BETTER OUTCOMES AT LOWER COSTS? THE EFFECT OF PUBLIC HEALTH EXPENDITURES ON HOSPITAL EFFICIENCY

by

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ABSTRACT

Local health departments play a critical role in the community that they serve as they comprise the foundation of the U.S. public health system. Providing public health services such as immunizations to the less affluent and advocating for state smoking bans, local health departments rely on government resources to fund their operations. Research indicates a positive impact of public health expenditures on the overall health of the population. However, individuals may not be the sole beneficiaries of public health expenditures. A healthier population may lead to efficiency gains for surrounding health care providers.

In this research, I use efficiency analysis to explore the relationship between public health expenditures and hospital efficiency. Specifically, I use the two-stage semi-parametric Data Envelopment Analysis proposed by Simar and Wilson (2007) to estimate how public health spending affects the technical efficiency of the surrounding hospitals. The results of this research suggest that hospitals are indeed positively affected by higher levels of public health spending that has occurred in their patient market two years prior. Specifically, hospitals operating in an area with a high level of per capita public health expenditures experience gains in efficiency of approximately 1.66 percentage points relative to those hospitals operating in low public health spending areas.

Chapter 1

INTRODUCTION

The World Health Organization (WHO) defines public health as all organized measures to prevent disease, promote health, and prolong life among the population as a whole (World Health Organization, 2014). Throughout the United States, approximately 2,800 local public health departments operate with the common purpose of promoting public health (National Association of City and County Health Organizations, 2014). With the majority of operations being financed using government funding, local public health departments rely on these funds to meet the health needs of the community they serve. By providing services ranging from individual immunizations and vaccines to advocating for state smoking bans, it is easy to assume increased funding of local public health departments will have a positive impact on the community, however, the magnitude is unclear.

In theory, the efficient allocation of public health funding will allow local public health departments to solve potential problems before they occur. Without a measurable outcome, determining a return on investment is difficult. As a consequence, policy makers are unable to determine if spending on public health is worth the costs. In an attempt to estimate the potential benefits of public health funding, I make an argument that community members are not the sole beneficiaries of public health spending. If increases in public health funding have a positive impact on the overall health of the community, then health care providers, specifically surrounding hospitals, should benefit as a result of a healthier population. In particular, hospitals should see efficiency gains as a result of public health spending.

In this research, I fill a gap in the literature by exploring how previous public health expenditures influence hospital efficiency. Specifically, using data on individual hospitals from 2007-2012 and a unique dataset on local public health expenditures, I employ the two-stage Data Envelopment Analysis (DEA) proposed by Simar and Wilson (2007) to estimate how the level of public health spending two years prior affects the technical efficiency of the surrounding hospital.[1] In the first-stage, I define several variables to serve as input and output proxies in the hospital production process. These variables will be used in the first-stage to construct an estimate of technical efficiency for each hospital in the sample. In the second-stage, I remain consistent with Simar and Wilson (2007) by using the first-stage technical efficiency estimate as the dependent variable in a truncated regression to analyze how public health expenditures impact hospital efficiency.[2]

Recent research supports the claim that there is a positive relationship between increased public health expenditures and overall health of the community (Brown, 2014; Brown et al., 2014; Rivera, 2001; Glick and Menon, 2009; Bailey and Goodman-Bacon, 2015). However, what effect does an increase in public health funding have on health care providers? If we accept the conclusion that an increase in public health spending makes the population healthier, then over time, a healthier population would need less medical care. In theory, this would allow hospitals to operate more efficiently. The results of this research suggest that hospitals are indeed positively affected by the level of public health spending that has occurred in their patient market two years prior. Specifically, hospitals operating in an area with a high level of per capita public health expenditures experience gains in efficiency of approximately 1.66 percentage points relative to those hospitals operating in low public health spending areas.

[1] A brief discussion on the background of technical efficiency and the Data Envelopment Analysis is provided in Section 2.2 of Chapter 2. Refer to Chapter 5 for a detailed technical discussion of the Data Envelopment Analysis as proposed by Simar and Wilson (2007).

[2] Simar and Wilson (2007) conclude through a Monte–Carlo simulation that a truncated regression outperforms the traditional tobit framework. See Section 5 for further discussion.

In the wake of the Great Recession and the implementation of the Affordable Care Act (ACA), the United States national debt is larger than it has ever been. According to predictions made by the Congressional Budget Office (CBO), steady increases in the federal budget deficits will exacerbate the national debt over the next three decades. The CBO reports the increased spending on major health programs, such as Medicare, as one of the factors that will drive this growth (CBO, 2016). Unfortunately, the issue of rising health care costs in the United States is not confined to federal government medical programs. In a report on National Health Expenditures, the Centers for Medicare and Medicaid Services (CMS) estimates that the U.S. has spent roughly $3 trillion in total on health care in 2014, with hospitals accounting for approximately one-third of that (CMS, 2014). The conclusions drawn from this research will not fix America's national debt problem nor will it immediately curb health care expenditures. The conclusions do however, provide policy makers with the evidence necessary to support the use of public health spending as an instrument to influence health care expenditures. Over time, preventing health problems from developing will make Americans healthier and potentially reduce health care expenditures in the process.

The remainder of this dissertation is structured as follows. Chapter 2 provides relevant background information. Chapter 3 and Chapter 4 provide a survey of the literature and a discussion of the contribution made by this research, respectively. Chapter 5 discusses the methods used in the empirical estimation and Chapter 6 contains a description of the data. Chapter 7 reviews the empirical findings and Chapter 8 includes concluding remarks and relevant discussion.

Chapter 2

BACKGROUND

This section of the proposal is structured as follows. Section 2.1 discusses the relevant institutional background information on local health departments. Section 2.2 provides an introduction of efficiency analysis by defining technical efficiency and briefly introduces popular estimation methods. I leave the technical details for a later discussion of methodology in Chapter 5.

2.1 Local Health Departments

All local health departments work to promote overall health and well-being of the communities in which they serve, but their organizational structure varies. Adapting to the needs of their respective population, local health departments vary in size, funding, and services provided to ensure these needs are met. Table 2.1 displays a list of the top ten public health services that were provided by local health departments in 2013. From inspecting restaurants to disease surveillance, local health departments play a critical role in the provision of public health.

The majority of local health department operations are funded using government allocated funds. Down from 72% in 2005 (National Association of City and County Health Organizations, 2006), local health departments collected 70% of total revenue from various levels of the government in 2010.[1] Reimbursements from public insurance programs (Medicaid and Medicare) contributed 16% of total revenue, regulatory and patient fees accounted for 7%, while other sources such as grants from private foundations accounted for 6% of total revenue (National Association of City and County Health Organizations, 2011).

[1] Government revenue sources - Local: 26%, State:21%, Total Federal: 23%

Table 2.1: Top Ten Public Health Programs and Services Provided by Local Health Departments in 2013

Rank	**Public Health Program/Service**
1.	Communicable/Infectious Disease Surveillance
2.	Adult Immunization Provision
3.	Child Immunization Provision
4.	Tuberculosis Screening
5.	Environmental Health Surveillance
6.	Food Service Establishments Inspection
7.	Tuberculosis Treatment
8.	Food Safety Education
9.	Population-Based Nutrition Services
10.	Schools/Daycare Center Inspection

Note: Adapted from a figure displayed in the 2013 National Association of City and County Health Officer Profile Study Summary, p. 36.

The revenue generated gives local health departments the ability to provide both population-based services and individual clinical services. For the top ten services listed in Table 2.1, individual clinical services include provision of immunizations, such as H1N1 vaccines, and tuberculosis screening and treatment. These individual client-based services have the potential to generate revenue as local health departments can bill insurance companies for services rendered. Table 2.1 also lists population-based services, such as infectious disease and environmental health surveillance, public education on food safety and nutrition, and inspections of schools and restaurants, that are considered public goods. These public goods are non-reimbursable, as there is no one to bill. Because it is not feasible to bill for population-based activities, local health departments are faced with the decision to provide these public health services and suffer a loss or eliminate them and sacrifice overall community health.

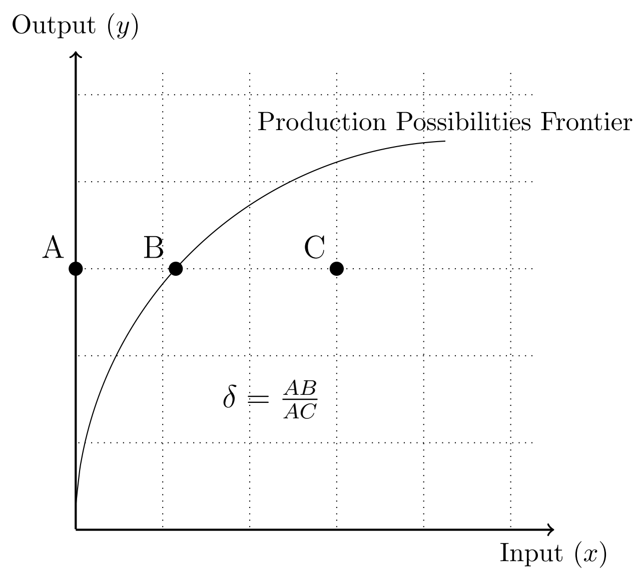
2.2 Efficiency Analysis

Technical Efficiency

Farrell (1957) defines technical efficiency as a measure of firm success in producing the maximum quantity of output with a fixed level of input. In the context of this research, hospital technical efficiency refers to how well a hospital is able to produce medical outputs, such as admissions and surgeries, given the quantity of medical inputs, such as beds and nurses, that has been chosen by the hospital manager.

Figure 2.1 illustrates this concept graphically, showing the typical production possibilities frontier from production theory. Consider the simple case where one input (x) is used to produce one output (y). Suppose points B and C represent two different hospitals, producing at two different input/output allocations. Hospital B lies on the boundary of the production possibilities frontier and is considered to be efficient. Hospital C is using a greater quantity of inputs to produce the same level of output as Hospital B. All else equal, Hospital C is able to reduce the magnitude of inputs without sacrificing output. Therefore, this implies Hospital C is less efficient than Hospital B.

Figure 2.1: Efficiency Frontier Estimation



Source: Adapted from a figure displayed in Cozad and Wichmann (2013), p. 4084.

Estimation Methods

The theoretical concept of efficiency is straightforward with the simple case can be illustrated by Figure 2.1. However, constructing efficiency estimates and explaining why a firm has deviated from the optimal allocation is particularly challenging. Depending on the assumptions the researcher is willing to make, there are the two popular methods used throughout the literature to estimate efficiency. The Stochastic Frontier Analysis (SFA) is a parametric approach to estimating efficiency whereas the Data Envelopment Analysis (DEA) is a non-parametric approach. Because of the DEA's flexibility, 67 percent of health care efficiency studies have used the DEA method since 2008 while 18 percent have employed SFA (Hollingsworth, 2008). In the discussion that follows, I briefly introduce the SFA and the DEA methods deferring the technical details for later consideration.

Stochasitic Frontier Analysis

First introduced by Aigner et al. (1977), the SFA is a parametric approach to estimating efficiency and identifying causes of inefficiency. Aigner et al. (1977) propose two explanations as to why firms may deviate from the ideal theoretical production function. They argue deviations could be a result of inefficiency or idiosyncratic effects that are unique to the individual firm. In a recent empirical application, Greene (2004) uses the SFA to distinguish between heterogeneity and inefficiency of WHO health care systems. Equation 2.1 shows the production function he defines which is consistent with the typical form used in SFA estimations. For country i, in year t, the SFA equation is defined to be:

$$y_{it} = \alpha + x_{it}'\beta + \nu_{it} - u_i \tag{2.1}$$

where y_{it} is the output, x_{it} is a vector of inputs, ν_{it} is the stochastic variable, and u_i represents the inefficiency of country i in year t.

The SFA is a regression based approach to estimating the efficient frontier. Typically, the SFA is estimated using corrected-OLS (Greene, 2012). The SFA requires an assumption be made regarding the functional form of the production process. Typically, production functions are assumed to follow a Cobb-Douglas form where multiple inputs are used to produce a single output.

Data Envelopment Analysis

First introduced by Farrell (1957) and made popular by Charnes et al. (1978), the traditional Data Envelopment Analysis (DEA) is a non-parametric approach to estimating efficiency (Coelli et al., 2005). The DEA uses linear programming to calculate the technical efficiency of each firm in the sample. Using the input/output allocations from the sample, the DEA establishes a best-practice frontier by enveloping the observed data. Once the best-practice frontier is determined, technical efficiency estimates for each unit can be determined by calculating the linear distance from each hospital to the most efficient peer, holding either input or output constant. In practice, solutions to the DEA linear programming problem provide the technical efficiency estimate for each hospital. This can be obtained using most statistical software packages, however my analysis will be completed with a combination of $STATA$ and R. A major benefit of the DEA is that it performs better when multiple outputs are specified. Additionally, because the DEA estimates efficiency by enveloping the data, the DEA does not force an assumption regarding the functional form of the production set as with the SFA.

The technical details of the linear programming problem are described in greater detail in Chapter 5. Instead, I illustrate the DEA graphically by revisiting the previous example depicted in Figure 2.1. Recall, two hospitals used one input (x) to produce (y) output. Let δ_i denote the technical efficiency for hospital i defined such that $\delta_i \in (0, 1]$. Furthermore, the efficient allocation is assigned a unitary value for technical efficiency such that $\delta_i = 1$ whereas inefficient hospitals have a technical efficiency such that $\delta_i < 1$.

