospital beds) is measured in concentric rings drawn around the geographic centroid of each county. The influence of activity in each concentric ring on the propensity of outsourcing for intermediate services is then examined. Evidence of a lesser effect from activity in more distant concentric rings is consistent with the spatial attenuation of spillover effects.

A second empirical challenge faced in this chapter is a sample selection issue. Each hospital makes a series of decisions, regarding whether to provide a service and, if so, how to provide the service. It is possible that, even after controlling for a variety of variables, hospitals that choose to provide a given intermediate service are not randomly selected from the overall distribution of hospitals, but are correlated with hospitals' outsourcing propensities. This implies

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[41] There are further implications that are drawn out of central place theory, including that the composition of activities tend to be different for large areas and small areas, and in that sense, small town is not merely a smaller microcopy of large towns.

[42] See Rosenthal and Strange (2003, 2005, 2008), Andersson, Quigley, and Wilhelmsson (2009), and Arzaghi and Henderson (2008).

that the estimated effect of agglomeration economies and the "Chinitz" effect based on the selected sample could suffer from selection bias.

To address this concern, I estimate a bivariate probit model that explicitly controls for sample selection. The first equation considers whether a hospital provides a given service while the second considers how the service is provided conditional on the service being made available. Identification of the model is from two sources. The first is the nonlinearity of the probit functional form. In addition, I adopt a set of exclusion conditions based on the following argument. I assume that the decision to provide a service depends on both the demand and supply for the service. How that service is provided (i.e., outsource or provide in-house), however, is based on efforts to minimize cost, and for that reason, is assumed to be driven only by the underlying technology and factor prices.[43] Hence, local population attributes, which are shifters of demand, are omitted from a second stage model of how medical services are provided.

Using the above methodology, I obtain estimates for both the agglomeration effect and the "Chinitz" effect. Results show that hospitals in more concentrated areas and areas with a higher percentage of small hospitals are more likely to outsource for intermediate medical services. In addition, the effect of an increase in the scale of local hospital service industry rises at a declining rate. For example, for a county with just ten hospital beds, adding one thousand additional beds will increase the propensity of local hospitals to outsource clinical lab services by 2.05 percentage points (relative to the mean 36.43 %). This effect drops to 1.09 percentage points if the county has ten thousand hospital beds present. Similar patterns are also identified for blood bank services and CAT scan services. Despite the nonlinearity of the relationship, estimated effects of agglomeration economies tend to be positive and significant. These patterns are consistent with the presence of agglomeration economies in the hospital service industry in

[43] Factor prices are assumed to be exogenously given in the context of this chapter.

that they confirm that the sharing of intermediate medical services is more prevalent in agglomerated locations.

The estimated "Chinitz" effects on the probability of outsourcing are also generally positive and significant. For instance, an increase in the share of small hospitals in a county, from 20% to 30%, is associated with a 1.86 percentage point increase in the outsourcing probability for clinical lab services (relative to the mean 36.43 %).[44] The corresponding effects on the propensity of outsourcing blood bank services, anatomical laboratory services, and CAT scan services are 2.74 (relative to 48.04), 1.73 (relative to 60.84), and 2.43 (relative to 21.57) percentage point increases, respectively.

Finally, similar to the existing urban literature that considers the geographic extent of agglomeration economies, the spillover effects attenuate when moving further away from the centroid of the county. To get a sense of the magnitude, for clinical lab services, doubling the number of hospital beds at a distance between 50 miles and 75 miles increases the outsourcing probability by 1.96 percentage points (relative to the mean 36.43 %). This is 6.44 percentage points smaller than if the change occurred within 25 miles instead.

The rest of the paper proceeds as follows: Section 3. 2 draws on central place theory and measures the extent to which the size of local population helps to explain geographic variation in the provision of health care services. Section 3.3 investigates the existence of agglomeration economies in the hospital service industry and, more precisely, whether intermediate input sharing is an important microfoundation of agglomeration economies. Finally, section 3.4 concludes.

[44] Small hospitals here are defined as those with number of hospital beds below the 10th percentile.

3.2 County-Level Analysis: Local Population and Medical Services

This section is motivated by central place theory and estimates a simple relationship between the size of local population at various distance bands and the presence of intermediate medical services in a county. Table 3-3 reports the estimated coefficients from a set of probit models that evaluate whether a service is provided in a given county or not.[45] Table 3-4 shows the marginal effects of local population at various distance bands on the probability of providing intermediate services in a county.

The population measures are transformed into logs so that the marginal effects can be interpreted as semi-elasticities. For clinical laboratory services, doubling population within 25 miles is associated with a 6 percentage point increase in the probability of providing the service in a county. The corresponding marginal effects for blood bank, anatomical lab, and CAT scan services are 8.8, 14.2, and 15.3 percentage point increases, respectively. This implies that the local population at closer distances is a key driver of the provision of intermediate medical services.

As the radius of the concentric ring gets larger, the sign of marginal effects alternates, but the magnitude consistently attenuates.[46] The attenuation pattern of the estimated marginal effects is striking and is plotted in Figure 3-4 to facilitate review. These results indicate that the presence of an intermediate medical service in a county depends largely on the scale of the population nearby; population further away also matters, but to a smaller extent.

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[45] Data sources include the provider of service (POS) file and the area resource file (ARF). The POS is as mentioned earlier in the paper. The ARF will be discussed in Section 3.2. The specific techniques used to construct the concentric ring variables are described also in Section 3.2. Summary statistics of variables that enter the county-level regressions are provided in Table 3-2.

[46] The alternation of the sign resembles patterns observed from autoregressive processes in time series models and can be revealed as the inherent nature of the spatial structure. It may also reflect a measurement issue associated with how the concentric rings are created or the misjudgment on spatial spans arbitrarily chosen.

3.3 Hospital-Level Analysis: Agglomeration and Input Sharing

This section explores whether agglomeration economies exist in the hospital service industry and, more precisely, whether the sharing of intermediate inputs is an important microfoundation of agglomeration economies. These questions will be addressed by establishing the relationship between agglomeration and hospital outsourcing decisions.

3.3.1 Empirical Model

As described earlier, a bivariate probit model with three cells is used to control for possible sample selection that might arise when hospital outsourcing propensities are correlated with the decision to provide intermediate services. Identification is based on both the nonlinearity of the probit function and a set of exclusion restrictions. For the latter, I argue that supply and demand jointly determine whether a service is provided, but how that service is provided is based on the underlying technology, and in that sense, is driven solely by the supply function. Hence, demand shifters are included in the first stage regression of whether a service is provided but omitted from the second stage regression of how the service is provided.[47]

The demand for medical services provided in hospital i is characterized by the price (P), the quantity of services provided (X), and potential demand shifters, as represented by local demographics (S). That is (i is omitted for convenience),

$$P = D(X, S). \tag{3.1}$$

The supply function associated with providing an intermediate medical service in-house is shown as follows

$$AC^{IH} = C(X, K), \tag{3.2}$$

[47] This assumption is also largely supported by empirical evidence that the estimates associated with demand shifters in an probit model of outsourcing decisions tend to be insignificant. Imposing the exclusion restrictions strengthens identification and helps to avoid multicolinearity.

where X is the quantity of services provided by this hospital and K represents the level and the type of capital in the hospital. The level of capital refers to the size of the hospital, which is measured by the number of beds in the hospital in the empirical work to follow. The type of capital varies with the hospital's attributes — teaching hospital, public hospital, etc. K is assumed to be exogenous since it is hard to vary the scale or the nature of a hospital in the short run.

An alternative way that a hospital provides an intermediate service is to outsource the service to nearby intermediate service suppliers. The supply function, in this instance, is sensitive to the scale of the hospital industry in the local area and the size distribution of nearby hospitals that may or may not contribute to a "Chinitz" effect. I treat variable A as a measure of the extent of agglomeration economies. Variable CZ is used to represent the "Chinitz" effect. The average cost associated with providing the service through outsourcing is as shown below,

$$AC^{OS} = C(X, K) - q(A, CZ, K). \tag{3.3}$$

In this expression, $q(A, CZ, K)$ shifts down the average cost function but does not change its shape.[48] I argue that both $\partial \mathrm{q}/\partial A$ and $\partial \mathrm{q}/\partial CZ$ are positive, meaning that the agglomeration effect and the "Chinitz" effect are both expected to shift down the average cost curve. The former is consistent with the idea that agglomerated firms offer a potentially higher demand for intermediate services that promotes the emergence of specialized suppliers, which then results in lower outsourcing prices.[49] The latter is based on the argument that the presence of small companies is more likely to attract intermediate input suppliers due to their higher tendency to outsource. The emergence of specialized input providers further brings down the average cost

[48] $q(A, CZ, K)$ is assumed to be independent of X conditional on A, CZ and K.
[49] See Ono (2001), for example.

for not only small companies but also for all other neighboring establishments that draw on the same input market.[50]

The decision on whether to contract out for intermediate inputs when providing certain types of medical services is based on efforts to minimize cost, and for that reason, is considered to be driven only by the underlying technology and factor prices. Factor prices are assumed to be exogenously given. The outsourcing propensity is, hence, determined solely by technological factors (i.e., the agglomeration effect, the "Chinitz" effect, and the type/level of the capital associated with each hospital) that might shift AC^{IH} down to AC^{OS}. Since, as with other markets, the first stage decision – whether provide or not – depends on both the supply and demand for the service, I argue that I can exclude demand shifters from a second stage outsourcing equation and use them as exclusion restrictions that help to identify the model.

3.3.2 Data and Variables

This chapter draws on two primary data sources: the provider of service (POS) file and the area resource file (ARF). The POS file, as mentioned earlier, contains hospital-level information on intermediate service provisions, the scale and property of each hospital, etc. The ARF, published by the Health Resources and Services Administration (HRSA), is a collection of county-level data from more than fifty sources.[51] It offers health-related information on personnel and facility counts, hospital utilization, hospital expenditures, social characteristics, etc. Both of these datasets are used for the county-level analysis in Section 2 and the exploration of outsourcing decisions at the hospital level in this section.

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[50] This idea is consistent with findings in Rosenthal and Strange (2010), and Glaeser, Kerr, and Ponzetto (2010).

[51] These sources include American Medical Association, American Hospital Association, US Census Bureau, Center for Medicare & Medicaid Services, Bureau of Labor Statistics, National Center for Health Statistics, etc. Details can be found at http://arf.hrsa.gov/.

In the POS file, I focus on four types of medical services that are commonly characterized as intermediate services: clinical laboratory, blood bank, anatomical laboratory, and CAT scan.[52] The clinical laboratory provides routine tests in the areas of hematology, chemistry, transfusion services, and microbiology. It is responsible for recording appropriate results on patients' charts in a manner that can be easily interpreted by physicians to guide further diagnosis and treatment. A blood bank is a repository of blood components gathered as a result of blood donation. It stores, preserves, and, eventually, provides blood products for patients in need. The anatomical laboratory provides specific services for surgical tissue specimens and cytology specimens. CAT scan (also called CT scan) is an X-ray technique that allows relatively safe, painless, and rapid diagnosis in previously inaccessible areas of the body and is an essential tool used for the diagnosis of many internal diseases. In a complete treatment process, the above services are considered as inputs since they are responsible for preparing intermediate reports or products that will facilitate further treatment fulfilled by doctors and nurses at a later stage.