Hospital B is considered to be the most technically efficient and is assigned a technical efficiency score $\delta_B = 1$. By operating in the interior of the best-practice frontier, Hospital C is operating at an inefficient level. Inefficient hospitals are able to reduce the quantity of inputs used without sacrificing output. Therefore, Hospital C is assigned a technical efficiency score such that $\delta_C < 1$. Generally, technical efficiency estimates for hospital i can be determined by calculating the linear distance to the efficiency frontier relative to the technically efficient hospital. In this simple example, technical efficiency is determined by taking the ratio of the quantity of inputs used to produce the most efficient allocation (B) to the quantity of inputs used in producing the less efficient allocation (C) holding output constant.

A critical consequence of estimating efficiency using the DEA is that, the DEA is not a regression analysis and therefore does not have an error term. This implies efficiency estimates are constructed without accounting for statistical error. Relative to the SFA, this marks a key shortcoming of the non-parametric approach. Traditional DEA technical efficiency estimates view deviations from the efficiency frontier as pure inefficiency. Estimates fail to distinguish between inefficiency and statistical discrepancy which leads to an overestimation of the best-practice frontier (Simar and Wilson, 2007). Using the bootstrapping algorithms proposed in Simar and Wilson (2007), it is possible to correct for this overestimation. Further discussion of estimation methods is provided in Chapter 5.

This background information on technical efficiency and the DEA estimation clarifies the research question previously stated. In particular, I will define a production process for hospitals consisting of relevant inputs and outputs. Solutions to the DEA linear programming problem provide estimates of hospital technical efficiency in the first-stage which establishes the efficient frontier like that of Figure 2.1. Following Simar and Wilson (2007), a truncated regression is estimated in the second-stage to explore the relationship between estimated hospital technical efficiency and per capita public health expenditures.

Chapter 3

LITERATURE REVIEW

This section provides a survey of relevant literature and is structured as follows. Section 3.1 provides a discussion of the literature focusing on public health and health care expenditures. Section 3.2 discusses the research estimating efficiency with particular focus on studies utilizing the two-stage semi-parametric Data Envelopment Analysis (DEA) proposed by Simar and Wilson (2007).

3.1 Public Health and Health Care Expenditures

In 2010, the Affordable Care Act (ACA) established the Public Health and Prevention Fund which allocates $15 billion each year to the U.S. public health system for the next ten years. Thus, the importance of public health and disease prevention is not foreign to health policy makers. Researchers have paid a significant amount of attention to public health expenditures (Brown, 2014; Brown et al., 2014; Duggan, 2000; Rivera, 2001; Self and Grabowski, 2003; Glick and Menon, 2009; Potrafke, 2010; Granlund, 2010; Herwartz and Theilen, 2014; Bailey and Goodman-Bacon, 2015), non of which explore the effect on hospital efficiency.

Brown (2014) and Brown et al. (2014) estimate the impact of public health expenditures on the health of the population. Both studies identify positive results using the Koyck distributed lag model. Focusing on the all-cause mortality rate, Brown (2014) concludes that increasing per capita public health expenditures by $10 will reduce mortality rates by 9.1 per 100,000.[1] Brown et al. (2014) estimate the impact

[1] The all-cause mortality rate captures all deaths occurring within the county for a given year regardless of the cause of death. It is defined in terms of all deaths per 100,000 residents.

of county per capita public health expenditures on reported health status from the California Health Interview Survey. Survey participants are asked to select one of five categories that best represents their current overall health status. From worst to best, health status can be reported as poor, fair, good, very good, and excellent. The authors conclude a $10 per capita increase in county public health expenditures results in a 0.065 percentage point increase in the population reporting good health status.

Duggan (2000) examines how public medical spending may differ as hospital ownership varies. He classifies hospital ownership as one of three types: profit maximizing, not-for-profit, and government owned. He exploits California's attempt to extend care to its impoverished citizens by changing the financial incentives of hospitals. He finds not-for-profit hospitals were equally as responsive to financial incentives as for-profit hospitals. Both not-for-profit and for-profit hospitals used new income to purchase financial assets rather than invest in better medical care for the poor. Overall, Duggan suggests that the significant public spending on medical care in California's attempt to increase care for the poor did not improve health outcomes. Duggan (2002) extends his original analysis to explore the reason behind not-for-profit behavior. He finds not-for-profit hospitals tend to act as profit maximizing hospitals when there is a high concentration of private hospitals competing with them.

Research focusing on public health primarily analyzes the impact of public health expenditures, typically on an aggregated health measure. However, little effort has been made to examine the organizations responsible for implementing public health programs and providing the community with public health services. In order for the population to realize the health benefits that are associated with public health expenditures, local health departments must allocate funding to successful programs and productive activities. Thus, exploring how effective local health departments are at operating in the community will help ensure funds are not wasted. To my knowledge, Mukherjee et al. (2010) has been the only attempt to estimate the efficiency of the local public health departments in the United States.

Using cross-sectional data from 2005, Mukherjee et al. (2010) use the method proposed by Simar and Wilson (2007) to conduct an exploratory analysis of local health department efficiency. Their results suggest there are two major influences of local health department technical efficiency. That is, variations in estimated efficiency stems from the variety of services offered by local health departments and the source of revenue. According to the results presented, local public health departments are most technically efficient when providing a large assortment of public health services as well as when the funding for these services is generated from the provision of billable services. They argue these results support the idea that the greater is the funding from the state or national government, the less efficient local public health departments become.

Mukherjee et al. (2010) use their results to suggest local health departments operate more efficiently when using lower government resources. However, their conclusions may be misleading to policy makers as their results are subject to interpretation. Local health departments use government funding to implement public health projects that will meet the needs of the community. In theory, these local health departments should choose to invest government funds in projects with the highest potential return on public health. If funding is increased, local health departments may have the "use it or lose it" mentality. Local health departments failing to allocate resources to a project may result in loss of access to unused funding. This mentality causes local health departments to explore projects with lower returns on investment. Consequently, local health departments with higher funding may appear to be more inefficient, making the results reported by Mukherjee et al. (2010) expected.

The Public Health and Prevention Fund that was established by the Affordable Care Act generously provides the public health system with the resources necessary to promote and maintain a healthy population. While it may be the case that the local health departments capable of generating their own revenue will operate more efficiently than those relying on government funding, the interpretation presented by Mukherjee et al. (2010) is deceiving. That is, their results do not necessarily imply that the resources provided by the Public Health and Prevention Fund will be wasted but utilized on projects with lower returns to public health.

3.2 Health Care Efficiency

The efficiency literature as a whole is vast. A subset of the efficiency literature has concentrated on the health care industry. Hollingsworth (2008) provides a comprehensive survey of the health care literature up until 2008. Of the 317 health care efficiency studies analyzed, 52 percent had hospitals as the primarily focus. The DEA and SFA are the two most popular methods used to estimate efficiency. This review will focus on health care studies employing the DEA method with a particular emphasis the modified version proposed by Simar and Wilson (2007) and its use in the two-stage framework.

Original applications of the DEA method only involved a one-stage analysis (Afonso and St. Aubyn, 2005; Hollingsworth and Wildman, 2003). Traditionally, research was only interested in estimating the efficiency of a given production process. As the health care literature expanded, there has been a growing interest in explaining the determinants of inefficiency. In particular, research has expanded the analysis to incorporate environmental variables in a second-stage regression as an attempt to explain deviations from the efficient frontier (Brown, 2003; Pilyavsky et al., 2006; Blank and Valdmanis, 2010; Ferrier and Trivitt, 2013; Herwartz and Strumann, 2014; Kawaguchi et al., 2014; Cozad and Wichmann, 2013; Afonso and St. Aubyn, 2011; Bernet et al., 2008; Deily and McKay, 2006; Nedelea and Fannin, 2013). Using the estimated efficiency scores from the first-stage as the dependent variable, the second-stage estimation examines the impact of environmental factors that are beyond the direct control of the hospital manager or more generally, the decision maker.

Prior to Simar and Wilson (2007), estimation of this second-stage has traditionally used a Tobit framework out of concern that first-stage estimates were censored. Other studies have transformed the data using logs and employed OLS. Both approaches are criticized by Simar and Wilson (2007). They argue that estimating the second-stage using these traditional methods is invalid. The presence of serial correlation in the second-stage makes it unclear as to what is actually being estimated. The modification of the traditional DEA procedure made by Simar and Wilson (2007) addresses concerns of biased efficiency scores and lays the foundation for consistent estimation of the second-stage. This approach is still relatively new and research applying this method is still growing.

Recent efficiency research examining several European countries applies the DEA procedure as proposed by Simar and Wilson (2007) to show that hospital efficiency indeed depends upon the operating environment (Pilyavsky et al., 2006; Blank and Valdmanis, 2010; Herwartz and Strumann, 2014; Ferrier and Trivitt, 2013). Pilyavsky et al. (2006) exploit the cultural division in the Ukraine to analyze the efficiency of hospitals. In particular, they analyzed the differences in hospital efficiency between East and West regions of the Ukraine. Although Ukraine gained sovereignty from the Soviet Union in 1991, ways of life remain divided. The Eastern region was resistant to the cultural influence of the western world which the Western region embraced. Pilyavsky et al. find that overall the operating region did not have a significant impact on hospital efficiency but as time progressed, the disparity in efficiency between the regions grew. They argue this is strong evidence in support the idea that independent thinking of the West allowed hospitals to outperform Eastern hospitals over time. Bernet et al. (2008) find similar results in their application of the modified DEA to estimate technical efficiency of Ukrainian polyclinics.

Blank and Valdmanis (2010) use the DEA procedure as proposed by Simar and Wilson (2007) to analyze the efficiency of hospitals located in the highly-regulated health care industry of the Netherlands. The Dutch government controls many aspects of the health care industry including allocation of capital resources such as number of beds per hospital. They hypothesize that inefficient allocations based on inaccurate government forecasting may have adverse effects on the patient. Having access to data on input costs allowed the authors to estimate cost efficiency rather than the technical efficiency I propose estimating in my analysis. Blank and Valdmanis find that hospital cost efficiency is indeed impacted by the operating environment. In particular, they find a significant factor causing cost inefficiency are physicians that are operating private practices within a hospital. Blank and Valdmanis have several theories as to the source that is driving this result. One theory argues that these physicians are acting as profit-maximizing agents who over utilize hospital resources by prescribing unnecessary procedures.

Other studies have taken an alternative approach to estimate the second-stage (Herwartz and Strumann, 2014; Ferrier and Trivitt, 2013; Kristensen et al., 2010). However, these studies acknowledge that traditional DEA estimates are serially correlated and biased. Thus, they use a bootstrapping procedure proposed in Simar and Wilson (2007) to estimate the bias-corrected DEA scores in the first-stage. Herwartz and Strumann (2014) estimate the impact of the 2004 German health care reform on hospital efficiency. In 2004, Germany made an attempt to slow the rapidly growing health care costs by introducing a new mechanism for hospital reimbursement based on diagnosis-related groups. Although the intentions of the reform were to incentivize hospitals to reduce length of stay and increase the patients treated, the authors argue the reform contained other incentives which adversely affected efficiency.

Herwartz and Strumann estimate the bias-corrected technical efficiency scores in the first-stage according to Simar and Wilson (2007). Although the authors proceed with an alternative approach for the second-stage, they also use the second-stage bootstrapping procedure of the Simar and Wilson approach as a robustness check and report negligible differences. Their results show no indication of the health reform having a positive impact on German hospitals. In fact, they find hospital efficiency decreased over time after the reform. Herwartz and Strumann attribute the decline in efficiency to the financial uncertainty of the reform. To eliminate bankruptcy risk, hospitals built up financial reserves to fund investments. This uncertainty caused a lag in the adoption of technology leading to the decline in the ability of hospitals to deliver efficient medical care.

Rather than use modified DEA approach for their two-stage analysis, Ferrier and Trivitt (2013) use the traditional DEA method twice to account for how quality of care influences the technical efficiency of U.S. hospitals. Like Herwartz and Strumann (2014), Ferrier and Trivitt (2013) acknowledge the critique made in Simar and Wilson (2007) regarding the bias contained in traditional DEA estimations and apply the Simar and Wilson approach as a robustness check. They report insignificant differences between the two alternatives and proceed with their approach. The authors dub this approach, the "Double DEA" and first use the DEA method to construct quality indices based on variety of process and outcome measures of quality. They then use the DEA approach a second time to estimate the technical efficiency of each hospital while controlling for quality using the estimates of quality from the first stage. They argue that failing to account for quality when estimating hospital technical efficiency will result in misleading estimates. Failing to control for quality of care will give hospitals the incentive to lower quality while still being able to appear efficient. Alternatively, other hospitals may appear inefficient while providing a higher quality of care.

In a macro context, a subset of the literature focuses on the health care delivery system as a whole (Cozad and Wichmann, 2013; Afonso and St. Aubyn, 2005; Hollingsworth and Wildman, 2003; Afonso and St. Aubyn, 2011). Using the WHO panel data for OECD countries, Afonso and St. Aubyn (2005) and Hollingsworth and Wildman (2003) estimate the technical efficiency of health care delivery systems for OECD countries but do not attempt to explain the causes of inefficiency. In a later study, Afonso and St. Aubyn (2011) extend their original analysis in 2005 by applying the modified DEA approach to estimate the impact of environmental variables. They find that inefficiency of health care delivery systems can be attributed to GDP per capita, education level, obesity, and smoking level. In the short-run, these variables are viewed as beyond the immediate control of governments thus impacting efficiency. Cozad and Wichmann (2013) conduct a similar study by estimating the technical efficiency of health care delivery systems in the U.S. by treating each state as a sovereign decision making unit.

Cozad and Wichmann (2013) were motivated by the 2010 implementation of the Affordable Care Act (ACA). Applying the DEA procedure as proposed by Simar and Wilson (2007) to panel data from 2000-2007, Cozad and Wichmann explore the relationship between the number of insured individuals residing within each state and the technical efficiency of the state health care delivery system. Overall, their results confirm the hypothesis that expanding insurance coverage at a magnitude similar to the expected expansion from the ACA will place a strain on state health care delivery systems, resulting in costly inefficiencies.

Cozad and Wichmann (2013) use their result to discuss the potential impact of a fully implemented ACA. They use total health care expenditures in 2007 as a base year to determine the cost of a hypothetical health insurance expansion. In a back of the envelope calculation, they convert the technical efficiency loss directly resulting from an increase in the number of insured into health care expenditures. For 2007, their results indicate that increasing the number of insured individuals within a state by 1 percentage point will cause technical efficiency to fall 1.3 percentage points. They argue that a decline in the technical efficiency of this magnitude will translate into a $50 billion increase in health care expenditures. Thus, if a hypothetical insurance expansion in 2007 increased the number of insured in all states by 1 percentage point, the resulting inefficiency would increase overall health care expendsures by $50 billion.

Other studies have also attempted to draw conclusions on the potential effect of a fully implemented health care reform (Bailey and Goodman-Bacon, 2015; Garthwaite, 2012; Levine et al., 2011). Bailey and Goodman-Bacon (2015) show the health benefit that is associated with public health funding in their recent study. They focus on the introduction of community health centers in 1965. Complementing local health departments, community health centers use federal funding to increase access to health care and provide primary care services to underserved populations. Their results imply a significant reduction in the age-adjusted mortality rate and mortality risk among the population served. The significant long-term health benefits from the community health center program shown in this study indicate the importance of efficiently allocating funding to the public health sector.

Levine et al. (2011) and Garthwaite (2012) use the introduction of the State Children's Health Insurance Program (SCHIP) to draw potential policy conclusions of a fully implemented ACA. Levine et al. (2011) analyze the introduction of SCHIP from the patient side and find it to be successful at increasing the coverage among American children. Alternatively, Garthwaite (2012) focus on the impact of SCHIP on physician behavior. He finds physicians act as profit maximizers and tend to maximize personal income. After the introduction of SCHIP, his results show physicians were more likely to see and accept new Medicaid patients. However, pediatricians were more likely to decrease the number of hours they spend on patient care, spending less time with each individual. Garthwaite suggests his results indicate the potential adverse effects that future health insurance expansions may have on physician behavior and thus patient care quality.

Chapter 4

CONTRIBUTION

Economic research focusing on the effects of public health is limited. This may be a result of lack of researcher interest stemming from the relatively insignificant share of overall spending that is dedicated to public health. In 2014, approximately 2.6% of U.S. national health expenditures can be attributed to public health activity (CMS, 2014). Several studies focusing on the efficiency of health care delivery systems have omitted the public health sector, only taking into account the production attributed to hospitals and general practitioners in their analysis (Afonso and St. Aubyn, 2005, 2011; Hollingsworth and Wildman, 2003; Greene, 2004; Bhat, 2005; Spinks and Hollingsworth, 2009; Cozad and Wichmann, 2013). Thus, the primary goal of this research is to provide a better understanding of the effects of public health and the role it plays in the U.S.

While the true reason many chose to exclude public health activity is unknown, a likely factor is data constraints. The nature of public health makes data collection complicated. By definition, the goal of public health is to provide the necessary conditions to ensure individual and community health (IMO, 1988). Efficient allocation of funds throughout the public health system should successfully prevent potential health problems before they occur. Without a measurable outcome, estimating a cause and effect relationship is particularly problematic. As a consequence, determining a return on investment is difficult and when attempted is often unclear.

Although difficult, empirical economists have not ignored the issue altogether. The existing literature reports significant health benefits associated with higher levels of public health spending. Because public health funding is meant to make the population as a whole healthier, researchers often calculate returns to higher levels of funding in terms of an aggregated health outcome. For example, Brown et al. (2014) report that a \$10 per capita increase in county public health expenditures results in a 0.065 percentage point increase in the population reporting "good" health status. While these results are indicative of the health benefits associated with public health expenditures, they offer policy makers little information regarding a return on allocated funds.

The first contribution that I make to the literature is to extend the economic analysis of public health. My analysis deviates from the existing literature by moving away from the use of an aggregated health outcome variable. In particular, I estimate the relationship between county public health expenditures and individual hospital production. Previous research has indicated significant health benefits associated with increased funding of the public health system. If we accept these conclusions, health care providers, or in this context hospitals, should be affected as a result of a healthier or unhealthier population. To my knowledge, approaching the problem in this manner has not been explored and will provide a new avenue to understanding public health effects.

Efficiency analysis provides the framework needed to estimate the relationship between public health spending and hospitals. Typical efficiency studies involve a two-stage analysis. Estimating the efficiency of the production process in the first stage and attempting to explain any inefficiency in the second. Researchers have found several factors that can explain hospital inefficiency, none of which are related to public health. Most studies exploit a unique feature that is believed to affect the ability of hospitals to efficiently deliver medical care. For example, Pilyavsky et al. (2006) conclude that the geographic region in the Ukraine impacts efficiency while Blank and Valdmanis (2010) report inefficiency of the highly regulated Dutch hospitals are a result of private physicians operating within the hospital.

A second contribution I make in this research is twofold. Making use of efficiency analysis as an empirical strategy, I expand the limited efficiency literature focusing on U.S. hospitals. Furthermore, the inclusion of public health activity as a non-discretionary factor furthers our understanding of public health and the effect it has on surrounding hospitals. To my knowledge, the use of public health expenditures to explain hospital efficiency has not been explored.

An unexpected result of this empirical strategy involves potential policy implications. In 2014, approximately one-third of the $3 trillion that the U.S. has spent on health care is be attributed to hospitals (CMS, 2014). The 2010 implementation of the Affordable Care Act aimed to increase to the health of all Americans by providing access to affordable health insurance, all the while reigning in on long-run health care costs. One mechanism to reduce expenditures in hospitals involves imposing hospital cost saving incentives. While the goal of this dissertation is not to uncover the impact of the Affordable Care Act, the conclusions of this research may provide policy makers with an alternative mechanism to influence United States health care costs. Specifically, using efficiency analysis, I provide researchers and policy makers with an alternative estimate of the return on public health funding.

Chapter 5

METHODS

In this chapter, I discuss the empirical strategy used to estimate the relationship between public health spending and hospital efficiency. This chapter is divided into three main sections. Section 5.1 presents a technical overview of the traditional non-parametric DEA approach. Section 5.2 provides a detailed description of the two-stage semi-parametric DEA proposed by Simar and Wilson (2007). Section 5.3 defines the variables that comprise the hospital production process as well as the environmental variables that constrain the production process indirectly.

5.1 Non-Parametric Data Envelopment Analysis

Although research concludes that the successful allocation of public health expenditures results in a healthier population, the effect that it has on hospitals is unclear. Hospitals should benefit from higher public health spending. A healthier population will demand less medical care, thus allowing hospitals to use critical resources more effectively. Alternatively, it is plausible that higher public health spending will adversely impact hospitals. Because hospital production is dependent upon the existence of an individual in need of medical attention, it is safe to assume that hospitals will not produce at maximum capacity but will operate with a normal degree of excess capacity. Failing to account for lower demand for hospital services as a consequence of a healthier population will result in costly excess capacity beyond this normal level. In this research, I use efficiency analysis to answer the question: "Do higher levels of public health expenditures have a positive or negative impact on hospital technical efficiency?"

Recall from a previous discussion in Chapter 2, technical efficiency is an indicator of how well a firm is using its resources. In the context of this research, hospital technical efficiency relies on how well hospital managers allocate inputs such as beds and nurses to produce medical outputs such as admissions and discharges. When technical efficiency is maximized, any reduction of inputs will subsequently cause a reduction of output. A hospital deemed to be technically inefficient can be interpreted as "wasteful" (Cooper et al., 2006). In other words, a technically inefficient hospital is "wasting" inputs. To move to an efficiency maximizing input/output allocation, an inefficient hospital can choose to either reduce inputs without sacrificing output or expand output by using current inputs more efficiently.

It is important to distinguish that technical efficiency does not refer to how efficiently an individual patient is treated. For example, suppose an individual with a broken arm visits the emergency department at the nearest hospital. This patient may receive excellent medical care. It is possible that in each step of the hospital process, the patient is treated as efficiently as possible. It is also possible that this hospital is considered to be technically inefficient. Hospital inefficiency is a result of the over allocation of inputs needed in the hospital production process. For example, a hospital may have hired more nurses or installed more beds than is necessary to provide an excellent level of medical care.

The true value of technical efficiency is unknown and must be estimated empirically. Initially proposed by Farrell (1957) and made popular by Charnes et al. (1978), the non-parametric DEA approach is the dominant method for constructing measures of efficiency (Hollingsworth, 2008). While each hospital possess its own production possibilities frontier, the estimates of technical efficiency produced by the DEA are dependent upon the remaining hospitals in the sample. Through mathematical programing, the DEA uses observed pairs of inputs and outputs to establish a deterministic or best-practice frontier (Cooper et al., 2006). The established best-practice frontier consists of those hospitals that have maximized efficiency. Once established, the DEA linear programming problem obtains an estimate of technical efficiency by comparing each hospital to its best performing peer.

For hospital i, let x_i be a $(p \times 1)$ column vector of inputs and y_i be a $(q \times 1)$ column vector of outputs where x_i is used to produce y_i. Assuming constant returns to scale, the input-oriented non-parametric DEA is defined by the following linear programing problem:

$$\widehat{\delta}_i = \min_{\delta_i, \lambda} \quad \delta_i \quad s.t. \quad Y'\lambda \geq y_i \qquad (5.1)$$
$$X'\lambda \leq \delta_i x_i$$
$$\lambda \geq 0$$

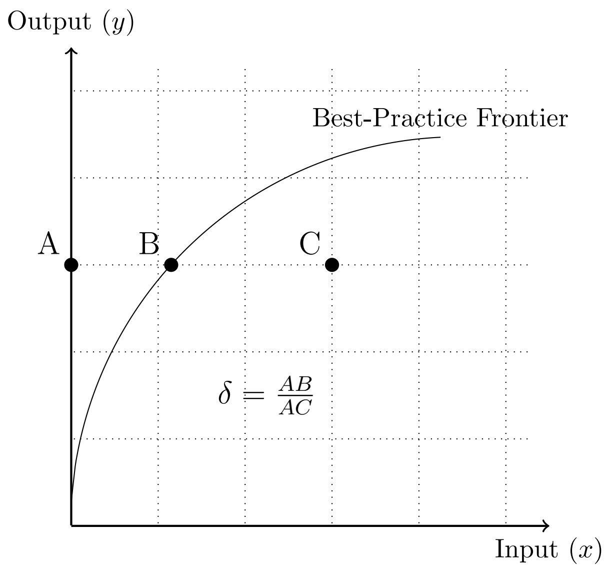
where λ is a $(n \times 1)$ vector of weight variables and $\widehat{\delta}_i \in (0, 1]$ is the estimated input-oriented technical efficiency score for hospital i (Greene, 2012). Equation 5.1 defines X as an $(n \times p)$ input matrix and Y as a $(n \times q)$ matrix of outputs where the i^{th} row of X and Y are x_i' and y_i' respectively.

Solving Equation 5.1 yields estimates of the input-oriented technical efficiency for each hospital in the sample. Technically efficient hospitals will be assigned a efficiency score such that $\widehat{\delta}_i = 1$. Hospitals deemed to be inefficient will be assigned an efficiency score such that $\widehat{\delta}_i < 1$. Figure 5.1 illustrates the simple case of Equation 5.1 where one input is used to produce one output.[1] Here, two hospitals are producing the same level of outputs which is held constant at A. Operating on the best-practice frontier, Hospital B is considered to be the most efficient hospital and will be assigned an efficiency score such that $\widehat{\delta}_B = 1$. A unitary technical efficiency estimate implies that if Hospital B wishes to remain producing A, then it cannot reduce capital and labor inputs any further. Moreover, any decision to reduce inputs by Hospital B will force a contraction of output.

Hospital C is operating on the interior of best-practice frontier and therefore is considered inefficient. Hospital C will be assigned an efficiency estimate such that $\widehat{\delta}_C < 1$. In other words, Hospital C can be thought of as wasteful. Relative to Hospital

[1] Figure 5.1 is the same graph used to introduce efficiency estimation in Chapter 2.