Four situations are specified in the POS file regarding the provision of these intermediate medical services: not provided, provided by staff (in-house), provided by arrangement or agreement (outsourcing), and provided by staff and through agreement (both). For the purpose of this chapter, the last two categories are grouped together to capture the idea of whether a hospital relies on outside specialized intermediate service providers at all. Table 3-5 summaries service provisions of various intermediate medical services for all hospitals in the data. Clinical laboratory services are most widely provided – 97% of hospitals offer this type of service – while CAT scan services are available in only 24% of hospitals in the country. The percentage of

[52] I also experimented with other types of services, such as diagnostic radiology, therapeutic radiology, MRI, etc, and obtained similar results. To avoid proliferation of results, I only focus on four types of intermediate services that are more frequently used.

hospitals that choose to outsource for a particular intermediate service out of the hospitals that offer the service also varies across different types of services.

The extent of agglomeration economies is initially captured by the total number of hospital beds in the county in which a hospital is located. To take into consideration potential spatial attenuation of agglomeration economies, this variable is then replaced by a set of concentric ring variables. Each of these variables measures hospital beds present at a given distance band from the centroid of the county: 0 to 25 miles, 25 to 50 miles, 50 to 75 miles, and 75 to 100 miles.

Several steps are taken to form these concentric ring variables. First, mapping software (MapInfo and MapBasic) is used to draw circles of radius 25, 50, 75, and 100 miles around the geographic centroid of each county. Second, treating hospital beds within a given county as uniformly distributed throughout the area, the number of beds contained in a created circle is calculated by constructing a proportional sum of the beds for those portions of the counties intersected by a given circle.[53] Finally, hospital beds for adjacent circles, such as beds within a 25-mile ring and that within the corresponding 50-mile ring, are differenced to obtain the number of hospital beds within the corresponding concentric ring.[54]

The "Chinitz" effect is represented by the percentage of small hospitals. The goal is to capture whether small establishments with flexible structure and higher motivation for innovation play an important role in generating productivity spillovers. Small hospitals are defined as hospitals with less than or equal to twenty-one hospital beds, which correspond to the 10th percentile based on the ranking of hospital size as shown in Table 3-6. As further robustness

[53] The construction of the proportional sum measure is better illustrated in Figure 3-3. For example, for county A, a 25-mile circle around its centroid intersects seven neighboring counties. The number of population within the circle is calculated as the sum of the population belonging to each shaded portion of these counties (including A itself) that overlaps the circle, assuming population within each county is uniformly distributed throughout the area.
[54] Same technique is used to construct the population concentric ring variables used in Section 2.2.

checks, estimates are also reported when small hospitals are defined as those with number of hospital beds below the 5^{th} percentile or the 25^{th} percentile.

The number of beds in a hospital captures the level of the capital – the extent to which internal economies of scale might affect the hospital's tendency to outsource for intermediate services. The type of the capital is represented by a set of dummy variables indicating whether the hospital is a teaching hospital, a public hospital, a short-term hospital, a children's hospital, or a psychiatric hospital.[55] Variables that shift the demand curve are captured by a series of county-level social demographic attributes and are obtained from the ARF. These variables include the number of population in a county, 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 Hispanic inhabitants, and the percentage of people with lower than high school education. Summary statistics for these variables at the hospital level are provided in Table 3-7.

3.3.3 Results

A. Model Coefficients

Table 3-8 reports estimated coefficients from bivariate probit models that address possible concerns about sample selection. Before discussing the coefficients, one thing that stands out in Table 3-8 is that the estimated correlation for two parts of model is strong and significantly identified. Estimated error correlations are generally greater than 0.8 and even reach up to 0.94 for CAT scan service. This indicates that a hospital's tendency to outsource intermediate services is strongly correlated with how the sample is selected. Potentially,

[55] A teaching hospital is a hospital that provides clinical education and training to future and current doctors, nurses, and other health professionals, in addition to delivering medical care to patients. A public hospital is a hospital that is owned by a government and receives government funding. A short-term hospital is a hospital intended for short-term medical and/or surgical treatment and care. A children's hospital is a hospital that offers its services exclusively to children. A psychiatric hospital is a hospital specializing in the treatment of serious mental disorders.

estimates of the outsourcing equation, based solely on hospitals providing the service, may suffer from selection bias. The degree of bias would be reflected by the difference between the estimated coefficients from the probit model and those from the bivariate probit model. In this study, probit models tend to overestimate the coefficient associated with the first order of agglomeration measure by 7% [(7.50-7.03)/7.03] for clinical laboratory services, 43% [(5.00-3.49)/3.49] for blood bank services, and 177% [(9.02-3.26)/3.26] for CAT scan services. This suggests that a careful assessment of outsourcing decisions requires proper handling of the selection problem. Therefore, I mainly focus on estimates from bivariate probit models in the following analysis.

Two patterns are present when examining the estimated coefficients of bivariate probit models. First, three key explanatory variables – the measures for agglomeration economies, the "Chinitz" effect, and the level of capital for each hospital – affect the second-stage outsourcing decisions in a nonlinear fashion.[56] Agglomeration economies and the "Chinitz" effect tend to impose a positive influence on hospital outsourcing propensities, though at a decreasing rate.[57] The hospital's own scale is negatively correlated with the decision to outsource, and the effect gets smaller as the number of beds in the hospital becomes larger. Since only raw estimates are reported in these tables, I will not discuss the magnitude of these effects here. Careful interpretation for marginal effects will be addressed below.

Second, agglomeration economies and the "Chinitz" effect tend not to be statistically influential in the first-stage "provide" equation. This may reflect the nature of the sample: there are not many hospitals positioned at the margin where a slight decrease in average cost induced

[56] To further capture the nonlinear feature of the influence of variables that represent economies of scale (either internal or external), I also adopt quadratic functional forms for measures of agglomeration economies, the "Chinitz" effect and the level of the capital in a hospital. I also experimented with including cubic terms to capture further curvatures of the relationship. Results show that the third order terms tend to be insignificant.

[57] The "Chinitz" effect here is captured by the percentage of small hospitals whose number of beds does not exceed 21. This definition is adjusted later for robustness checks.

by outsourcing opportunities would make a significant difference in whether to provide a particular intermediate service. It is also likely that agglomeration economies and the "Chinitz" effect influence the decision to "provide" through other channels other than potential cost saving generated by external economies of scale.[58]

One concern to the robustness of the estimates is the definition of small hospitals that is used to construct proxies for the "Chinitz" effect. Small hospitals are initially defined as those with number of beds below the 10th percentile (21 hospital beds). However, "small" is a relative term and there is no absolute definition for how small is "small" in this context. It is useful to check how estimates vary when small hospitals are defined in another sensible way. To this end, I experiment with defining small hospitals as those with the number of beds below the 5th percentile or the 25th percentile (corresponding to 15 beds and 33 beds, respectively). Estimated coefficients of the second-stage bivariate probit models are reported in Table 3-9. It shows that qualitatively the impact of the "Chinitz" effect is robust to various ways of defining small hospitals: the first-order proxy tends to be significantly positive, while the second-order tends to be significantly negative. In the meanwhile, estimated coefficients associated with other explanatory variables are generally robust to how small hospitals are defined.

B. Marginal Effects

To properly interpret the results, two sources of nonlinearities need to be addressed: the nonlinearity of bivariate probit function and the inclusion of quadratic terms.[59] Figure 3-6 shows the estimated marginal effects of three key explanatory variables (i.e., measures of

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[58] For example, hospitals may enter the market sequentially and make decisions in response to other hospitals' actions. If there have already been a lot of hospitals providing a service in a fully developed market, new-comers may choose not to provide this service to avoid competition. This potential negative influence on the decision to "provide" may neutralize the expected positive effect of productivity spillovers discussed earlier and yields zero or even negative coefficients.

[59] An intermediate step in deriving the marginal effects, which has only addressed the nonlinearity of the bivariate probit model, is calculated but not reported. These intermediate marginal effects are calculated as the average of the marginal effect associated with each observation. Based on that, marginal effects for variables with quadratic specifications are then calculated as $\frac{\Delta\hat{y}}{\Delta x} \approx \hat{\beta}_1 + 2\hat{\beta}_2 x$, where $\hat{\beta}_1$ and $\hat{\beta}_2$ represent the estimated partial effects of the first order and the second order regressors.

agglomeration economies, the "Chinitz" effect, and internal economies of scale) and how the effects change within the major range of corresponding regressors.[60]

As shown in the upper panel of the figure, estimated marginal effects of agglomeration economies for clinical laboratory services, blood bank services, and CAT scan services are generally positive at a decreasing rate. This suggests that hospitals in more concentrated areas are more likely to outsource intermediate services to specialized intermediate service suppliers, though this tendency decreases as the local industrial scale gets larger. This evidence is consistent with findings in Holmes (1999) and further suggests that agglomeration of economic activities promotes emergence of specialized intermediate service suppliers and encourages intermediate input sharing.[61]

The middle panel of Figure 3-6 shows the estimated impact of the "Chinitz" effect on the tendency of local hospitals to outsource for intermediate medical services. For all four types of services considered in this chapter, the impact of the size distribution of local hospitals is generally positive at a decreasing rate. This implies that higher percent of small hospitals are associated with a higher tendency to outsource, which is consistent with Chinitz's view. Another thing to notice is that the estimated marginal effect decreases, reaches zero, and may even turn negative near the very end of the horizontal axis for some services. This suggests that when the local industry is comprised of "too many" small hospitals, individual hospitals may become less likely to outsource for intermediate medical services. Possibly, it is caused by that the increase

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[60] For each of these variables, the horizontal axis extends up to the 95th percentile. This helps to leave out the influence of potential outliers and capture the major trend of the marginal effect. The vertical axis represents the effect of these variables on the probability of outsourcing intermediate medical services.

[61] Note that the agglomeration effect on a hospital's decision to outsource anatomical lab services does not behave in the same way. This is probably due to the specialized nature of this particular service. The work of processing anatomical specimens requires more skilled medical professionals who may sort into big cities. The lack of sufficient expertise in small cities forces local hospitals to contract out this particular service to facilities available in large cities.

in transaction costs associated with managing a lot of small hospitals tends to offset potential gains from specialization.

The marginal effect of an individual hospital's own scale is plotted in the lower panel of Figure 3-6. Hospitals with larger scales are less likely to outsource intermediate services and the magnitude of this effect decreases as the number of beds in the hospital gets larger. This evidence is in line with the idea that large hospitals are more likely to provide intermediate services in-house by taking advantages of cost savings generated by internal economies of scale.

To get a better sense of magnitude, Table 6 reports the estimated effects of the three key explanatory variables on local hospital outsourcing propensities at selected points. For a county with just ten hospital beds, adding one thousand additional beds increase local hospitals' tendency to outsource intermediate services by 2.05 percentage points. This effect drops to 1.09 percentage points if the county has ten thousand hospital beds present. Similar patterns are also identified for blood bank services and CAT scan services. As for the "Chinitz" effect, an increase in small hospitals from 20% to 30% raises outsourcing propensities for clinical lab services, blood bank services, anatomical laboratory services, and CAT scan services by 1.86, 2.74, 1.73, and 2.43 percentage points, respectively. From the perspective of internal economies of scale, adding one hundred additional beds for a hospital with ten beds available decreases the probability of outsourcing clinical laboratory services by 5.94 percentage points. This effect drops to 5.04 percentage points when the hospital has one hundred and fifty beds present and further reduces to 3.44 percentage points when the hospital has four hundred beds available.