Figure 5.1: Input-Oriented Efficiency Estimation



Source: Adapted from a figure displayed in Cozad and Wichmann (2013), p. 4084.

B, Hospital C is utilizing a greater level of inputs to produce the same level of output. Thus, it is possible for Hospital C to proportionally reduce its capital and labor inputs without sacrificing output. For example, suppose it is estimated that Hospital C has an efficiency score such that $\widehat{\delta}_C = 0.85$. Hospital C can proportionally contract its inputs by $1 - \widehat{\delta}_C = 0.15$ or 15% while still achieving an output level equal to A. Graphically, a reduction of all inputs by $1 - \widehat{\delta}_C$ will horizontally project Hospital C onto the best-practice frontier.

The solution to the DEA linear programing problem yields a set of efficiency estimates which can be thought of as performance indicators. Hospitals using the least amount of input necessary to produce a given level of output are considered to be the best performing. The concept of comparing hospital efficiencies is similar to that of modern portfolio theory in finance. In modern portfolio theory, different combinations of risk and return are compared to one another to determine an optimal portfolio choice. Portfolios minimizing risk exposure for a given expected return are considered efficient. Plotting the possible combinations of risk and return yields an implied efficient frontier. Similarly, the best-practice frontier is implied by the input/output allocations in the sample. That is, the best-practice frontier envelopes the data with the boundary consisting of the set of best performing input/output allocations.

5.2 Semi-Parametric Data Envelopment Analysis

Original applications were only concerned with solving the DEA linear programing problems to obtain an estimate of efficiency for a given production process. Over time, researchers have developed an interest in explaining why a firm is operating away from the efficient allocation. Thus, recent efficiency studies extend the analysis to a two-stage estimation. The general structure of a two-stage efficiency estimation is as follows. In the first-stage, Equation 5.1 is solved for each firm to obtain estimates of technical efficiency $\widehat{\delta_i}$. In the second-stage, $\widehat{\delta_i}$ is used as the dependent variable in a regression analysis to identify environmental factors constraining the production process. For hospital i, the general second-stage regression is defined such that

$$\widehat{\delta_i} = z_i'\beta + \varepsilon_i \tag{5.2}$$

where $\widehat{\delta_i}$ is the estimated input-oriented efficiency and z_i is an $(k \times 1)$ vector of environmental variables that constrain the production process indirectly. I purposely define Equation 5.2 such that it remains consistent with the compact notation used in Simar and Wilson (2007). This will facilitate a straightforward description of the steps taken to estimate the second-stage. In a later discussion, I define a more specific second-stage regression.

Traditionally, Equation 5.2 has been estimated using an OLS or Tobit model. Simar and Wilson (2007) criticize studies for using the non-parametric DEA estimates with traditional empirical approaches in the second-stage. Simar and Wilson (2007, 2014) argue that the vast majority of studies reviewed ignore two critical shortcomings of the non-parametric DEA estimates. First, because each hospital is compared to another in an unknown fashion, the authors argue that $\widehat{\delta_i}$ is serially correlated in a complex, ambiguous manner. Because of this, the authors argue traditional maximum likelihood approaches to statistical testing are rendered invalid.

Compounding the problem, the non-parametric DEA does not allow for statistical error when constructing $\widehat{\delta}_i$. This implies any deviation from the best-practice frontier is viewed as pure inefficiency as it cannot distinguish between inefficiency or statistical error (Coelli et al., 2005). Because the non-parametric DEA does not allow for statistical error, Simar and Wilson argue that all second-stage coefficient estimates will be biased. Moreover, Simar and Wilson show mathematically that the non-parametric DEA estimate will always overestimate efficiency for all hospitals in the sample. Failing to take these shortcomings into consideration is particularly problematic for statistical testing as the bias will subsequently translate into the error term during the second-stage.

The benefit of using a non-parametric approach is its ability to handle multiple outputs and its flexibility when estimating the best-practice frontier (Cooper et al., 2011). However, relative to the parametric counterpart, the flexibility of the DEA is the source of several complications (Greene, 2007). To solve problems associated with the non-parametric DEA, Simar and Wilson impose several assumptions on the data generating process to develop a semi-parametric DEA estimator. They present researchers with two bootstrapping algorithms to consistently estimate the coefficients in the second-stage. Explained in detail below, both approaches provide a mechanism for consistent estimation and valid statistical testing for the environmental variables in the second-stage.

The algorithms proposed in Simar and Wilson (2007) require efficiency to be estimated by an output-oriented model, a variation of the input-oriented model specified by Equation 5.1. Mathematically, the choice of orientation is trivial as it has no impact on estimated efficiency scores (Coelli et al., 2005). The selection of orientation should be based on the industry of focus, paying attention to what the decision maker has more control over. In the context of hospital production, hospitals must meet demand as needed and possess little direct control over output levels. Thus, an input-oriented DEA will provide a more intuitive interpretation of hospital efficiency. Although Simar and Wilson's algorithms are defined using output-oriented efficiency estimates, Nedelea and Fannin (2013) make the necessary modifications to allow for the use of an input-oriented

DEA. Thus, I estimate hospital technical efficiency using an adapted version of the algorithms defined in Simar and Wilson (2007).

The first approach, denoted Algorithm 1, provides a mechanism for valid statistical testing by implementing one bootstrap procedure. Algorithm 1 can be summarized in the following steps:

Algorithm 1

1. Compute $\widehat{\delta_i}$ $\forall$ $i = 1, ..., n$ using Equation 5.3.

$$\widehat{\delta_i} = \min_{\delta_i, \lambda} \quad \delta_i \quad s.t. \quad \begin{aligned} & Y'\lambda \geq y_i \\ & X'\lambda \leq \delta_i x_i \\ & \lambda \geq 0 \\ & \iota'\lambda = 1 \end{aligned} \tag{5.3}$$

   where λ is a $(n \times 1)$ vector of weight variables, ι is a $(n \times 1)$ vector of ones, and $\widehat{\delta_i} \in (0, 1]$.

2. For $m < n$ observations, use the method of maximum likelihood to obtain an estimate $\widehat{\beta}$ of β as well as $\widehat{\sigma_\varepsilon}$ of σ_ε in the truncated regression of $\widehat{\delta_i}$ on z_i in Equation 5.4.

$$\widehat{\delta_i} = z_i'\beta + \varepsilon_i \tag{5.4}$$

3. Loop over the next three steps L times to obtain a set of bootstrap estimates $\left\{\left(\widehat{\beta}^*, \, \widehat{\sigma_\varepsilon}^*\right)_b\right\}_{b=1}^{L}$:

   3.1. For each $i = 1, ..., m$, draw ε_i from the $N(0, \widehat{\sigma_\varepsilon}^2)$ distribution with left-truncation at $-z_i'\widehat{\beta}$ and right-truncation at $1 - z_i'\widehat{\beta}$.

   3.2. Again, for each $i = 1, ..., m$, compute $\delta_i^* = z_i'\widehat{\beta} + \varepsilon_i$

   3.3. Use the maximum likelihood method to estimate the truncated regression of δ_i^* on z_i, yielding estimates $\left(\widehat{\beta}^*, \, \widehat{\sigma_\varepsilon}^*\right)$.

4. Use the bootstrap values in $\left\{\left(\widehat{\beta}^*, \, \widehat{\sigma_\varepsilon}^*\right)_b\right\}_{b=1}^{L}$ and the original estimates $\widehat{\beta}$, $\widehat{\sigma_\varepsilon}$ to construct estimated confidence intervals for each independent variable.

Algorithm 1 completes the first-stage in Step 1. Here, estimates of $\widehat{\delta_i}$ are obtained by solving the non-parametric DEA linear programing problem defined in Equation 5.3. This equation differs from the previously discussed model in Equation 5.1 in that an additional constraint is added. Previously, I introduced the general DEA model which assumes constant returns to scale. This assumption is only appropriate when every hospital is at the optimal scale (Coelli et al., 2005). Adding this convexity constraint ($\iota'\lambda = 1$) allows for variable returns to scale while ensuring that all hospitals will only be compared to hospitals similar in size (Coelli et al., 2005).

Algorithm 1 estimates the second-stage using the process defined in Steps 2-4. For a randomly selected number (m) of hospitals such that $m < n$, Equation 5.4 is estimated using $\widehat{\delta_i}$ as the dependent variable in a truncated regression. Here, estimates of $\widehat{\beta}$ and $\widehat{\sigma_\varepsilon}$ are stored as the baseline result. It is important to note that Algorithm 1 proceeds to the second-stage without correcting for the bias term contained in the traditional estimates. Because $\widehat{\delta_i}$ is a consistent estimator of δ_i, the bias will disappear in large sample sizes, however, by construction $\widehat{\delta_i}$ will remain serially correlated. In this case, Simar and Wilson argue one bootstrap routine will be sufficient to provide consistent statistical inference in the second-stage.

Step 3 of Algorithm 1 defines a single bootstrap procedure. For the same $m < n$ randomly selected hospitals, Step 3 is repeated L times without replacement to obtain L sets of bootstrapped estimates of $\widehat{\beta}^*$ and $\widehat{\sigma_\varepsilon}^*$ (Simar and Wilson, 2000). This procedure first draws a value of ε_i from the $N(0, \widehat{\sigma_\varepsilon}^2)$ distribution with left-truncation at $-z_i'\widehat{\beta}$ and right-truncation at $1 - z_i'\widehat{\beta}$. Next, an implied efficiency estimate, δ_i^*, is calculated using the stored estimates of $\widehat{\beta}$ obtained from Step 2 and the random draw of ε_i obtained from Step 3.1. Lastly, Step 3.3. then estimates Equation 5.2 using δ_i^* in a truncated regression to obtain bootstrapped estimates of $\widehat{\beta}^*$. Simar and Wilson (2007) argue setting $L = 2000$ is sufficiently large enough to consistently estimate and test the second-stage, however, they provide no suggestion for the size of m.

The final step is to determine the significance of each environmental variable. For a given regressor j, Simar and Wilson (2007) accomplish this by constructing percentile bootstrapped confidence intervals such that:

$$\Pr\left[a_{\alpha/2} \leq \beta_j - \widehat{\beta}_j \leq b_{1-\alpha/2}\right] = 1 - \alpha \tag{5.5}$$

where β_j is the true value and $\alpha \in (0,1)$ is the probability of making an Type I error. Unfortunately, the distribution of $\beta_j - \widehat{\beta}_j$ is unknown which makes finding critical values problematic (Simar and Wilson, 2007). To overcome this hurdle, Simar and Wilson use the stored bootstrap estimates of each coefficient to approximate the unknown critical values such that:

$$\Pr\left[a^*_{\alpha/2} \leq \widehat{\beta}_j - \widehat{\beta}_j^{\,*} \leq b^*_{1-\alpha/2}\right] \approx 1 - \alpha \tag{5.6}$$

where, for a given α, $a^*_{\alpha/2}$ and $b^*_{1-\alpha/2}$ are selected such that $100 \times (1-\alpha)\%$ remain in the distribution. The percentile bootstrapped confidence intervals are then determined after substituting the approximated critical values $a^*_{\alpha/2}, b^*_{1-\alpha/2}$ back into Equation 5.5. The resulting $(1-\alpha)$ percentile bootstrapped confidence interval for variable j is:

$$\widehat{\beta}_j + a^*_{\alpha/2},\ \widehat{\beta}_j + b^*_{1-\alpha/2} \tag{5.7}$$

Empirical implementation of their process is straightforward. For each independent variable, a temporary variable is created by subtracting the bootstrapped value $\widehat{\beta}_j^{\,*}$ from $\widehat{\beta}_j$. Using this variable, we will find the observation such that it is $\alpha/2$ percentile and the $1-\alpha/2$ percentile. These will serve as the critical values $a^*_{\alpha/2}$ and $b^*_{1-\alpha/2}$. At a standard significance level of 95%, if the number of bootstrap replications is set to 2000 as suggested, values of $a^*_{\alpha/2}$ correspond to the 50^{th} observation and values of $b^*_{1-\alpha/2}$ correspond to the 1950^{th} observation. Percentile bootstrapped confidence intervals are then constructed by adding $a^*_{\alpha/2}$ and $b^*_{1-\alpha/2}$ to the estimates of $\widehat{\beta}_j$ obtained in step 2.

Simar and Wilson (2007) propose a second approach that extends Algorithm 1 to correct the coefficient estimates in the second-stage. The procedures defined in Algorithm 2 differ from that of Algorithm 1 in that it implements an additional bootstrapping procedure to first construct a bias-corrected estimate of efficiency $\widehat{\widehat{\delta}}_i$ that will serve as the dependent variable in the second-stage. Algorithm 2 is summarized using the following steps:

Algorithm 2

1. Compute $\widehat{\delta_i}$ $\forall\ i = 1, ..., n$ using Equation 5.8.

$$\widehat{\delta_i} = \min_{\delta_i, \lambda} \quad \delta_i \quad s.t. \quad \begin{aligned} & Y'\lambda \geq y_i \\ & X'\lambda \leq \delta_i x_i \\ & \lambda \geq 0 \\ & \iota'\lambda = 1 \end{aligned} \tag{5.8}$$

   where λ is a $(n \times 1)$ vector of weight variables, ι is a $(n \times 1)$ vector of ones, and $\widehat{\delta_i} \in [0, 1]$.

2. For $m < n$ observations, use the method of maximum likelihood to obtain an estimate $\widehat{\beta}$ of β as well as $\widehat{\sigma}_\varepsilon$ of σ_ε in the truncated regression of $\widehat{\delta_i}$ on z_i in Equation 5.9.

$$\widehat{\delta_i} = z_i'\beta + \varepsilon_i \tag{5.9}$$

3. Loop over the next four steps L_1 times to obtain a set of bootstrap estimates $\left\{\widehat{\delta}^*_{ib}\right\}_{b=1}^{L_1}$:

   3.1. For each $i = 1, ..., n$, draw ε_i from the $N(0, \widehat{\sigma_\varepsilon}^2)$ distribution with left-truncation at $-z_i'\widehat{\beta}$ and right-truncation at $1 - z_i'\widehat{\beta}$.

   3.2. Again, for each $i = 1, ..., n$, compute $\delta^*_i = z_i'\widehat{\beta} + \varepsilon_i$

   3.3. Set $x^*_i = x_i\widehat{\delta_i}/\delta^*_i$, $y^*_i = y_i$ for all $i = 1, \ldots, n$.

   3.4. Compute $\widehat{\delta_i}^*$ for each i using initial hospital inputs x_i, y_i and $X^* = [x^*_1 \ldots x^*_n]$ and $Y^* = [y^*_1 \ldots y^*_n]$ as the new best practice frontier reference.

4. For each $i = 1, \ldots, n$, use $\widehat{\delta_i}$ and the bootstrapped estimates in $\left\{\widehat{\delta}^*_{ib}\right\}_{b=1}^{L_1}$ obtained in step 3.4 to compute the bias-corrected estimator $\widehat{\widehat{\delta_i}}$ defined in Equation 5.10:

$$\widehat{\widehat{\delta_i}} = \widehat{\delta_i} - \widehat{bias}(\widehat{\delta_i}) \tag{5.10}$$

   where Simar and Wilson (2000) define $\widehat{bias}(\widehat{\delta_i}) = L_1^{-1} \sum_{b=1}^{L_1} \widehat{\delta}^*_{ib} - \widehat{\delta_i}$.

5. Use the method of maximum likelihood to estimate the truncated regression of $\widehat{\widehat{\delta_i}}$ on z_i, yielding estimates $\left(\widehat{\widehat{\beta}}, \widehat{\widehat{\sigma}}\right)$.

6. Loop over the next three steps L_2 times to obtain a set of bootstrap estimates $\left\{(\widehat{\widehat{\beta}}^*, \widehat{\widehat{\sigma_\varepsilon}}^*)_b\right\}_{b=1}^{L_2}$:

6.1. For each $i = 1, ..., n$, draw ε_i from the $N\left(0, \widehat{\widehat{\sigma}}_\varepsilon^{\,2}\right)$ distribution with left-truncation at $-z_i'\widehat{\widehat{\beta}}$ and right-truncation at $1 - z_i'\widehat{\widehat{\beta}}$.

6.2. Again, for each $i = 1, ..., n$, compute $\delta_i^{**} = z_i'\widehat{\widehat{\beta}} + \varepsilon_i$

6.3. Use the maximum likelihood method to estimate the truncated regression of δ_i^{**} on z_i, yielding estimates $\left(\widehat{\widehat{\beta}}^*, \widehat{\widehat{\sigma}}_\varepsilon^{\,*}\right)$.

7. Use the bootstrap values in $\left\{\left(\widehat{\widehat{\beta}}^*, \widehat{\widehat{\sigma}}_\varepsilon^{\,*}\right)_b\right\}_{b=1}^{L}$ and the original estimates $\widehat{\widehat{\beta}}$, $\widehat{\widehat{\sigma}}_\varepsilon$ to construct estimated confidence intervals for each independent variable.[2]

The majority of the steps defined in Algorithm 2 are duplicated from Algorithm 1. Step 1 and 2 of Algorithm 1 are repeated to Step 1 and 2 of Algorithm 2, respectively. The second-stage bootstrap procedure defined in Step 3 of Algorithm 1 is the exact bootstrap procedure defined in Step 6 of Algorithm 2. Where Algorithm 2 differs from Algorithm 1 is in Step 3-5. In Step 3 of Algorithm 2, bootstrap procedure is used to adjust the production frontier in order to correct for the overestimation of the non-parametric DEA estimate. Once the bootstrapped estimates $(\widehat{\delta}_i^*)$ are obtained, a bias-corrected estimator $\widehat{\widehat{\delta}}_i$ is constructed in Equation 5.10 by subtracting the estimated bias from the original estimates. Algorithm 2 then follows similar steps as in Algorithm 1 to obtain the bootstrapped coefficients $\widehat{\widehat{\beta}}^*$ that will be used to construct the percentile bootstrapped confidence intervals for each environmental variable.

Algorithm 1 and Algorithm 2 differ only by which dependent variable is used in the second-stage. Although Algorithm 1 is less of a computation burden, Simar and Wilson cite significant advantages to using Algorithm 2. Results from their Monte-Carlo simulation suggest that including the biased estimate will improve consistency of statistical estimates. This is especially true when the dimension of the first-stage is increased. However, in large sample sizes, Simar and Wilson (2007) report Algorithm

[2] With the following substitutions, the process for obtaining critical values and constructing the percentile bootstrap confidence intervals is identical steps defined for Algorithm 1. Using Equation 5.6, substitute $\widehat{\widehat{\beta}}$ and $\widehat{\widehat{\beta}}^*$ for $\widehat{\beta}$ and $\widehat{\beta}^*$ respectively.

1 may dominate Algorithm 2 as correcting for the overestimation may add unnecessary noise. In this research, I estimate both Algorithm 1 and 2 for comparison.

Second-Stage Regression Equation

Finally, I expand Equation 5.2 to give a better understanding of the second-stage specification. For hospital i, in county j, in health service area s, at time t, the second-stage regression equation is defined to be:

$$\widehat{\widehat{\delta}}_{ijst} = \alpha + \eta'_{ijst}\beta_1 + \gamma'_{jt}\beta_2 + \beta_3 pcphe_{s,t-2} + \varepsilon_{ijst} \tag{5.11}$$

where γ_{jt} is a $(m \times 1)$ vector consisting all county-level environmental variables thought to influence the production process and η_{ijst} be a $(r \times 1)$ vector of individual hospital-level control variables. These variables will account for inefficiencies arising from differences in hospital organizational structure and county demographics.

The variable of interest, denoted $pcphe_{s,t-2}$, is defined as a categorical variable indicating the level of per capita public health expenditures that has occurred in each hospital's relevant market two years prior. The intuition behind using the lagged expenditures values stems from the assumption that increasing the amount of funds spent on health today will not result in a significant increase in health tomorrow. If higher public health spending truly has a positive impact on community health as research suggests, the effect, if any, will not be immediate. The following discussion describes the process by which the lagged public health expenditures are used to define the categorical variable $pcphe_{s,t-2}$.

Estimating the relationship of public health spending on hospital efficiency is problematic as the markets that hospitals and public health departments serve may not completely coincide. Recall, each local public health department allocates funds to increase the wellness of the individuals residing within the county it serves. Because hospitals are not restricted to only treating and admitting local individuals, their patient market may extend past the county in which they are located. Therefore, the magnitude of public health spending in neighboring counties may influence hospital efficiency and must be taken into consideration.

To account for the public health influence of neighboring counties, I use the Dartmouth Atlas of Health Care to construct an aggregated measure of public health spending. For each hospital, the Dartmouth Atlas of Health Care assigns a health service area to indicate the geographic region it serves. That is, the Dartmouth Atlas of Health Care analyzed hospital admission records to determine the area where each hospital is most likely to derive patients. Subsequently, per capita county public health expenditures (2005 dollars) are aggregated within each health service area.

Once the expenditures are aggregated by hospital market, I define the categorical variable $pcphe_{s,t-2}$ by grouping the health service areas into three spending levels. Specifically, relative to the public health spending in other health service areas, each health service area and its respective hospitals are ranked as: low-level, mid-level, or high-level public health spending areas.[3] The resulting measure will provide a superior indication as to the level of public health spending occurring in relevant market for a particular hospital.

5.3 Hospital Production and Environmental Variables

The DEA linear programming problem uses observed pairs of inputs x_i and outputs y_i to construct an estimate of technical efficiency for hospital i. Here, hospital managers choose an optimal amount of capital and labor inputs necessary to efficiently meet the demand for medical services. Thus, defining the hospital production process is a necessary step to constructing an estimate of technical efficiency. In the remainder of this section, I briefly introduce the input and output variables used to estimate hospital technical efficiency as well as the environmental and control variables that constrain the production process indirectly. For a detailed description, Chapter 6 provides an in-depth description and summary of the data.

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[3] Descriptive statistics for each level of $pcphe_{s,t-2}$ are reported in Tables 6.10 - 6.12 of Chapter 6.

5.3.1 Hospital Inputs/Output Variables

I define the input and output variables such that they are consistent with previous hospital efficiency literature. Table 5.1 provides a summary of the inputs and outputs used in this analysis. I consider three measures of labor: number of full-time equivalent registered nurses (RNs), full-time equivalent physicians and dentists ($Doctors$), and the remaining full-time equivalent hospital staff ($Staff$). I use number of beds ($Beds$) as an input to serve as a measure of hospital capacity. Virtually every study measuring hospital efficiency has defined some combination of the four inputs listed here.

Table 5.1: Hospital Production Function Variables and Definitions

Variable	**Description**
Inputs	
Beds	Total Number of Staffed Hospital Beds
RNs	Hospital FTE Registered Nurses
Doctors	Hospital FTE Physicians & Dentists
Staff	Other FTE Hospital Employees
Outputs	
Admissions	Total Number of Admissions (thousands)
Medicare	Total Number of Medicare Discharges (thousands)
Medicaid	Total Number of Medicaid Discharges (thousands)
ER	Total Number of Emergency Room Visits (thousands)
Surgeries	Total Number of Surgical Procedures Performed (thousands)
Days	Total Number of Hospital Inpatient Days (thousands)

Hospitals use these four inputs to produce several outputs: number of admissions ($Admissions$), number of emergency room visits (ER), number of medicare discharges ($Medicare$), number of medicaid discharges ($Medicaid$), total surgical operations performed ($Surgeries$), and number of hospital inpatient days ($Days$). With the exception of $Days$, all variables are defined in terms of thousands. These input/output variables are used to find a solution to the linear programing problem in Equation 5.1. The solution will provide the first-stage estimate of output technical efficiency for each hospital.

5.3.2 Environmental Variables

Table 5.2 summarizes the environmental variables considered to constrain the hospital production process indirectly. During the hospital optimization problem, hospital managers choose a level of medical inputs deemed necessary to efficiently meet demand. Environmental variables fall into two groups: hospital specific characteristics and regional health conditions of the surrounding population. Hospital-specific controls refer the uncontrollable characteristics such as hospital organizational structure or management type. Variables such as the percentage of individuals with insurance refer to regional conditions where hospitals operate. While these factors can influence efficiency, they are beyond the direct control of hospital managers. Thus, environmental variables appear in the second-stage regression of this analysis.

Table 5.2: Second-Stage Enviromental Variables and Definitions

Variable	**Description**
Enviromental	
Rural	Indicator of Operating Environment
Insured	Percentage of County Pop. < 65 w/ Health Insurance
Elderly	Percentage of County Pop. 65+
Poverty	Percentage of County Pop. Below the Poverty Level
$\text{pcphe}_{s,t-2}$	Real Per Capita Public Health Expenditures Indicator by Health Service Area
Hospital Specific Controls	
Teach	Hospital Medical School Affiliation
Org	Hospital Organizational Structure
	- Government Operated
	- Church Operated
	- For-Profit Operated
	- Non-Profit Operated

In addition to the previously discussed public health expenditures ($pcphe_{s,t-2}$) variable, I include several county variables to control for region specific factors. I define $Rural$ to be a dummy variable to distinguish between rural and metropolitan areas. I define three rate variables to account for health market conditions. $Insured$ is defined as the proportion of county population under 65 with health insurance. $Poverty$ is the proportion of county population living at or under the poverty level. $Elderly$ represents the proportion of the county population 65 years and older.

Each rate variable is defined in terms of per one hundred residents. That is, each variable is calculated by dividing the total number by the total county population and multiplying by one hundred. For example, suppose County A has a population of one hundred thousand residents, fourteen thousand of which are considered to be living in poverty. County A will have a poverty rate set equal to fourteen. Lastly, I include dummy variables that serve as an indicator of ownership status (Org) and medical school affiliation ($Teach$). These variables are hospital-specific control variables to account for efficiency differences between hospitals structure. The purpose of this section was to introduce the variables used in this analysis. The discussion in Chapter 6 provides a detailed summary the variables in Table 5.1 and Table 5.2.

Chapter 6

DATA

Data collected from three sources has been combined to construct a custom dataset for this research. This chapter provides a discussion of each source as well as the steps taken to integrate the three. Section 6.1 describes the hospital-specific data obtained from the American Hospital Association. Section 6.2 describes the public health data provided by the National Association for City and County Health Officers. Section 6.3 describes the county demographic data collected from the U.S. Department of Health and Human Services. Lastly, Section 6.4 provides a summary of the constructed dataset.