C. Attenuation

In the above setting, agglomeration economies are assumed to take place within county boundaries. However, the geographic scope of agglomeration effect is not necessarily restricted by political boundaries as indicated in Rosenthal and Strange (2003, 2005, 2008), Andersson, Quigley, and Wilhelmsson (2009), and Arzaghi and Henderson (2008). The next approach in this chapter is, therefore, geographically oriented. Specifically, I adopt a specification with concentric ring variables that capture the number of beds within 0 to 25 miles, 25 miles to 50 miles, 50 miles to 75 miles, and 75 miles to 100 miles, respectively. These concentric ring measures help to investigate the geographic scope of agglomeration economies and the potential attenuation pattern.

Table 3-11 reports estimated impacts of nearby medical activities within various distance bands on a hospital's tendency to outsource for intermediate medical services. The concentric ring variables are transformed into log terms. [62] The estimated marginal effects, hence, represent semi-elasticities. As shown in the table, the magnitude of the estimated semi-elasticities attenuates as moving further away from the centroid of the county, which is consistent with previous findings in the urban literature. The sign of the marginal effects alternates similarly as that in the county-level regressions, but the attenuation pattern is striking and is plotted in Figure 3-7.

Quantitatively speaking, for clinical lab services, doubling the number of hospital beds within 25 miles is associated with a 8.40 percentage point increase in the probability of outsourcing. The influence of agglomeration economies drops to 1.96 percentage points if the change occurred at a distance between 50 miles and 75 miles. Similarly for CAT scan services, the magnitude of the marginal effect decreases from 6.95 percentage points for the 25 mile ring to 2.70 percentage points for the 50-75 mile concentric ring. The spatial attenuation is strong

[62] The transformation is expected to capture the concavity of the relationship identified earlier. It also helps to avoid a specification with both linear and quadratic terms associated with each of four concentric ring. Accordingly, the number of beds in a hospital is transformed into logs as well. The nonlinearity of the "Chinitz" effect is captured by a spline linear function with a kink at 0.3 that corresponds to the 75th percentile of the distribution of the percentage of small hospitals.

and clear for clinical lab, blood bank, and CAT scan services as the marginal effects for the 75-100 mile concentric ring almost diminish to zero.

3.4 Conclusion

This chapter considers two important factors that may contribute to geographic variation in the hospital service industry. The first factor is variation in population distribution: medical resources are drawn to areas with higher demand for health care services. The second factor, which receives relatively little attention in the literature, is agglomeration economies that may generate increasing returns and attract hospitals to locate in concentrated areas. The existence of agglomeration economies in the hospital service industry is addressed indirectly by examining whether hospitals in agglomerated areas are more likely to outsource for intermediate medical services.

I obtain the following results. Firstly, evidence suggests that a particular service will be provided in a county when there is enough population nearby to spread out the high fixed costs associated with providing the service. The effect attenuates when people are located further away. Secondly, agglomeration economies tend to increase the tendency of local hospitals to outsource for clinical lab services, blood bank services, and CAT scan services. This effect also attenuates with geographic distance. Thirdly, the "Chinitz" effect, as captured by the percentage of small hospitals in a county, increases local hospitals' outsourcing propensities. The evidence is robust to different ways of defining small hospitals. Finally, large hospitals, measured by the number of beds in a hospital, are more likely to provide intermediate medical services in-house. This is consistent with the idea that large hospitals are more likely to exploit internal economies of scale when providing certain types of medical services.

The findings suggest that agglomeration economies exist in the hospital service industry. It further implies that, apart from concentration of population distribution, productivity spillovers generated by agglomeration may also contribute to geographic variation in access to medical services. Furthermore, the evidence that hospitals in agglomerated locations are more likely to outsource for intermediate medical services is consistent with intermediate input sharing as an important microfoundation of agglomeration economies.

References

Andersson, R., Quigley, J.M., Wilhelmsson, M., 2009. Urbanization, productivity, and innovation: Evidence from investment in higher education. Journal of Urban Economics 66, 2–15.

Arzaghi, M., Henderson, J.V., 2008. Networking off Madison Avenue. The Review of Economic Studies 75, 1011–1038.

Baicker, K., Chandra, A., 2010. Understanding agglomerations in health care. In: Glaeser, E.L. (Ed.), Agglomeration Economics. University of Chicago Press, pp. 211–364.

Casey, M.M., Thiede Call, K., Klingner, J.M., 2001. Are rural residents less likely to obtain recommended preventive healthcare services? American Journal of Preventive Medicine 21, 182–188.

Chinitz, B., 1961. Contrasts in agglomeration: New York and Pittsburgh. American Economic Review 51, 279–289.

Christaller, W., 1933. Central Places in Southern Germany (CW Baskin, Tran.). Prentice-Hall, Englewood Cliffs, NJ.

Cohen, J.P., Morrison Paul, C., 2008. Agglomeration and cost economies for Washington state hospital services. Regional Science and Urban Economics 38, 553–564.

Costa, D.L., Kahn, M.E., 2000. Power couples: changes in the locational choice of the college educated, 1940–1990. The Quarterly Journal of Economics 115, 1287–1315.

Coughlin, S.S., Thompson, T.D., Hall, H.I., Logan, P., Uhler, R.J., 2002. Breast and cervical carcinoma screening practices among women in rural and nonrural areas of the United States, 1998-1999. Cancer 94, 2801–2812.

Ellison, G., Glaeser, E.L., Kerr, W.R., 2010. What causes industry agglomeration? evidence from coagglomeration patterns. American Economic Review 100, 1195–1213.

Glaeser, E.L., Kerr, W.R., Ponzetto, G.A.M., 2010. Clusters of entrepreneurship. Journal of Urban Economics 67, 150–168.

Glaeser, E.L., Gottlieb, J.D., 2009. The wealth of cities: agglomeration economies and spatial equilibrium in the United States. Journal of Economic Literature 47, 983–1028.

Glaeser, E.L., Maré, D.C., 2001. Cities and skills. Journal of Labor Economics 19, 316–342.

Goodman, D.C., 2004. Trends: twenty-year trends in regional variations in the U.S. physician workforce. Health Affairs, 90–97.

Goodman, D.C., Fisher, E.S., Bubolz, T.A., Mohr, J.E., Poage, J.F., Wennberg, J.E., 1996. Benchmarking the us physician workforce: an alternative to needs-based or demand-based planning. JAMA 267, 1811–1817.

Holmes, T.J., 1999. Localization of industry and vertical disintegration. Review of Economics and Statistics 81, 314–325.

Hsu, W.-T., 2008. Central Place Theory and Zipf's Law. ProQuest.

Jacobs, J., 1969. The economy of cities. New York: Vintage.

King, L.J., 1984. Central Place Theory. Sage publications, Beverly Hills: CA.

Li, J., 2012. The influence of state policy and proximity to medical services on health outcomes. Syracuse University. Unfinished working paper.

Lösch, A., 1940. The economics of location. Yale University Press, New Haven: CT.

Marshall, A., 1920. Principles of Economics. London: Macmillan.

Moretti, E., 2004. Workers' education, spillovers, and productivity: evidence from plant-level production functions. American Economic Review 94, 656–690.

Mori, T., Nishikimi, K., Smith, T.E., 2008. The number-average size rule: a new empirical relationship between industrial location and city size. Journal of Regional Science 48, 165–211.

O'Sullivan, A., 2011. Urban Economics. McGraw-Hill/Irwin.

Ono, Y., 2003. Outsourcing business services and the role of central administrative offices. Journal of Urban Economics 53, 377–395.

Piore, M., Sabel, C., 1984. The Second Industrial Divide: Possibilities For Prosperity. Basic Books, New York.

Quigley, J.M., 1998. Urban diversity and economic growth. The Journal of Economic Perspectives 12, 127–138.

Rosenthal, S.S., Strange, W.C., 2010. Small establishments/big effects: agglomeration, industrial organization, and entrepreneurship. In: Glaeser, E. (Ed.), Agglomeration Economies. University of Chicago Press, pp. 1–27.

Rosenthal, S.S., Strange, W.C., 2008. The attenuation of human capital spillovers. Journal of Urban Economics 64, 373–389.

Rosenthal, S., Strange, W., 2005. The geography of entrepreneurship in the New York metropolitan area. Federal Reserve Bank of New York Economic Policy Review 11, 29–53.

Rosenthal, S.S., Strange, W.C., 2004. Evidence on the nature and sources of agglomeration economies. Handbook of Regional and Urban Economics 4, 2119–2171.

Rosenthal, S.S., Strange, W.C., 2003. Geography, industrial organization, and agglomeration. Review of Economics and Statistics 85, 377–393.

Rosenthal, S.S., Strange, W.C., 2001. The determinants of agglomeration. Journal of Urban Economics 50, 191–229.

Saxenian, A., 1994. Regional advantage: cultural and competition in Silicon Valley and Route 128. Harvard University Press, Cambridge, MA.

Table 3-1: Service Provision (County-Level)

	# of counties that provide the service [b]	% of counties that provide the service
Clinical Laboratory	2,609	84.00%
Blood Bank	2,419	77.88%
Anatomical Laboratory	2,081	67.00%
CAT Scan	1,291	41.56%

[a] Sample at the county level contains 3,106 observations.
[b] A particular service is provided in a county if there is at least one hospital in the county offering the service.

Table 3-2: Summary Statistics (County-Level)

	Mean	Std. Dev.	Min.	Max.
Population_0-25 [a]	306348.21	824523.25	78.39	1.29e+07
Population_25-50 [b]	768396.75	1165970.11	190.25	1.49e+07
Population_50-75 [c]	1176949.02	1410475.25	24.25	1.57e+07
Population_75-100 [d]	1567141.52	1662115.14	121.71	1.56e+07
Population in the county	96396.59	311603.9	55	9878554
% of Uninsured	20.73	6.69	7.91	50.62
% of > 65 Years Old	15.63	4.22	2.60	37.21
Per Capita Income	30346.55	8098.04	8579.00	132728.00
% in Poverty	15.10	6.24	2.40	55.90
% Black	8.68	14.44	0.00	86.50
% Hispanic	6.21	12.05	0.10	97.50
% of < High School	9.09	5.26	0.00	46.30

[a] Population_0-25 represents the number of population within the 25-mile ring around the centroid of each county, assuming population within a given county is uniformly distributed throughout the area.
[b] Population_25-50 represents the number of population within the donut ring bounded by the 25-mile and the 50-mile rings around the centroid of each county, assuming population within a given county is uniformly distributed throughout the area.
[c,d] Population_50-75 and Population_75-100 are defined in a similar fashion.