6.1 Hospital Data

Proprietary hospital-level data is provided by the American Hospital Association (AHA). Since 1946, the AHA has conducted an annual survey on all member hospitals (AHA, 2014). Collectively, the annual surveys form an extensive database containing information on over 6,000 hospitals throughout the United States. (AHA, 2014). Each annual survey collects a wide range of data on the organization structure of the hospital, facility characteristics, services provided, utilization rates, finances, staffing levels, and geographic indicators.[1]

The primary need for hospital-specific data is during the first-stage of this analysis. Hospitals use medical inputs x to produce medical outputs y. Once determined, these input/output pairs are then used to construct a measure of efficiency, which is

[1] A copy of the questionnaire used in the 2014 AHA Annual Survey can be found using the following link: http://www.ahadataviewer.com/Global/survey%20instruments/2014AHAAnnualsurvey.pdf

provided by the solution to the DEA linear programing problem defined in Equation 5.1. The secondary need for hospital-level data comes during the second-stage. Here, I add hospital specific control variables to control for efficiency differences between various organizational structures. The hospital variables used in this analysis are defined in Table 6.1.

Table 6.1: Description of Hospital Production and Characteristic Variables

Variable	**Description**
Beds	Total Number of Staffed Hospital Beds
RNs	Hospital FTE Registered Nurses
Doctors	Hospital FTE Physicians & Dentists
Staff	Other FTE Hospital Employees
Admissions	Total Number of Admissions (thousands)
Medicare	Total Number of Medicare Discharges (thousands)
Medicaid	Total Number of Medicaid Discharges (thousands)
ER	Total Number of Emergency Room Visits (thousands)
Surgeries	Total Number of Surgical Procedures Performed (thousands)
Days	Total Number of Hospital Inpatient Days (thousands)
Teach	Hospital Medical School Affiliation
Org	Hospital Organizational Structure
	- Government Operated
	- Church Operated
	- For-Profit Operated
	- Non-Profit Operated

I consider four inputs used to produce six outputs. Of the four inputs, I consider one capital input and three labor inputs. Serving as a proxy for hospital capacity, $Beds$ is defined as the total number of staffed beds. For a bed to be considered as staffed bed, the hospital must have the labor resources necessary to service that bed in the event it is occupied. Hospitals use three labor inputs: RNs denote registered nurses, $Doctors$ denote physicians and dentists, and $Staff$ represents any remaining hospital staff. To account for full-time and part-time employees, all labor inputs are defined in full-time equivalent terms (FTE). It is a straightforward calculation to transform each labor input into FTE terms. Each full-time employee is treated as one FTE employee whereas each part-time employee is valued as half of a FTE employee. For example, a hospital with one full-time and three part-time registered nurses therefore employs 2.5 FTE registered nurses.

A benefit to using the non-parametric DEA is its ability to handle multiple outputs. In this analysis, hospitals will use these four inputs to produce six outputs, all of which are defined in thousands. Total number of adult and pediatric admissions is represented by $Admissions$. I define $Medicare$ and $Medicaid$ as the total number of hospital discharges billed to Medicare and Medicaid, respectively. All patient visits to the emergency room are defined to be ER. Total number of inpatient surgical procedures performed is defined by $Surgeries$. Lastly, $Days$ denotes the total number of hospital inpatient days. A hospital inpatient day, otherwise known as an occupied bed day, is calculated for a given patient by subtracting date of discharge from the date of admission. The total number of inpatient days for each facility is determined by summing each individual patient day (AHA, 2014).

Spanning several decades, the AHA Annual Survey Database contains a wealth of information on U.S. hospitals. Unfortunately, due to the high cost of accessing the AHA database, the data acquired for this research is limited. To minimize costs, I have restricted the years purchased such that they coincide with the irregularity of the public health data. Thus, I make use of following years of AHA data: 2007, 2010, and 2012. Table 6.2 summarizes the hospital inputs and outputs by year using the raw data provided by the AHA. Table 6.2 shows that the majority of the variables listed have remained relatively constant over time. Over the five year period, the number of FTE registered nurses and emergency room visits are among those with largest deviations whereas the number of hospital $Beds$ has remained unchanged at 174 on average. In 2012, the average number of RNs employed increased by just over 14% since 2007. During the same time span, the number of visits to the ER increased by approximately 12%.

Table 6.2: Summary Statistics of Hospital Production Variables for All American Hospital Association Survey Respondents

Variable	**Mean**	**S.D.**	**Min**	**Max**	**N**
2007					
Beds	174.3	188.2	6	2,207	4,329
RNs	259.9	369.4	0	4,347	4,329
Doctors	18.9	81.4	0	2,067	4,329
Staff	686.6	918	13	12,655	4,329
Admissions	7.88	9.6	0.01	108.6	4,329
Medicare	3.32	3.75	0	37.5	4,329
Medicaid	19.1	23.2	0	255	4,329
ER	27.1	27	0.001	326.8	4,329
Surgeries	6.09	7.54	0.002	104.2	4,329
Days	42.3	53.9	0.011	679.9	4,329
2010					
Beds	173.9	193.7	0	2,261	4,301
RNs	281.3	406.2	0	5,121	4,301
Doctors	21.7	94.6	0	2,045	4,301
Staff	685	943.7	0	167,97	4,301
Admissions	7.83	9.76	0.021	119.5	4,301
Medicare	3.38	3.92	0.002	38.5	4,301
Medicaid	18.7	23.1	0	267.8	4,301
ER	28.7	29.6	0.001	387.6	4,301
Surgeries	6.07	7.66	0.001	101.7	4,301
Days	40.9	53.3	0.2	712.4	4,301
2012					
Beds	174	196.5	4	2,338	4,234
RNs	296.7	434.7	1	5,752	4,234
Doctors	24.3	100.8	0	2,236	4,234
Staff	706.1	1,016.1	11	18,887	4,234
Admissions	7.77	9.86	0.021	130.1	4,234
Medicare	3.41	3.98	0.006	39.8	4,234
Medicaid	18.4	23.2	0	271.2	4,234
ER	30.4	31.8	0.012	446.6	4,234
Surgeries	6.08	7.77	0.001	112.2	4,234
Days	40.2	53.5	0.032	670.5	4,234

Note: All labor inputs in FTE terms. All outputs quoted in thousands.

Tables 6.3 and 6.4 summarize the last pieces of information gathered from the AHA Annual Surveys. Table 6.3 tabulates the organizational structure (Org) of the hospitals by year. Each hospital is placed into one of five separate categories based on the hospital's management structure. The five categories are as follows: Non-Profit, For-Profit, Church, Non-Federal Government, and Federal Government. Over time, the number of hospitals in each category has remained relatively constant. Non-Profit hospitals comprise approximately half of the hospitals within each cross section. Hospitals managed by the state and local government make up approximately 20% of the hospitals each year while for-profit and religious run hospitals split the remaining 30%. Additionally, Table 6.3 shows the total number of AHA survey respondents has remained stable over time. Relative to the 4,329 hospitals in 2007, the number of hospitals participating in the survey decreased marginally to 4,301 in 2010 and 4,234 in 2012.

Table 6.3: Total Hospitals By Organization Structure and Year

Year	**Non-Profit**	**For-Profit**	**Church**	**Non-Fed. Govt.**	**Federal Govt.**	**Total**
2007	2,154	684	493	981	17	4,329
2010	2,149	711	483	948	0	4,301
2012	2,125	723	474	911	1	4,234
Total	12,910	4,184	2,918	5,705	18	25,735

The purpose behind including management structure in the second-stage is to account for any differences in hospital efficiency that are directly related to management type. Because the incentives vary as the management structure changes, it is reasonable to assume hospital efficiency will also vary. For example, for-profit hospitals have the incentive to maximize profits and will therefore produce at an allocation that minimizes costs. Conversely, the "use it or lose it" mentality of government managed hospitals may result in inefficiencies relative to for-profits. Typically, publicly managed hospitals will lose the privilege to any unused government funding if not used by a particular date. Therefore, publicly managed hospitals have the incentive to exhaust any funding received from local, state, and federal governments. Exhausting the available funding may result in funds being allocated to less productive projects or inefficient areas of the hospital. For-profit hospitals should therefore appear more efficient relative to their government counterpart as they should allocate resources more effectively.

Lastly, Table 6.4 describes the final hospital control variable $Teach$ to account for differences in efficiency related to training new doctors. $Teach$ is defined to be a dummy variable that classifies each hospital based on their affiliation with a medical school. The AHA provides two indicators describing a given hospital's participation in medical education. For this research, any hospital running their own residency program as well as any hospital affiliated with a medical school will be considered a "teaching" hospital. Otherwise, the remaining hospitals are classified as non-academic or general practice hospitals. Over time, the number of teaching hospitals has increased from 1,022 in 2007 to 1,112 in 2012. Furthermore, relative to non-academic hospitals, the proportion of teaching hospitals has increased marginally from 23% in 2007 to just under 28% in 2012.

Table 6.4: Total Hospitals By Medical School Affiliation and Year

Year	**Non-Academic**	**Medical School**	**Total**
2007	3,307	1,022	4,329
2010	3,257	1,044	4,301
2012	3,121	1,113	4,234
Total	19,511	6,224	25,735

Note: The variable teach refers to the hospitals that are part of a medical school as well as those that have an approved residency program.

The inclusion of $Teach$ is motivated by the uncertainty of its impact on hospital technical efficiency. Teaching hospitals could appear less efficient as they are faced with the cost of training new, inexperienced doctors. In the context of technical efficiency, teaching hospitals may employ a larger number of staff in order to effectively train new residents. Thus, teaching hospitals may appear as though they are over utilizing labor resources. Alternatively, teaching hospitals may arguably be more efficient. In order to provide the best training and quality of medical care, teaching hospitals typically have the most technologically advanced equipment. Academic hospitals also employ a vast network of highly-skilled physicians and specialists in order to attract patients from around the world as well as gain notoriety through cutting-edge research.

6.2 Public Health Data

Data on public health expenditures is collected from the National Association of City and County Health Officers (NACCHO). NACCHO conducts a National Profile of local health departments on a sporadic basis. Since 1989, NACCHO has conducted a total of seven profile studies, each gathering information on local health department infrastructure and operations (NACCHO, 2013). Local health departments across the U.S. are asked to report information pertaining to management, finances, staffing, and activities as well as any relevant public health topics. After examination of the individual profile studies, it is clear that the survey has evolved with each iteration. Moreover, as time has progressed, many variable definitions are now derivatives of a previous description. Fortunately, this research only uses information regarding county public health expenditures which has not been redefined.

Table 6.5 summarizes the raw county public health expenditure data provided by NACCHO, reporting real per capita and total real public heath expenditures in 2005 dollars. In 2005, the average county allocated \$6.97 million to public health or \$46.80 per capita. Total expenditures increased by 4% in 2008 to \$7.2 million and continued to rise over the next two years. In 2010, total real public health expenditures increased by 19.8% to \$8.7 million. Table 6.5 shows per capita public heath expenditures in the average county increased to \$58.30 in 2008 and subsequently decreased to \$57.30 in 2012. However, the significant increase in 2008 may be driven by a reporting error. Specifically, the maximum value for per capita public health expenditures in 2008 is reported to be \$6,582, a value substantially larger than that of 2005 and 2010. The data reveals a small rural county in Missouri spent over \$200 million on public health to service a population of just under 29,000 residents in 2008. Examining the remaining sample suggests a value of per capita public health spending of this magnitude is unlikely and as a result, Marion County, Missouri has been excluded from this analysis.[2]

Table 6.5: Summary Statistics for County Public Heatlh Expenditures (2005 Dollars)

	Mean	**S.D.**	**Min**	**Max**	**N**
Total					
2005	6,970,982	35,552,718	11,866	687,000,000	1,172
2008	7,281,562	36,309,743	6,949	619,716,736	1,261
2010	8,723,176	48,474,987	26,313	1,194,142,976	1,263
Per Capita					
2005	46.80	48.60	0.78	659.60	1,172
2008	58.30	192	0.91	6,582	1,261
2010	57.3	64.20	1.72	1,476	1,263

Table 6.6 provides a summary of the public health spending by county type. As with Table 6.5, the summary statistics listed here indicate the presence of Marion County, Missouri discussed above. Further comparison of the two geographical region types reveals a significant difference in the average level of resources utilized in these areas. Each year, rural counties spend approximately \$1.15 million on public health whereas metropolitan areas spend just under \$18 million on average. Although rural counties comprise roughly two-thirds of the sample, rural counties spend, on average, 10% of what their urban counterparts spend on public health in total. When total public health expenditures are adjusted for county population, the relationship is

[2] Comparing the populations of counties with a similar level of public health spending suggests this is likely a reporting error. In 2008, Philadelphia County, PA spent \$196 million to service 1.5 million residents. Relative to Marion County, Missouri, Philadelphia County, PA spent approximately the same nominal amount on public health services to serve a population 5,000 times the size.