Table 3-3: Estimated Coefficients from County-Level Probit Regressions

	Clinical Laboratory	Blood Bank	Anatomical Laboratory	CAT Scan
Log(Population_0-25)	0.276	0.316	0.404	0.393
	(3.14)	(3.96)	(5.64)	(7.08)
Log(Population_25-50)	-0.238	-0.258	-0.262	-0.212
	(-1.86)	(-2.22)	(-2.52)	(-2.58)
Log(Population_50-75)	0.220	0.228	0.179	0.082
	(2.35)	(2.64)	(2.27)	(1.19)
Log(Population_75-100)	-0.102	-0.143	-0.100	-0.151
	(-1.05)	(-2.46)	(-1.87)	(-3.10)
% of Uninsured	-0.038	-0.032	-0.025	-0.014
	(-6.87)	(-6.42)	(-5.35)	(-3.27)
% of > 65 Years Old	0.034	0.033	0.029	0.021
	(3.88)	(4.14)	(3.91)	(3.07)
Per Capita Income	2.71e-05	2.64e-05	2.55e-05	1.51e-05
	(3.18)	(3.64)	(3.65)	(3.53)
% in Poverty	0.044	0.038	0.040	0.033
	(4.23)	(4.37)	(5.23)	(5.24)
% Black	0.001	-0.002	-0.009	-0.003
	(0.47)	(-0.71)	(-4.10)	(-1.43)
% Hispanic	0.024	0.024	0.023	0.012
	(5.51)	(6.18)	(7.04)	(4.61)
% of < High School	-0.048	-0.041	-0.046	-0.029
	(-6.17)	(-5.82)	(-6.87)	(-4.44)
No. of Observations	3,106	3,106	3,106	3,106
Log Likelihood	-1229.674	-1496.560	-1758.030	-1971.156
Pseudo R-squared	0.099	0.089	0.108	0.065

[a] Concentric ring variables representing the distribution of local population are defined the same as in Table 3-2.

Table 3-4: Marginal Effects from County-Level Probit Regressions

	Clinical Laboratory	Blood Bank	Anatomical Laboratory	CAT Scan
Log(Population_0-25)	0.060	0.088	0.142	0.153
	(3.14)	(3.96)	(5.64)	(7.08)
Log(Population_25-50)	-0.051	-0.072	-0.092	-0.082
	(-1.86)	(-2.22)	(-2.52)	(-2.58)
Log(Population_50-75)	0.048	0.063	0.063	0.032
	(2.35)	(2.64)	(2.27)	(1.19)
Log(Population_75-100)	-0.022	-0.040	-0.035	-0.059
	(-1.05)	(-2.46)	(-1.87)	(-3.10)
Predicted Prob. (at $\bar{X}$)	0.865	0.803	0.694	0.412
No. of Observations	3,106	3,106	3,106	3,106
Log Likelihood	-1229.674	-1496.560	-1758.030	-1971.156
Pseudo R-squared	0.099	0.089	0.108	0.065

[a] Marginal effects are calculated as the average of the marginal effects of all observations based on the estimated coefficients in Table 3-3. Same set of control variables as in Table 3-3 is used for estimation. Social economic control variables include % of Uninsured, % of > 65 Years Old, Per Capita Income, % in Poverty, % Black, % Hispanic, and % of < High School. Concentric ring variables representing the distribution of local population are defined the same as in Table 3-2.

Table 3-5: Service Provision (Hospital-Level)

	# of hospitals That PROVIDE	% of hospitals that PROVIDE Out of ALL hospitals	# of hospitals That OUTSOURCE	% of hospitals that OUTSOURCE Out of Hospitals that PROVIDE
Clinical Laboratory	9,077	97.08%	3,307	36.43%
Blood Bank	6,788	72.60%	3,261	48.04%
Anatomical Laboratory	5,759	61.59%	3,504	60.84%
CAT Scan	2,207	23.60%	476	21.57%

[a] Sample at the hospital level contains 9.350 observations.

Table 3-6: The Distribution of Hospital Beds

Percentiles	Beds Count in the Hospital
1%	8
5%	***15***
10%	***21***
25%	***33***
50%	70
75%	170
90%	347
95%	483
99%	845

[a] Detailed percentile summary statistics for the number of beds in a hospital.

Table 3-7: Summary Statistics (Hospital-Level)

	Mean	Std. Dev.	Min.	Max.
# Beds in the County	4152.54	8206.04	5	45749
# Beds in the County_0-25 [a]	6065.30	10445.50	1.62	68514.82
# Beds in the County_25-50 [b]	7154.91	9940.50	12.73	78377.31
# Beds in the County_50-75 [c]	7977.45	9572.56	26.28	87175.69
# Beds in the County_75-100 [d]	10208.54	12089.22	64.32	84101.07
% of Small Hospitals (defined as # beds <= 15) [e]	0.05	0.13	0	1
% of Small Hospitals (defined as # beds <= 21) [f]	0.11	0.19	0	1
% of Small Hospitals (defined as # beds <= 33) [g]	0.26	0.29	0	1
# Beds in the Hospital	138.34	178.53	1	2400
Short-term Hospital [h]	0.72	0.45	0	1
Children's Hospital [i]	0.01	0.10	0	1
Psychiatric Hospital [g]	0.11	0.31	0	1
Public Hospital [k]	0.24	0.42	0	1
Teaching Hospital [l]	0.20	0.40	0	1
Population	750679.60	1630788	736	9878554
% of Uninsured	20.58	6.86	7.90	49.45
% of > 65 Years Old	13.94	3.84	4.81	37.23
Per Capita Income	35829.61	11188.65	13854	132728
% in Poverty	14.47	5.47	2.40	47.40
% Black	12.11	14.71	0	86.53
% Hispanic	10.40	14.37	0.12	97.54
% of < High School	8.10	4.57	0.63	46.35

[a] # Beds in the County_0-25 represents the number of hospital beds within the 25-mile ring around the centroid of each county, assuming beds within a given county are uniformly distributed throughout the area.
[b] # Beds in the County_25-50 represents the number of hospital beds within the donut ring bounded by the 25-mile and 50-mile rings around the centroid of each county, assuming beds within a given county are uniformly distributed throughout the area.
[c,d] # Beds in the County_50-75 and # Beds in the County_75-100 are defined in a similar fashion.
[e] Small hospitals here are defined as the hospitals whose number of beds does not exceed 15. In this way, the hospitals with the number of beds below the 5th percentile are labeled as small hospitals.
[f] Small hospitals here are defined as the hospitals whose number of beds does not exceed 21. In this way, the hospitals with the number of beds below the 10th percentile are labeled as small hospitals.
[g] Small hospitals here are defined as the hospitals whose number of beds does not exceed 33. In this way, the hospitals with the number of beds below the 25th percentile are labeled as small hospitals.
[h] A short-term hospital is a hospital intended for short-term medical and/or surgical treatment and care.
[i] A children's hospital is a hospital which offers its services exclusively to children.
[g] A psychiatric hospital is a hospital specializing in the treatment of serious mental disorders.
[k] A public hospital is a hospital owned by a government and receiving government funding.
[l] A teaching hospital is a hospital that provides clinical education and training to future and current doctors, nurses, and other health professionals, in addition to delivering medical care to patients.

Table 3-8: Estimates from Hospital-Level Bivariate Probit Models

	Clinical Laboratory		Blood Bank		Anatomical Laboratory		CAT Scan	
	Provide	Outsource	Provide	Outsource	Provide	Outsource	Provide	Outsource
# Beds in the County	2.05e-05	7.03e-05	5.97e-06	3.49e-05	-2.02e-06	-1.14e-05	-2.64e-05	3.26e-05
	(1.34)	(12.79)	(0.69)	(6.53)	(-0.25)	(-2.01)	(-2.83)	(3.43)
# Beds in the County Sq	-1.60e-10	-1.63e-09	3.48e-10	-9.28e-10	8.52e-11	1.76e-10	9.24e-11	-8.47e-10
	(-0.78)	(-11.73)	(2.00)	(-6.91)	(0.53)	(1.30)	(0.51)	(-2.86)
% of Small Hospitals	-0.2158	1.0825	-0.1140	1.1689	0.1033	0.6438	-0.2851	0.9449
(defined as # beds <= 21)	(-0.51)	(5.74)	(-0.56)	(6.06)	(0.55)	(2.82)	(-1.45)	(3.23)
% of Small Hospitals Sq	0.9000	-1.1468	0.1891	-1.2034	-0.3696	-0.4294	0.0084	-1.1173
(defined as # beds <= 21)	(1.31)	(-4.96)	(0.75)	(-5.31)	(-1.67)	(-1.41)	(0.04)	(-2.95)
# Beds in the Hospital	-0.0004	-0.0021	0.0018	-0.0022	0.0028	-0.0028	0.0016	-0.0004
	(-1.11)	(-10.70)	(7.71)	(-9.49)	(12.67)	(-11.31)	(8.59)	(-1.39)
# Beds in the Hospital Sq	1.42e-07	1.07e-06	-7.76e-07	1.16e-06	-1.36e-06	1.40e-06	-5.75e-07	2.24e-07
	(0.67)	(6.35)	(-3.57)	(4.80)	(-6.55)	(5.58)	(-3.66)	(1.21)
Short-term Hospital	0.9039	-0.7172	0.5664	-0.1911	0.7226	0.0315	-0.5699	-0.7237
	(11.71)	(-18.75)	(13.93)	(-3.69)	(18.16)	(0.40)	(-14.55)	(-11.94)
Children’s Hospital	0.5373	-0.1454	0.3728	-0.0454	0.6535	0.0372	-1.0228	-1.3012
	(2.00)	(-1.05)	(2.50)	(-0.31)	(4.70)	(0.24)	(-5.50)	(-3.38)
Psychiatric Hospital	0.0945	0.9609	-1.8288	-0.3133	-0.7635	0.0889	-1.2311	0.1318
	(1.11)	(14.37)	(-26.83)	(-1.85)	(-12.85)	(0.60)	(-17.03)	(0.65)
Public Hospital	0.1818	-0.2561	0.0848	0.0117	-0.0178	0.1234	0.0195	-0.0611
	(2.46)	(-7.00)	(2.15)	(0.33)	(-0.51)	(3.01)	(0.54)	(-1.02)
Teaching Hospital	0.1298	-0.0908	0.0466	-0.0800	0.1072	-0.1325	0.1467	0.0168
	(1.65)	(-2.17)	(1.02)	(-1.94)	(2.59)	(-3.08)	(3.60)	(0.24)
Population	-8.36e-08		-6.82e-08		7.47e-09		5.85e-08	
	(-0.91)		(-1.52)		(0.17)		(1.27)	
% of Uninsured	0.0084	-	-0.0045	-	-0.0063	-	0.0026	-
	(1.50)	-	(-1.66)	-	(-2.58)	-	(0.99)	-
% of > 65 Years Old	0.0075	-	0.0071	-	-0.0013	-	0.0092	-
	(0.78)	-	(1.51)	-	(-0.30)	-	(2.06)	-
Per Capita Income	-5.08e-06	-	-8.98e-06	-	-1.77e-07	-	-1.45e-06	-
	(-1.69)	-	(-5.13)	-	(-0.09)	-	(-0.80)	-
% in Poverty	-0.0202	-	-0.0150	-	-0.0010	-	0.0064	-
	(-2.20)	-	(-3.31)	-	(-0.23)	-	(1.49)	-
% Black	-0.0023	-	-0.0014	-	-0.0043	-	-0.0061	-
	(-0.88)	-	(-1.05)	-	(-3.40)	-	(-4.50)	-
% Hispanic	-0.0068	-	-0.0036	-	0.0027	-	-0.0056	-
	(-1.87)	-	(-2.07)	-	(1.80)	-	(-3.35)	-
% of < High School	0.0540	-	0.0183	-	-0.0125	-	0.0014	-
	(4.13)	-	(3.63)	-	(-2.94)	-	(0.32)	-
Error Term Correlation (ρ)	0.8485		0.8744		0.8397		0.9373	
Wald Test for ρ=0	60.18		77.72		138.28		67.94	
No. of Observations	9,350		9,350		9,350		9,350	
Log Likelihood	-5795.36		-8339.03		-8258.44		-5733.22	

Table 3-9: Alternate Measures of Small Hospitals [a]

	Clinical Laboratory		Blood Bank		Anatomical Laboratory		CAT Scan	
# Beds in the County	7.03e-05	6.21e-05	3.53e-05	3.78e-05	-1.20e-05	-5.92e-06	3.17e-05	2.52e-05
	(13.00)	(11.34)	(6.60)	(7.17)	(-2.13)	(-1.02)	(3.43)	(2.73)
# Beds in the County Sq	-1.63e-09	-1.44e-09	-9.45e-10	-9.85e-10	1.85e-10	7.63e-11	-8.24e-10	-6.90e-10
	(-11.92)	(-10.53)	(-7.01)	(-7.29)	(1.37)	(0.55)	(-2.85)	(-2.39)
% of Small Hospitals (defined as # beds <= 15)	1.0198	-	1.2195	-	0.4550	-	1.3234	-
	(4.22)	-	(4.84)	-	(1.58)	-	(3.17)	-
% of Small Hospitals Sq (defined as # beds <= 15)	-1.0422	-	-1.5579	-	-0.7189	-	-2.0174	-
	(-3.13)	-	(-4.67)	-	(-1.74)	-	(-2.74)	-
% of Small Hospitals (defined as # beds <= 33)	-	0.8980	-	1.0794	-	0.6224	-	-0.0586
	-	(5.83)	-	(6.95)	-	(3.44)	-	(-0.23)
% of Small Hospitals Sq (defined as # beds <= 33)	-	-1.2411	-	-0.8997	-	-0.1226	-	-0.3398
	-	(-7.52)	-	(-5.62)	-	(-0.58)	-	(-1.28)
# Beds in the Hospital	-0.0022	-0.0023	-0.0023	-0.0020	-0.0028	-0.0028	-0.0004	-0.0006
	(-10.79)	(-11.35)	(-9.65)	(-9.00)	(-11.49)	(-10.87)	(-1.37)	(-2.04)
# Beds in the Hospital Sq	1.07e-06	1.18e-06	1.20e-06	1.06e-06	1.40e-06	1.36e-06	2.17e-07	3.34e-07
	(6.37)	(6.80)	(4.85)	(4.60)	(5.59)	(5.57)	(1.18)	(1.87)
Short-term Hospital	-0.7216	-0.7276	-0.2013	-0.1504	0.0598	0.0013	-0.7357	-0.8043
	(-18.86)	(-18.69)	(-3.88)	(-2.93)	(0.79)	(0.02)	(-12.34)	(-12.15)
Children's Hospital	-0.1467	-0.1580	-0.0502	0.0126	0.0667	0.0149	-1.2898	-1.3715
	(-1.06)	(-1.15)	(-0.35)	(0.09)	(0.43)	(0.09)	(-3.36)	(-3.59)
Psychiatric Hospital	0.9741	0.9049	-0.3058	-0.2921	0.0668	0.2043	0.1081	0.0041
	(14.54)	(13.58)	(-1.80)	(-1.70)	(0.45)	(1.39)	(0.59)	(0.02)
Public Hospital	-0.2637	-0.2064	0.0166	0.0095	0.1301	0.1103	-0.0666	-0.0416
	(-7.23)	(-5.64)	(0.47)	(0.26)	(3.23)	(2.58)	(-1.12)	(-0.70)
Teaching Hospital	-0.0939	-0.0883	-0.0812	-0.0851	-0.1284	-0.1414	0.0149	0.0223
	(-2.24)	(-2.12)	(-1.97)	(-2.06)	(-3.00)	(-3.23)	(0.21)	(0.31)
Error Term Correlation (ρ)	0.8453	0.8889	0.8683	0.8818	0.8555	0.7888	0.9388	0.9446
Wald Test for ρ=0	60.56	60.94	80.29	80.65	153.16	94.27	92.34	95.15
No. of Observations	9,350	9,350	9,350	9,350	9,350	9,350	9,350	9,350
Log Likelihood	-5795.91	-5755.39	-8344.12	-8323.47	-8266.79	-8238.07	-5734.36	-5737.34

[a] Only second-stage coefficients from bivariate probit models are reported. Variable are defined the same as in Table 3-3. t stats are reported in parenthesis using delta-method standard errors.

Table 3-10: Marginal Effects on the Probability of Outsourcing at Selected Points

# Beds in the County			
Marginal Effects at Selected Points	At 10 Beds	At 1000 Beds	At 10000 Beds
Clinical Laboratory	2.05e-05	1.95e-05	1.09e-05
Blood Bank	1.28e-05	1.20e-05	4.56e-06
Anatomical Laboratory	-3.66e-06	-3.57e-06	-2.71e-06
CAT Scan	1.78e-05	1.72e-05	1.13e-05
% of Small Hospitals (defined as # beds <= 21)			
Marginal Effects at Selected Points	At 5%	At 20%	At 45%
Clinical Laboratory	0.2992	0.1862	-0.0021
Blood Bank	0.4232	0.2741	0.0257
Anatomical Laboratory	0.1991	0.1726	0.1283
CAT Scan	0.3637	0.2433	0.0425
# Beds in the Hospital			
Marginal Effects at Selected Points	At 10 Beds	At 150 Beds	At 400 Beds
Clinical Laboratory	-5.94e-04	-5.04e-04	-3.44e-04
Blood Bank	-1.09e-03	-9.31e-04	-6.50e-04
Anatomical Laboratory	-1.39e-03	-1.19e-03	-8.28e-04
CAT Scan	-4.96e-04	-4.36e-04	-3.30e-04

Table 3-11: Attenuation of Agglomeration Effects on Outsourcing Propensity [a]

	Clinical Laboratory *Pr(OS|PV)*	Blood Bank *Pr(OS|PV)*	Anatomical Laboratory *Pr(OS|PV)*	CAT Scan *Pr(OS|PV)*
Log (# Beds in the County_0-25)	0.0840	0.0461	0.0004	0.0695
	(19.68)	(8.45)	(0.07)	(8.31)
Log(# Beds in the County _25-50)	-0.0572	-0.0327	-0.0118	-0.0497
	(-8.12)	(-3.72)	(-1.40)	(-3.91)
Log(# Beds in the County _50-75)	0.0196	-0.0053	-0.0024	0.0270
	(2.22)	(-0.49)	(-0.23)	(1.69)
Log(# Beds in the County _75-100)	-0.0067	-0.0118	-0.0081	-0.0009
	(-0.98)	(-1.40)	(-1.05)	(-0.07)
% of Small Hospitals (below 0.3)	0.1551	0.2642	0.0794	0.2600
	(3.41)	(4.58)	(1.36)	(3.34)
% of Small Hospitals (greater than or equal to 0.3)	-0.2514	-0.5648	-0.0953	-0.2847
	(-3.14)	(-5.68)	(-0.74)	(-1.96)
Log(# Beds in the Hospital)	-0.0953	-0.1265	-0.1577	-0.0598
	(-18.56)	(-20.76)	(-28.26)	(-5.74)
Error Term Correlation (ρ)	0.8465	0.7976	0.8218	0.9542
Wald Test for ρ=0	58.33	34.15	118.05	77.43
No. of Observations	9,350	9,350	9,350	9,350
Log Likelihood	-5636.133	-8300.803	-8229.30	-5702.17

[a] Marginal effects are calculated as the average of the marginal effects on the conditional probability for all observations based on the estimated coefficients. Other control variables include indicators for short-term hospital, children's hospital, psychiatric hospital, public hospital, and teaching hospital, county-level measure of % of uninsured, % of > 65 years old, per capita income, % in poverty, % Black, % Hispanic, and % of < high school for the "provide" equation; indicators for short-term hospital, children's hospital, psychiatric hospital, public hospital, and teaching hospital for the "outsource" equation. These variable, along with the core regressors included in the table are defined the same as in Table 3-3.

Figure 3-1: State Variation in Mortality Rates (per 100,000 Residents) for Heart Disease

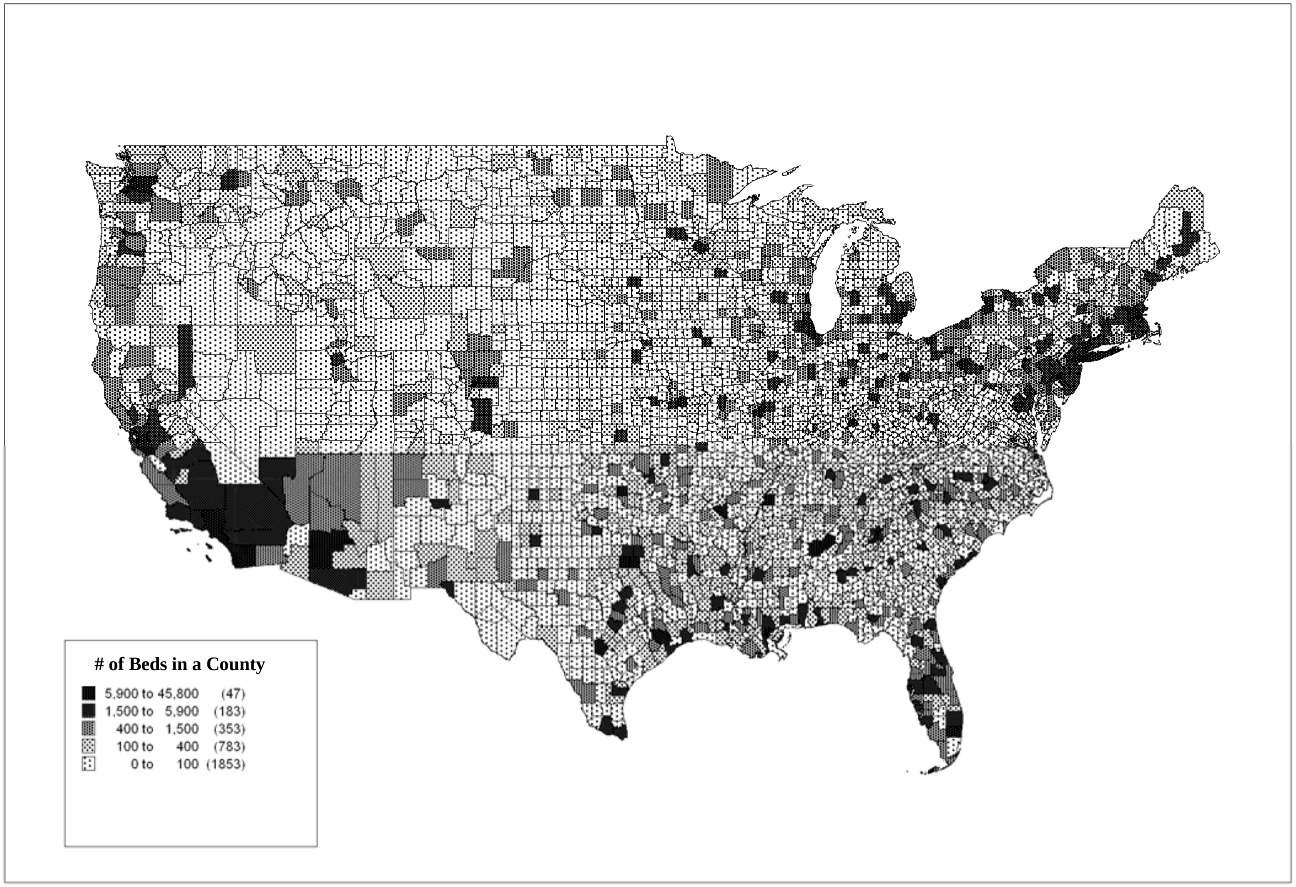


Figure 3-2: Distribution of Hospital Beds per 1,000 Residents in the U.S.