Table 6.6: Descriptive Statistics for County Public Health Expenditures By Year and Rural (2005 Dollars)

	Mean	**S.D.**	**Min**	**Max**	**N**
Total					
Rural					
2005	956,542	1,535,778	11,866	30,000,000	737
2008	1,301,328	6,782,766	6,949.3	188,636,640	789
2010	1,200,098	1,199,853	26,313	9,925,967	731
Metro					
2005	17,188,747	56,974,054	246,000	687,000,000	435
2008	17,278,182	57,357,649	231,224	619,716,736	472
2010	19,060,338	73,469,408	391,034	1,194,142,976	532
Per Capita					
Rural					
2005	46.94	47.39	0.78	652.17	737
2008	62.61	237.74	4.13	6,582.10	789
2010	61.92	51.39	3.00	339.85	731
Metro					
2005	46.73	50.88	1.11	659.63	435
2008	51.05	61.53	0.91	802.26	472
2010	50.98	78.08	1.72	1,476.10	532

reversed. Per capita, rural counties spend more on public health than urban counties on average. In 2010, rural counties spent on average $61.92 per capita whereas metropolitan counties allocated $50.98 per capita on public health.

While Table 6.6 shows the distribution of county types has remained relatively constant over time, there has been significant increases in the total and per capita public health expenditures. On average, total public health expenditures increased by approximately 25.4% for rural counties from $956,000 in 2005 to $1.2 million in 2010. Over the same five year period, total public health expenditures increased by only 10.8% for metropolitan counties moving from $17.1 million in 2005 to $19 million in

2010. Adjusting for population size reveals significant differences in the growth of per person public health spending between the two county types. Relative to 2005, per capita public health expenditures increased 32% in 2010 in rural counties. During the same time, metropolitan counties experienced an increase in per capita public health expenditures of about 9%. In 2010, rural counties have increased spending by $15 per person since 2005 whereas metropolitan counties raised public health spending by only $4.25 per person.

6.3 Demographic Data

The remaining variables necessary for this study are gathered from the Area Health Resource Files (AHRF). The U.S. Department of Health and Human Services (HHS) maintains this database, releasing new data on a yearly basis. The AHRF is a collection of national, state, and county-level socioeconomic and demographic variables aggregated from over fifty sources (AHRF, 2013). The variables used in this analysis are defined in Table 6.7.

Table 6.7: Description of County-Level Socioeconomic Variables

Variable	**Description**
Rural	County Type Indicator
Elderly	Percentage of County Population 65+
Poverty	Percentage of County Population Below the Poverty Level
Insured	Percentage of County Population < 65 w/ Health Insurance

Note: Percentage variables are expressed in hundreds (e.g. If County X has a 9.3% poverty rate, it is encoded as 9.3 in the data).

To control for the operating environment, I define *Rural* as a dummy variable indicating if a given hospital is operating outside of a metropolitan statistical area (MSA). *Elderly* represents the portion of the county population that is older than 65 years of age. It is safe to assume that elderly citizens typically have a higher need for medical care. The inclusion of this variable as a control will account for differences in efficiency relating to treating more or less of this population demographic. The poverty rate is defined as *Poverty*, which measures the percentage of the county population at or below the poverty level. Lastly, *Insured* will represent the rate of insurance within each county. That is, the percentage of the county population younger than 65 with health insurance. The motivation behind including this variable stems from Cozad and Wichmann (2013). The authors find the rate of insurance to be a significant factor when explaining inefficiency of a health care delivery system at the state-level.

Table 6.8 provides the summary statistics for variables gathered from the raw Area Health Resource File files. Brief examination reveals expected results on average. On average, the proportion of the elderly population has increased by roughly 10% from 15.1% in 2007 to 16.8% in 2012. The growth of *Elderly* is expected as more of the baby boomer population becomes eligible for retirement. A clear consequence of the Great Recession, the average county poverty rate has increased by 14.5% from 14.5% in 2007 to 16.6% in 2012. Lastly, the proportion of the county population under 65 with health insurance has remained relatively constant during the five year span. Although the Affordable Care Act was passed in 2010, the health care market place was not implemented until 2014. Thus, little to no change in the insured population is expected, all else equal. Although the average county insurance rate has decreased from 2007 to 2012 by 0.87%, this is likely driven by the reporting error in 2007.

One potential problem reported in Table 6.8 occurs with the *Insured*. In 2007, the maximum value reported is 156. This implies that 156% of the population in St. Bernard Parish, Louisiana has insurance which is clearly an error. Examining the data for St. Bernard Parish reveals abnormal fluctuations in the population estimates around 2005-2008. Given the time frame and the county's geographic location in Louisiana, it is safe to conclude that Hurricane Katrina is the likely cause of such volatility and reporting errors. Consequently, this observation will be excluded in the following analysis. Up until this point, the raw data from each of three sources has been summarized with minimal cleaning performed. The following section provides a discussion of the constructed dataset to be used in this research. In this section, I

Table 6.8: County Demographic Descriptive Statistics By Year

Variable	**Mean**	**S.D.**	**Min**	**Max**	**N**
2007					
Elderly	15.3	4.15	4.04	36.4	3,109
Poverty	14.5	5.87	2.35	56	3,109
Insured	80.6	7.43	38	156	3,109
2010					
Elderly	15.9	4.14	3.73	43.4	3,109
Poverty	16.2	5.83	3.15	50.3	3,109
Insured	79	6.68	40	94.8	3,109
2012					
Elderly	16.8	4.27	3.61	49.3	3,109
Poverty	16.6	6.05	3.1	47.2	3,109
Insured	79.9	6.56	39.2	94.9	3,109

Note: Data is obtained from the Area Health Resource Files. Each variable is defined as a proportion of the county population (hundreds).

discuss the assumptions made and the steps taken to merge the individual data files into a custom dataset.

6.4 Dataset Construction

The following discussion reports the steps taken to assemble the custom dataset that is used in this research. Merging the three data files depends on being able to uniquely identify each county. Here, I rely on the 5-digit Federal Information Processing Standard (FIPS) codes to do so. The goal for the final product is to correctly match each individual hospital variable such that it is aligned with the respective county public health and demographic variables. Because neither the AHA nor the NACCHO dataset is all inclusive, I expect to lose several unmatched observations from both sources.

As a starting point, I began by cleaning the hospital-level data from the AHA. In anticipation of the merger with NACCHO's public health data, I focus solely on the years that will have a two year public health lag. That is, I keep 2007, 2010, and 2012 and remove the following years from the AHA datafile: 2004, 2008, and 2013. I then restrict the focus of this research to the continental the U.S., dropping any observations referencing U.S. territories as well as any observations pertaining to Alaska and Hawaii.

To obtain the most general result possible, I restrict focus on general medical and surgical hospitals. This will not only ensure the results are not subject to outliers but will make them applicable to the general case. Table 6.9 displays the frequencies of each hospital service category for all three cross sections. The AHA requires each hospital to select a category that best describes the services it provides. Of the 18,588 hospitals in the sample, Table 6.9 reports 14,245, approximately 76%, as being General Medical and Surgical hospitals. The second largest is service type belongs to the 1,382 Psychiatric hospitals, making up just over 7% of the observations in the sample. As a close third, 1,154 Acute Long-Term Care hospitals comprise approximately 6% of the remaining hospitals. Restricting the analysis to focus primarily on general medical and surgical hospitals will drop 4,343 observations or approximately 23.36% of the purchased AHA data.

Prior to merging the cleaned hospital data, I first aggregated the two county-level datasets independently. Using county FIPS codes, I combined the raw data from the AHRF with the public health data from NACCHO, dropping any unmatched AHRF observations. Because the AHRF data is an exhaustive list of U.S. counties, I did not lose any public health observations during the merge. Following the merge, I then used hospital market identifiers to construct an aggregated measure of per capita public health spending. Recall from the previous discussion in Chapter 5, hospitals do not restrict treatment to those individuals residing in their county at which they operate. Thus, hospitals may be affected by public health spending of a neighboring county as patients migrate across state and county borders to seek treatment.

Table 6.9: Hospital Service Category Frequencies Aggregated over 2007, 2010, & 2012

Primary Service	**Freq.**	**Percent**	**Cum.**
General Medical and Surgical	14,245	76.64	76.64
Hospital Unit of an Institution	46	0.25	76.88
Hospital Unit within Mentally ill Institution	7	0.04	76.92
Surgical	123	0.66	77.58
Psychiatric	1,382	7.43	85.02
Tuberculosis and Other Respiratory	4	0.02	85.04
Cancer	37	0.20	85.24
Heart	40	0.22	85.45
Obstetrics and Gynecology	34	0.18	85.64
Eye, Ear, Nose, and Throat	14	0.08	85.71
Rehabilitation	717	3.86	89.57
Orthopedic	64	0.34	89.91
Chronic Disease	13	0.07	89.98
Other Specialty	149	0.80	90.78
Children's General	167	0.90	91.68
Children's Psychiatric	129	0.69	92.38
Children's Rehabilitation	33	0.18	92.55
Children's Orthopedic	41	0.22	92.77
Children's Chronic Disease	6	0.03	92.81
Children's Other Speciality	45	0.24	93.05
Institution for Mental Retardation	21	0.11	93.16
Acute Long-Term Care	1,154	6.21	99.37
Alcoholism and Other Chemical Dependency	109	0.59	99.96
Children's Acute Long-Term	8	0.04	100.00
Total	18,588	100.00	

To account for the public health spending likely experienced by each hospital, I use the identifiers provided by The Dartmouth Atlas of Health Care to group counties into health service areas and construct an aggregated measure of per capita public health spending. I then use the resulting aggregated measure to define the variable of interest, $pcphe_{s,t-2}$, as a categorical variable indicating the level of per capita public health expenditures in each health service area. Specifically, each health service area is defined to be Low, Medium, or High. That is, for a given year, low-level public health spending areas fall in the bottom third of the distribution or below the 33 percentile, mid-level public health spending areas fall in the middle third, and high-level public health spending areas fall above the 66 percentile.

I then proceeded to integrate the cleaned files with the AHA data to form a single working data file. During the file merge, I lost approximately 200 public health observations per cross-section. These observations were not matched with a corresponding hospital. From the hospital perspective, there were about 1,400 hospitals per year that are without public health expenditure data. In total, 4,589 unmatched observations are dropped. Each hospital has now been placed into a health service area with a corresponding indicator of public health spending level.

Tables 6.10, 6.11, and 6.12 provide summary statistics for the hospitals operating in 2007, 2010, and 2012 respectively. The resulting cleaned cross-sections contain between 2,092 and 2,334 observations each. Upon review of the descriptive statistics for each year, a surprising and problematic theme emerges over time. Logic dictates that medical doctors play a critical role in the operation of a typical hospital, however, roughly 25% of hospitals in each year report having zero *Doctors* on staff. If correct, this implies 25% of hospitals are admitting patients and providing them with emergency services and surgical procedures without staffing a doctor.

To investigate the problem, I took a random sample of hospitals that have reported a zero value for *Doctors*. The appearance of several large, well-known hospitals within this subset suggests staffing zero *Doctors* is not only highly unlikely but clearly impossible in several cases. Notable hospitals belonging to this subset include Johns Hopkins Hospital in Maryland and Duke University Hospital in North Carolina. While both hospitals operate using a vast number of doctors throughout their facility, these doctors may not be directly employed by the hospital. That is, contract employees may be one possible explanation for 25% of hospitals reporting a zero value for *Doctors*. Moreover, hospitals may hire a physician group or hire contract doctors in order to staff their facility as needed.

Table 6.10: Summary Statistics for Constructed Dataset - Year: 2007

Variable	**Mean**	**S.D.**	**Min**	**Max**	**N**
Hospital Production Variables					
Beds	186	192	6	2,157	2,102
RNs	281	381	5.5	3,441	2,102
Doctors	17.6	74.8	$0^{\dagger}$	1,696	2,102
Staff	715	928	19.5	12,655	2,102
Admissions	8.51	9.71	0.019	109	2,102
Medicare	3.56	3.79	0.001	37.5	2,102
Medicaid	20.4	23.1	0.001	223	2,102
ER	28	27.1	0.005	327	2,102
Surgeries	6.42	7.31	0.014	100	2,102
Days	45.3	54.7	0.046	603	2,102
County Variables					
$\text{pcphe}_{s,t-2}$	46.39	61.07	0.57	674.99	2102
- Low	12.91	6.50	0.57	23.85	699
- Medium	32.71	5.47	23.89	43.14	694
- High	92.70	86.89	43.16	674.99	709
Elderly	13.8	4.08	4.13	36.4	2,102
Poverty	12.7	4.65	2.97	36.7	2,102
Insured	81.8	6.38	50.3	94.1	2,102

† 628 observations report having zero Doctors (FTE) staffed

Including an observation with a zero value for a given input is particularly problematic for estimating efficiency. Specifically, observations with zero inputs violate the "No Free Lunch" assumption imposed by Simar and Wilson (2007). Recall, DEA develops an estimate of technical efficiency by comparing each hospital to its best practicing peer. If a significant number of hospitals are producing a positive levels of output with a zero value for a given input, then these hospitals will be automatically more technically efficient. For example, suppose Hospital A is producing 10,000 surgeries with zero doctors and Hospital B producing 10,000 surgeries with one hundred doctors. Hospital A will be interpreted as operating more efficiently as it is able to produce the same output with less inputs.

Hospitals with zero values for *Doctors* is an empirical dilemma. While *Doctors* are critical in the production of medical care, the DEA will interpret observations with zero *Doctors* as producing something from nothing. Thus, zero values for input variables should not be included in the first-stage estimation of δ_i. Rather than dropping any observation reporting a zero value for *Doctors*, I modify the inputs used to solve the DEA linear programing problem. Specifically, I estimate hospital technical efficiency in the first-stage with one less labor input. By eliminating the *Doctors* variable as a hospital labor input, I am able to avoid dropping 25% of the sample observations.