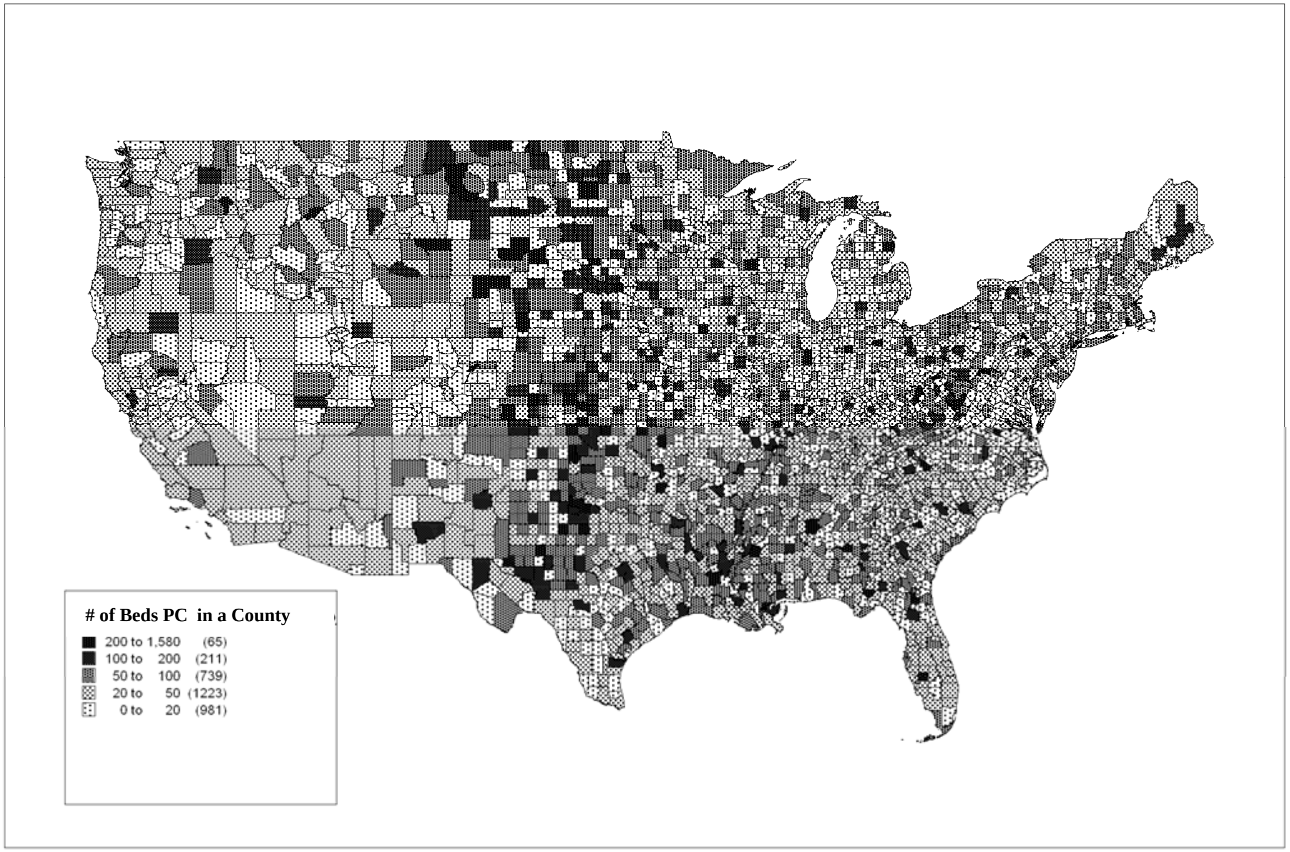


Figure 3-3: Proportional Sum Measure Based on Geographic Information System (GIS) Procedures

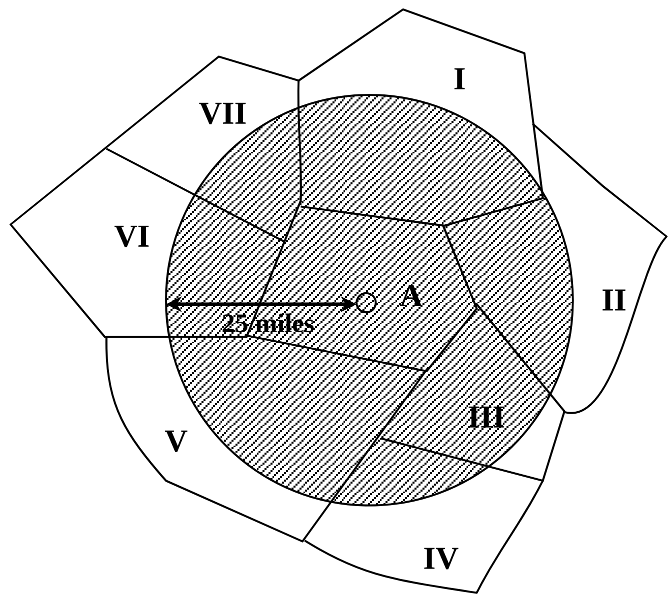


Figure 3-4: Marginal Effects of Local Population on Service Provision in a County

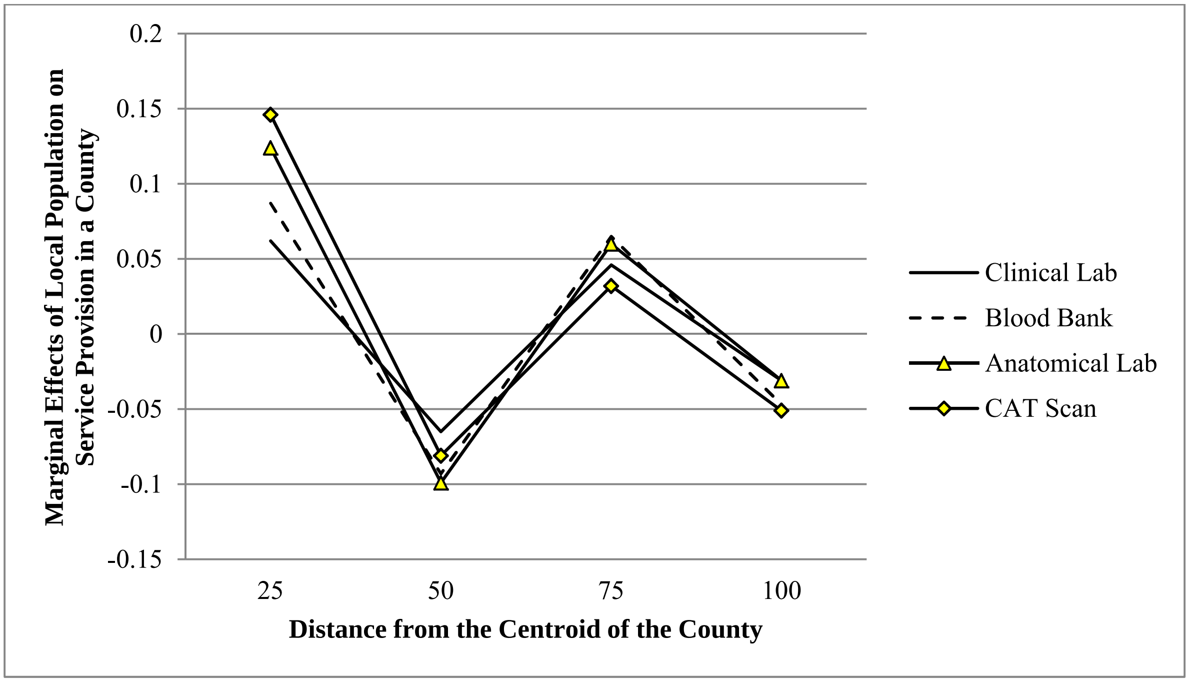


Figure 3-5: Decision Tree

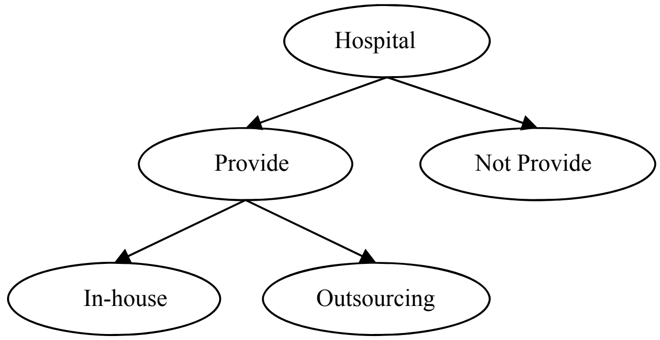


Figure 3-6: Marginal Effects of Three Key Explanatory Variables with Quadratic Terms

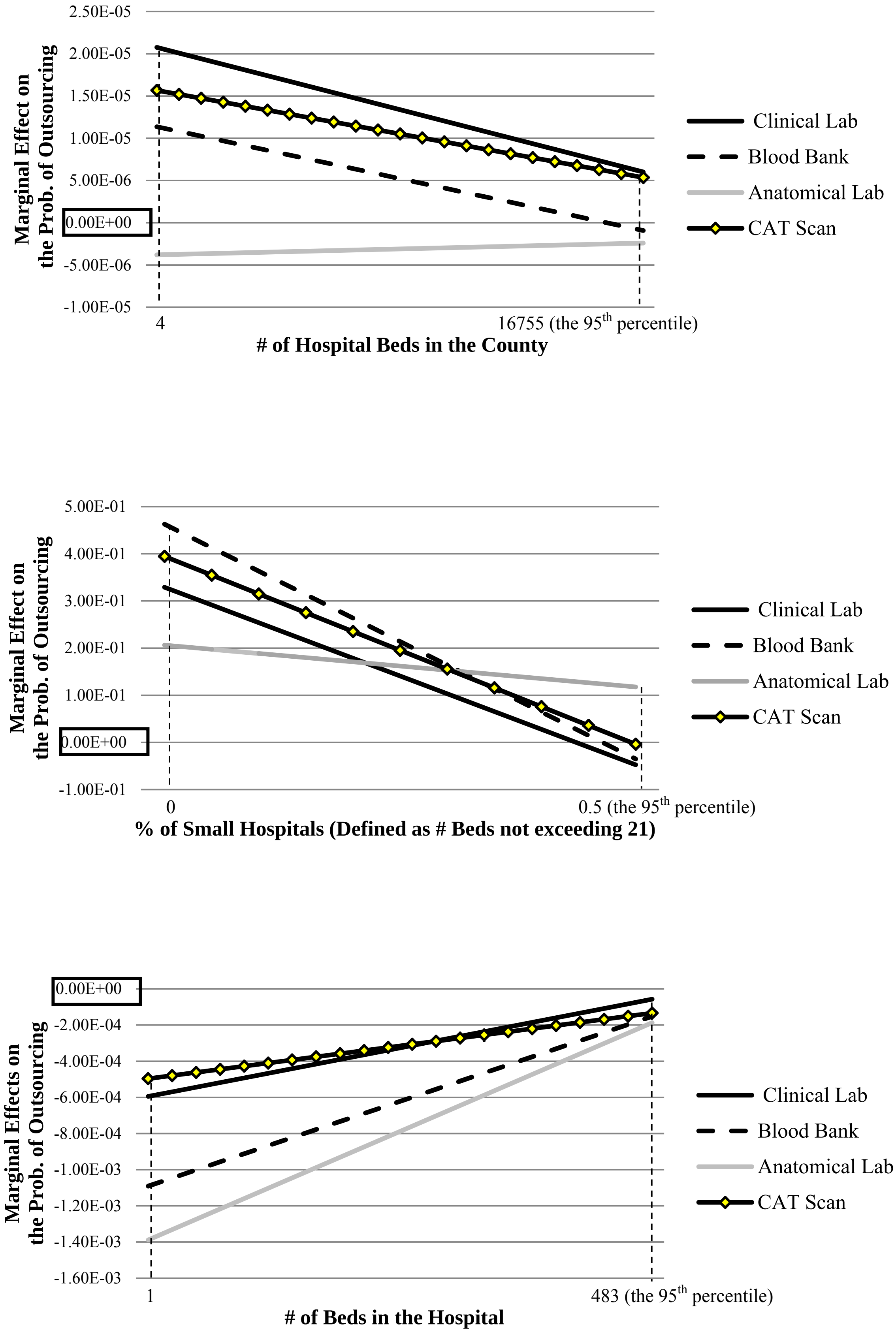
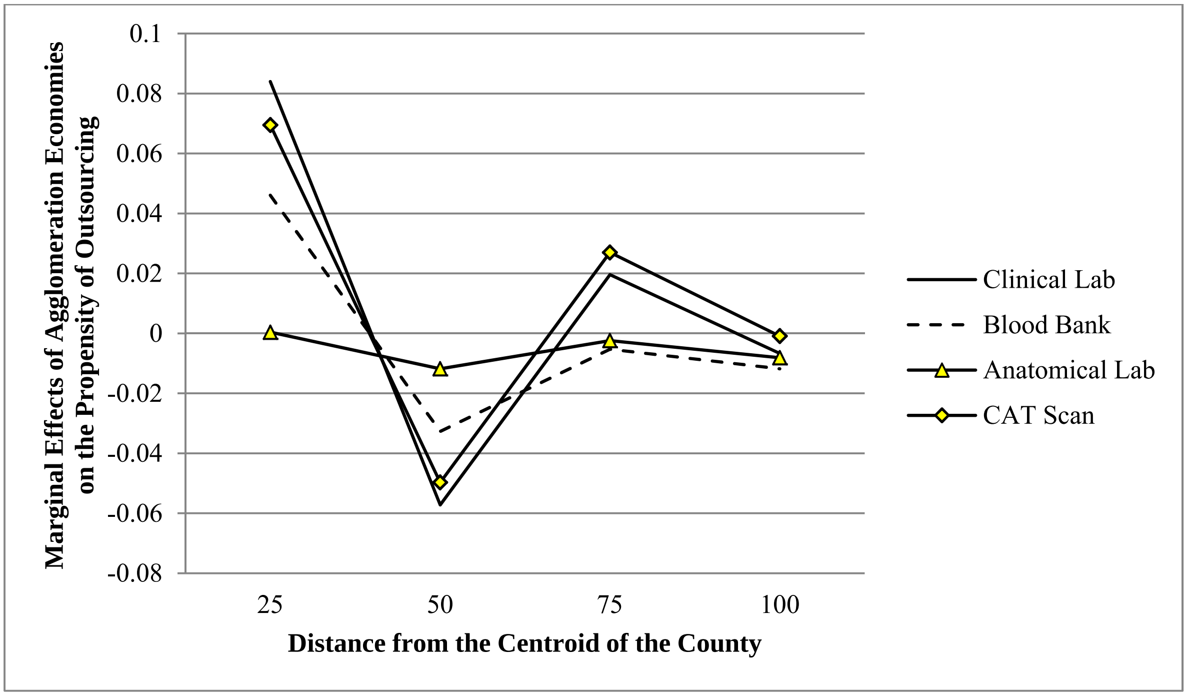


Figure 3-7: Marginal Effects of Agglomeration Economies on the Propensity of Outsourcing



Chapter 4 Further Evidence On The Spatio-Temporal Model Of House Prices In The United States

(Coauthored with Badi Baltagi)

4.1 Introduction

The U.S. housing market has been through significant boom and bust in recent years. The U.S. housing price indexes, published by the Federal Housing Finance Agency (FHFA), ran up by almost 40% from January 2003 to June 2006, followed by a 28% drop, unprecedented in the U.S. history. Time series studies on housing price movements using the U.S. national data include Meen (2002) and Gallin (2006). Also, Malpezzi (1999) uses a panel of 133 metropolitan areas in the USA over the period 1979 to 1996. More recently, Holly, Pesaran, and Yamagata (2010) use a panel of 49 states over the period of 1975 to 2003 to show that state-level real housing prices are driven by economic fundamentals, such as real per capita disposable income, as well as by common shocks, such as changes in interest rates, oil prices, and technological change. They apply the common correlated effects (CCE) estimator of Pesaran (2006) which takes into account spatial interactions that reflect both geographical proximity and unobserved common factors. This estimator is consistent under heterogeneity and cross-sectional dependence. It also copes with the presence of spatial effects, see Pesaran and Tosetti (2011).

This study replicates the results of Holly, Pesaran, and Yamagata (2010), hereafter HPY, using a slightly different data set. We first extend the period of study to 2010, incorporating the information reflected by the most recent housing market crash in 2007. We also examine more refined geographical units focusing on Metropolitan Statistical Areas (MSAs) instead of state level data.[63] This level of aggregation is important because housing price fluctuations are generally considered a local phenomenon and are specific to economic integrated areas, such as an MSA. In fact, within a particular state, the extent to which housing prices appreciate or depreciate over a certain period of time varies significantly across locations. For example, even in the same state, housing prices in New York City depreciated by 22.13%, from June of 2006 to January of 2012, while the similar depreciation rate in Syracuse, NY, over the same period, was only 3.47%.

Using housing price indexes for 384 MSAs rather than 49 states, and over the period 1975-2010, rather than 1975-2003, we find that the HPY results are fairly robust. More specifically, after taking into account both cross-sectional dependence and heterogeneity, we find a co-integrating relationship between real housing prices and real per capita disposable income. We also find that the degree of spatial correlation at the MSA level is slightly stronger than that found at the state level.

4.2 Empirical evidence

Following HPY, we report within and between correlation coefficients for both real housing prices and real per capita disposable income, but now at the MSA level rather than the state level. Tables 4-1 and 4-2 are comparable to Tables 3 and 4 in HPY.[64] The general patterns demonstrated in these tables are consistent with the original findings: within region correlations tend to be larger than between region correlations. This suggests a possible spatial pattern in both real housing prices and real per capita income.

[63] MSAs are defined by the Office of Management and Budget (OMB) as urban centers of at least 10,000 population and adjacent areas that are socioeconomically tied to the urban centers by commuting.
[64] MSAs overlap state boundaries – there are three MSAs sitting on the boundaries of two Bureau of Economic Analysis (BEA) regions, and one MSA crosses the boundary of the East region and the Middle region. In these cases, we assign the MSA to the region within which the larger portion of the MSA is located.

Cross-sectional dependence (CD) tests are reported in Table 4-3. These are comparable to Table 5 in HPY. These CD tests are statistically significant, with larger magnitudes than those reported by HPY. The average correlated coefficients of real housing prices, along with those associated with population growth and net cost of borrowing are around the same magnitudes as those reported in HPY.

Pesaran's CIPS test results that take into account cross-sectional dependence are reported in Table 4-4. These results are comparable to Table 6 of HPY. The same conclusions can be drawn from these test results as in HPY: real housing price indexes and real per capita income can be treated as I(1) processes especially if the trended nature of the series is taken into account, whereas population growth and net cost of borrowing should be considered as I(0) processes.

The first column of Table 4-5 gives the naive mean group estimates. These are comparable to Table 7 in HPY. The estimate of the coefficient on income is 0.57 compared to 0.30 For HPY. The other two columns report the common correlated effects mean group (CCEMG) and the common correlated effects pooled (CCEP) estimates. The coefficients on income are 0.99 and 1.18 compared to 1.14 and 1.20 for HPY. The residual cross-sectional dependence has been purged with the average error cross-correlation coefficient reduced from 0.32 for the MG estimates to 0.022 and 0.026 for the CCEMG and CCEP estimates, respectively.

We computed CIPS(p) panel unit root test statistics for log(real housing price)-log(real per capita income) including MSA specific intercepts, for different augmentation and lag orders, p = 1, 2, 3 and 4, and obtained the following statistics: -11.63, -10.46, -10.41, -3.90, respectively.[65] Unit root in log(real housing price)-log(real per capita income) is rejected for all

[65] Due to the unbalanced nature of the MSA house price panel used for analysis, only standardized Z[t-bar] statistics are computed.

the augmentation orders at 1% level. We consider this as strong evidence for the cointegrating relationship between real housing prices and its fundamental market driver.

Next, we estimate an error correction model without net cost of borrowing and population growth in Table 4-6. This is comparable to Table 9 in HPY.

The CCEMG and CCEP estimators are close and yield error correction coefficients of -0.204(0.010) and -0.186(0.006). This is close to the estimates reported in HPY: -0.183(0.016) and -0.171(0.015), respectively. The average half-life estimates are around 3.3 years, much smaller than the half-life estimates of 5.1 years obtained using the MG estimators. But the MG estimators are likely to be biased, since the residuals from these estimates show a high degree of cross-sectional dependence. The same is not true of the CCE-type estimators. By including population growth and net cost of borrowing, we also find a significant negative effect associated with net cost of borrowing and a significant positive effect for population growth, as shown in Table 4-7. This is comparable to Table 10 in HPY.

As shown in HPY, the strong dependence in overall residuals is captured by a common factor, whereas the remaining dependence across the idiosyncratic components captures weak cross-sectional dependence. The former is addressed by a multi-factor decomposition and estimated by principle components. The latter is identified using a spatial autoregressive model. Different from the spatial weight matrix generated based on contiguity between states in HPY, our spatial weight matrix is calculated based on row-standardized spatial distances between MSAs.[66] The maximum likelihood estimates of the spatial coefficients for the number of factors specified as 1, 2, and 3, are 0.689(0.036), 0.491(0.023), and 0.348(0.019), respectively.[67] These

[66] This is calculated as the distance between the geographic centroids of these two MSAs.
[67] Note that our panel is unbalanced due to the fact that some MSAs start reporting housing price indexes much later than 1975. In order to overcome the missing data problem when applying the spatial autoregressive model, we use data from 1985 forward.

estimates are slightly larger than the state-level estimates reported in HPY.

HPY obtain differential factor loadings by regressing log(real housing price)-log(real per capita income) on their average over states and a constant, see their Table 11. They find significantly negative factor loadings for New York, Massachusetts, and California. We report a similar table with selected MSAs in Table 4-8. The first two columns report factor loading estimates for the five largest MSAs in each of the three states. The last two columns present all MSAs that are associated with negative and statistically significant factor loading estimates in our results. We find that the estimated factor loadings for MSAs in New York, Massachusetts, and California tend to be positive. In addition, MSAs that report negative factor loadings based on the new data set had positive factor loading estimates at the state level in HPY. Despite this switch in sign perhaps due to looking at MSAs rather than states, HPY's conclusion still holds: States that originally deviate from the equilibrating relationship tend to eventually revert.

References

Gallin J. 2006. The long-run relationship between house prices and income: evidence from local housing markets. *Real Estate Economics* **34**(3): 417–438.

Holly S, Pesaran MH, Yamagata T. 2010. A spatio-temporal model of house prices in the USA. *Journal of Econometrics* **158**: 160–173.

Malpezzi S. 1999. A simple error correction model of house prices. *Journal of Housing Economics* **8**: 27–63.

Meen G. 2002. The time-series behavior of house prices: a transatlantic divide? *Journal of Housing Economics* **11**: 1–23.

Pesaran MH, Tosetti E. 2011. Large panels with common factors and spatial correlation. *Journal of Econometrics* **161**: 182–202.

Pesaran MH. 2006. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica* **74**(4): 967–1012.

Table 4-1: Average correlation coefficients within and between regions first difference of log real per capita income

(i) Three geographical regions

	East	Middle	West
East	0.48	-	-
Middle	0.49	0.62	-
West	0.35	0.39	0.34

(ii) Eight BEA regions

	New England	Mid-East	South-East	Great Lakes	Plains	South-West	Rocky mountain	Far West
New England	0.68	-	-	-	-	-	-	-
Mid-East	0.58	0.58	-	-	-	-	-	-
South-East	0.47	0.47	0.46	-	-	-	-	-
Great Lakes	0.50	0.53	0.50	0.68	-	-	-	-
Plains	0.44	0.46	0.44	0.56	0.55	-	-	-
South-West	0.23	0.27	0.30	0.32	0.32	0.36	-	-
Rocky mountain	0.36	0.38	0.39	0.45	0.42	0.34	0.45	-
Far West	0.41	0.41	0.38	0.44	0.39	0.25	0.38	0.39

Table 4-2: Average correlation coefficients within and between regions first difference of log real house prices

(i) Three geographical regions

	East	Middle	West
East	0.50	-	-
Middle	0.37	0.68	-
West	0.37	0.33	0.40

(ii) Eight BEA regions

	New England	Mid-East	South-East	Great Lakes	Plains	South-West	Rocky mountain	Far West
New England	0.86	-	-	-	-	-	-	-
Mid-East	0.62	0.62	-	-	-	-	-	-
South-East	0.41	0.41	0.57	-	-	-	-	-
Great Lakes	0.32	0.26	0.41	0.62	-	-	-	-
Plains	0.29	0.22	0.47	0.52	0.62	-	-	-
South-West	0.16	0.21	0.45	0.21	0.45	0.56	-	-
Rocky mountain	0.08	0.16	0.46	0.38	0.50	0.47	0.57	-
Far West	0.30	0.40	0.39	0.34	0.28	0.24	0.32	0.57

Table 4-3: Average Correlation Coefficients and CD Tests

Average Correlation Coefficient				
	ADF(1)	ADF(2)	ADF(3)	ADF(4)
Log (real housing price index)	0.387	0.357	0.369	0.360
Log (real per capita income)	0.423	0.368	0.361	0.301
Population growth rate	0.047	0.044	0.046	0.042
Real cost of borrowing	0.391	0.355	0.349	0.341
CD test statistics[1]				
	ADF(1)	ADF(2)	ADF(3)	ADF(4)
Log (real housing price index)	512.94	460.10	466.41	448.22
Log (real per capita income)	628.18	537.48	519.04	426.50
Population growth rate	72.67	67.14	67.87	61.58
Real cost of borrowing	483.41	426.35	408.86	390.55

[1] Under the null hypothesis of cross-section independence, CD test statistic ~ N(0,1).

Table 4-4: Pesaran's CIPS panel unit root test results[1]

With an intercept				
	CADF(1)	CADF(2)	CADF(3)	CADF(4)
Log(real housing price index)	-13.093***	-8.198***	-4.651***	-0.832
Log(real per capita income)	0.211	1.719	0.674	-0.104
ΔLog(real housing price index)	-15.237***	-12.062***	-9.239***	-1.512*
ΔLog(real per capita income)	-35.868***	-18.676***	-8.155***	1.140
Population growth rate	-19.586***	-10.935***	-4.938***	-0.118
Real cost of borrowing	-14.266***	-8.577***	-4.319***	5.037
With an intercept and a linear trend				
	CADF(1)	CADF(2)	CADF(3)	CADF(4)
Log(real housing price index)	-6.643***	0.634	5.960	16.415
Log(real per capita income)	11.886	14.260	13.486	12.474

[1] Under the null hypothesis of existing unit root, Z(t-bar) ~ N(0,1). * signifies that the test is significant at the 10% level. ** signifies that the test is significant at the 5% level. *** signifies that the test is significant at the 1% level.

Table 4-5: Income Elasticity of Real Housing Price: 1975-2010

	MG	CCEMG	CCEP
Constant	1.1143	-5.2212	-0.6258
	(0.448)	(0.338)	(0.412)
Log(real per capital income)	0.5660	0.9920	1.1809
	(0.061)	(0.036)	(0.070)
Average Cross Correlation Coefficients	0.315	0.022	0.026
CD test statistic	419.11	29.42	30.13

Note: standard errors are reported in parenthesis.

Table 4-6: Panel Error Correction Estimates Without Net Cost of Borrowing and Population Growth: 1975-2010

	MG	CCEMG	CCEP
One period lag of Log(real housing price index) - Log(real per capital income)	-0.1282	-0.2041	-0.1855
	(0.005)	(0.010)	(0.006)
One period lag of ΔLog(real housing price index)	0.6769	0.3438	0.5478
	(0.017)	(0.018)	(0.017)
ΔLog(real per capita income)	0.3192	0.2307	0.4061
	(0.025)	(0.026)	(0.019)
Half life	5.052	3.036	3.378
Average cross-correlation coefficients	0.276	0.027	0.033
CD test statistics	341.36	31.58	39.74

Note: standard errors are reported in parenthesis.

Table 4-7: Panel Error Correction Estimates with Net Cost of Borrowing and Population growth: 1975-2010

	MG				CCEMG				CCEP			
One period lag of Log(real housing price index) – Log(real per capital income)	-0.1268	-0.1286	-0.1269	-0.1286	-0.2392	-0.2249	-0.2255	-0.2191	-0.2100	-0.2024	-0.2106	-0.2042
	(0.004)	(0.005)	(0.005)	(0.004)	(0.013)	(0.009)	(0.011)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
One period lag of ΔLog(real housing price index)	0.7262	0.7338	-	-	0.0606	0.0651	-	-	0.3806	0.4227	-	-
	(0.029)	(0.029)	-	-	(0.037)	(0.034)	-	-	(0.043)	(0.039)	-	-
ΔLog(real per capita income)	0.3292	0.3183	0.3296	0.3184	0.2400	0.2153	0.2394	0.2317	0.3977	0.3910	0.5084	0.5040
	(0.029)	(0.022)	(0.028)	(0.025)	(0.030)	(0.025)	(0.027)	(0.025)	(0.021)	(0.020)	(0.021)	(0.021)
Population growth rate	0.2274	-	0.2276	-	0.6893	-	0.6515	-	0.5165	-	0.7774	-
	(0.047)	-	(0.049)	-	(0.110)	-	(0.100)	-	(0.089)	-	(0.090)	-
Real cost of borrowing	0.0654	0.0567	-0.6608	-0.6772	-0.1558	-0.2593	-0.2167	-0.3302	-0.1021	-0.1009	-0.4090	-0.4438
	(0.024)	(0.026)	(0.017)	(0.018)	(0.041)	(0.038)	(0.019)	(0.018)	(0.041)	(0.037)	(0.018)	(0.017)
Half life	5.110	5.035	5.107	5.035	2.535	2.721	2.712	2.803	2.941	3.065	2.931	3.035
Average cross-correlation coefficients	0.266	0.283	0.273	0.286	0.020	0.023	0.022	0.025	0.032	0.031	0.033	0.032
CD test statistics	329.28	350.85	340.50	355.99	22.98	27.43	25.84	30.09	37.60	36.97	39.14	37.76

Note: standard errors are reported in parenthesis.

Table 4-8: Factor Loading Estimates for Selected MSAs: 1975-2010

MSAs	Estimates	MSAs	Estimates
New York-White Plains-Wayne, NY-NJ	1.08** (0.43)	Anniston-Oxford, AL	-0.14** (0.06)
Buffalo-Niagara Falls, NY	0.22 (0.66)	Clarksville, TN-KY	-0.70*** (0.13)
Rochester, NY	0.15 (0.42)	Columbus, IN	-0.32** (0.13)
Albany-Schenectady-Troy, NY	0.96** (0.41)	Danville, VA	-0.24* (0.12)
Poughkeepsie-Newburgh-Middletown, NY	2.05*** (0.51)	Fayetteville, NC	-1.13** (0.42)
Boston-Quincy, MA	1.18** (0.58)	Florence-Muscle Shoals, AL	-0.30*** (0.09)
Providence-New Bedford-Fall River, RI-MA	1.47*** (0.48)	Goldsboro, NC	-0.39* (0.19)
Worcester, MA	1.23** (0.52)	Jackson, TN	-0.58* (0.29)
Springfield, MA	0.86* (0.49)	Lafayette, IN	-0.61*** (0.16)
Barnstable Town, MA	3.50*** (0.44)	Laredo, TX	-0.49* (0.28)
Los Angeles-Long Beach-Glendale, CA	2.03*** (0.43)	Lawton, OK	-0.80** (0.31)
San Francisco-San Mateo-Redwood City, CA	1.55*** (0.45)	Pine Bluff, AR	-0.32** (0.15)
Riverside-San Bernardino-Ontario, CA	2.86*** (0.46)	Terre Haute, IN	-0.35** (0.14)
Sacramento-Arden-Arcade-Roseville, CA	2.23*** (0.39)	Texarkana, TX-Texarkana, AR	-0.45** (0.19)
San Jose-Sunnyvale-Santa Clara, CA	1.60*** (0.44)	Tuscaloosa, AL	-0.16* (0.08)
		Victoria, TX	-0.46* (0.23)

Note: standard errors are reported in parenthesis. * signifies that the test is significant at the 10% level. ** signifies that the test is significant at the 5% level. *** signifies that the test is significant at the 1% level.

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