Relative to hospitals in 2007, Table 6.11 reports hospitals hired on average seven additional RNs, expanding their nursing staff by about 3% in 2010. Hospitals operating in 2010 reduced both their average supply of *Beds* by 4% and other FTE $Staff$ by 5% since 2007. Subsequently, as expected hospitals experienced a decline in all but one output variable in 2010. The number of visits to the hospital ER increased by about 800 since 2007, however, this increase is small considering the average hospital treats roughly 28,000 ER patients per year. Among the outputs with the largest decreases, hospital *Days* fell the most with a 7% decrease. Average hospital *Admissions* fell from by 4.2% from 8,510 in 2007 to 8,150 in 2010.

While hospitals were experienced contractions in most inputs and outputs from 2007 to 2010, Table 6.11 cites significantly higher values of lagged public health spending in 2010 than that of Table 6.10. In 2010, hospitals in every health service area spending category experienced an increase in per capita public health from two years prior. Between 2005 and 2008, real per capita public health expenditures in the low-level health service area increased by 19% from \$12.91 per capita in 2005 to \$15.33 per capita in 2008. Similarly, hospitals belonging to a mid-level public health spending area witnessed an average increase of 14% per capita. Relative to the lower spending areas, the largest increase in real per capita public health expenditures was realized by hospitals operating within a high-level health service area. From \$92.7 in 2005 to

Table 6.11: Summary Statistics for Constructed Dataset - Year: 2010

Variable	Mean	S.D.	Min	Max	N
Hospital Production Variables					
Beds	179	190	6	2,083	2,091
RNs	289	402	4	5,121	2,091
Doctors	18.4	83.8	0†	1,967	2,091
Staff	679	910	26.5	16,797	2,091
Admissions	8.15	9.55	0.039	119	2,091
Medicare	3.52	3.84	0.002	38.5	2,091
Medicaid	19.2	22.2	0.005	212	2,091
ER	28.8	28.7	0.001	388	2,091
Surgeries	6.17	7.29	0.002	80.7	2,091
Days	42.1	51.7	0.219	569	2,091
County Variables					
$\text{pcphe}_{s,t-2}$	55.95	157.5	0.87	683.3	2091
- Low	15.33	6.82	0.87	26.10	697
- Medium	37.20	6.55	26.1	49.10	696
- High	115.20	262.20	49.20	683.30	698
Elderly	14.6	4.17	5.63	43.4	2,091
Poverty	14.9	4.82	3.69	35.6	2,091
Insured	80.3	5.73	54	91.7	2,091

† 571 observations report having zero Doctors (FTE) staffed

\$115.2 in 2008, the magnitude of per capita public health expenditures experienced by hospitals increased by approximately 24% in high spending areas.

As expected, hospital production expanded post Great Recession. Comparing Table 6.11 and 6.12, hospital inputs and subsequently outputs have clearly increased from 2010 to 2012. The average hospital added roughly 19 *Beds* to their existing capital stock between 2010 and 2012. Hospitals also expanded their labor inputs between 2010 and 2012. Adding an average of 60 *RNs* to the facility, hospitals expanded the nursing department by 21% in 2012. Additionally, hospitals added about 17% of other *Staff*, increasing the average number of other hospital *Staff* from 679 in 2010 to 797 in 2012.

Table 6.12: Summary Statistics for Constructed Dataset - Year: 2012

Variable	**Mean**	**S.D.**	**Min**	**Max**	**N**
Hospital Production Variables					
Beds	198	205	4	2,338	2,334
RNs	349	466	6	5,752	2,334
Doctors	25.7	104	0†	2,236	2,334
Staff	797	1,062	19.5	18,887	2,334
Admissions	9.17	10.3	0.021	130	2,334
Medicare	3.97	4.11	0.006	39.8	2,334
Medicaid	21.1	23.6	0.006	214	2,334
ER	33.9	33.3	0.012	447	2,334
Surgeries	6.95	8.01	0.001	112	2,334
Days	46	55.1	0.032	622	2,334
County Variables					
pcphe$_{s,t-2}$	53.86	100.6	0.38	1483	2334
- Low	14.18	7.08	0.38	25.3	771
- Medium	35.14	6.67	25.4	47.9	779
- High	111.5	157.6	48.1	1483	784
Elderly	14.7	4.09	6.25	49.3	2,334
Poverty	15.8	4.97	4.44	38.5	2,334
Insured	80.6	5.6	0.581	93.7	2,334

† 681 observations report having zero doctors FTE staffed

Although increasing nurses and beds gives hospitals the ability to treat more individuals, the expansion of capital and labor inputs in 2012 may not be justified by significantly higher output. Hospitals may be responding to the uncertainty surrounding the implementation of the Affordable Care Act. Hospitals may have been speculating the magnitude of resources needed to meet demand in 2014 when Affordable Care Act officially took effect. Thus, the expansion of inputs in 2012 may cause inefficiencies from costly excess capacity.

Table 6.12 shows the increased inputs enabled hospitals to see a higher number of patients which indeed increased output in 2012. The largest expansion in hospital output being an 18% increase in patient visits to the the emergency department. In 2012, the average hospital treated 33,908 *ER* patients, a increase from 2010 of about 5,145. Relative to 2010, hospitals were able to increase *Admissions* and *Surgeries* by just under 13% as well as treat 10-12% more *Medicare* & *Medicaid* patients in 2012.

Relative to 2010, Table 6.12 shows hospitals in 2012 were subjected to decreases in per capita public health expenditures in each health service area group. Hospitals in the high-level public health spending areas saw the largest nominal decline of $3.70 per capita, moving from $115.2 per capita in 2008 to $111.5 per capita in 2010 whereas hospitals operating in health service areas with low-level public health spending only experienced a $1.15 nominal reduction. Adjusting for the magnitude of spending occurring within each health service area suggests the low-level health service areas will be impacted the most by the decreases in public health spending. Relative to 2010, hospitals in low-level health service areas will experience a 7.5% drop in public health spending whereas mid-level and high-level areas will experience reductions of 5.54% and 3.21% respectively.

Chapter 7

RESULTS

The goal of this dissertation is to bridge the knowledge gap between public health and a hospital's ability to efficiently deliver medical services. In a two-stage analysis, I estimate the relationship between real per capita public health expenditures and hospital technical efficiency. This chapter presents the empirical results of this two-stage estimation and is structured as follows. Section 7.1 presents the calculated technical efficiency scores obtained in the first-stage. Section 7.2 provides the empirical results from the second-stage. Here, I apply the semi-parametric Data Envelopment Analysis (DEA) proposed by Simar and Wilson (2007) in a pooled cross-section regression to identify several factors that are beyond the hospital managers control and therefore constrain the hospital production process indirectly. Lastly, Section 7.3 compares Simar and Wilson's double bootstrap approach to the conventional econometric techniques used in previous efficiency studies.

7.1 Stage 1: Estimating Hospital Technical Efficiency

The objective of the first-stage is to construct a measure of technical efficiency to be used as the dependent variable in the second-stage regression. I obtain estimates of efficiency for each hospital in the sample using the DEA approach described in Chapter 5. By definition, the DEA is a non-parametric approach for estimating efficiency. More specifically, the DEA uses mathematical programing techniques to construct a measure of hospital efficiency $\widehat{\delta}_i$ without accounting for random error. As a result, any deviation from the efficient allocation is viewed as pure inefficiency as $\widehat{\delta}_i$ is unable to distinguish between statistical error and inefficiency. Consequently, the non-parametric estimate for $\widehat{\delta}_i$ is a biased estimator and will always overshoot the true value of δ_i (Simar and

Wilson, 2000). Failing to address the problems associated with the non-parametric DEA can be problematic for the second-stage. Any bias in $\widehat{\delta_i}$ will transfer to the error term in the second-stage regression. Therefore, conventional maximum-likelihood estimations will produce biased coefficients and invalid statistical tests (Simar and Wilson, 2007).

To adjust for the shortcomings of non-parametric DEA, Simar and Wilson (2007) provide two algorithms to consistently estimate the second-stage. Algorithm 1 implements a single bootstrap routine to improve statistical testing without correcting $\widehat{\delta_i}$ for any overestimation. Algorithm 2 extends Algorithm 1 using an additional bootstrapping procedure to construct a bias-corrected efficiency measure $\widehat{\widehat{\delta_i}}$ prior to the second-stage. Although Simar and Wilson (2007) suggest Algorithm 2 will produce superior estimates of technical efficiency, I report both $\widehat{\delta_i}$ and $\widehat{\widehat{\delta_i}}$ for comparison.

Table 7.1 provides a yearly summary of the input-oriented technical efficiency estimates. Panel A reports the non-parametric efficiency estimates of $\widehat{\delta_i}$ obtained from Step 1 of Algorithm 1. Panel B reports the bias-corrected estimates of $\widehat{\widehat{\delta_i}}$ obtained after completing Steps 1-4 of Algorithm 2. Each panel is broken down to summarize hospital efficiency by management type, academic affiliation, and geographic area of operation. The interpretation of the estimates in Table 7.1 remains the same regardless of which panel is being considered. Technically efficient hospitals are assigned a unitary value for δ_i. Inefficient hospitals are able to reduce inputs without sacrificing output which is indicated by an efficiency value such that $\delta_i < 1$. Mathematically, inefficient hospitals can simultaneously produce the same level of output and achieve the best-practice allocation by proportionally reducing inputs by $100 \times (1 - \delta_i)\%$.

On average, several expected relationships emerge in both Panel A and Panel B of Table 7.1. Hospitals operating within a metropolitan statistical area are 15% to 20% more technically efficient than hospitals operating in rural areas. Panel A indicates the average efficiency estimate for all rural hospitals to be 8.7 percentage points lower than their metropolitan counterparts at $\widehat{\delta_i} = 0.55$. Although adjusting for the bias in $\widehat{\delta_i}$ reduces the overall technical efficiency estimate, the relative relationship

Table 7.1: Pooled Summary Statistics for Traditional and Bias-Corrected Technical Efficiency Estimates - By Year

	2007		2010		2012		Total	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: Traditional Non-Parametric Estimates ($\widehat{\delta}_i$)								
Rural	0.581	(0.17)	0.546	(0.16)	0.521	(0.17)	0.550	(0.17)
Metro	0.653	(0.17)	0.635	(0.15)	0.623	(0.16)	0.637	(0.16)
Teach	0.689	(0.16)	0.662	(0.15)	0.661	(0.16)	0.670	(0.16)
Non-Academic	0.615	(0.17)	0.593	(0.16)	0.571	(0.16)	0.593	(0.17)
Non-Profit	0.644	(0.17)	0.620	(0.16)	0.603	(0.17)	0.622	(0.17)
For-Profit	0.630	(0.17)	0.630	(0.16)	0.612	(0.17)	0.623	(0.17)
Church	0.652	(0.16)	0.619	(0.15)	0.608	(0.15)	0.626	(0.15)
Govt (Non-Fed)	0.590	(0.18)	0.557	(0.16)	0.553	(0.17)	0.567	(0.17)
Total	0.632	(0.17)	0.608	(0.16)	0.596	(0.17)	0.612	(0.17)
Panel B: Bias-Corrected Semi-Parametric Estimates ($\widehat{\widehat{\delta}}_i$)								
Rural	0.467	(0.13)	0.443	(0.13)	0.423	(0.13)	0.444	(0.13)
Metro	0.548	(0.13)	0.533	(0.12)	0.523	(0.13)	0.534	(0.13)
Teach	0.578	(0.12)	0.557	(0.12)	0.554	(0.13)	0.562	(0.12)
Non-Academic	0.508	(0.14)	0.491	(0.13)	0.473	(0.13)	0.491	(0.13)
Non-Profit	0.537	(0.13)	0.516	(0.13)	0.502	(0.13)	0.518	(0.13)
For-Profit	0.528	(0.14)	0.529	(0.12)	0.515	(0.14)	0.524	(0.14)
Church	0.544	(0.12)	0.522	(0.12)	0.509	(0.12)	0.525	(0.12)
Govt (Non-Fed)	0.474	(0.14)	0.455	(0.13)	0.451	(0.14)	0.460	(0.14)
Total	0.523	(0.14)	0.506	(0.13)	0.496	(0.14)	0.508	(0.14)
Observations	1,884		1,928		1,946		5,758	

between rural and urban hospitals remains unchanged with regard to $\widehat{\widehat{\delta}}_i$. For the entire sample, Panel B reports the average efficiency estimate for metropolitan hospitals as $\widehat{\widehat{\delta}}_i = 0.534$ whereas rural hospitals now $\widehat{\widehat{\delta}}_i = 0.444$. The bias-corrected estimate widens the difference in average efficiency. That is, the bias-corrected efficiency estimates for rural hospitals are now 9.9 percentage points lower than metropolitan hospitals in Panel B.

Hospitals affiliated with a medical school have an estimated technical efficiency of $\widehat{\delta}_i = 0.67$ in Panel A and a bias-corrected estimate of $\widehat{\widehat{\delta}}_i = 0.562$ in Panel B. Non-academic hospitals have an estimated efficiency of $\widehat{\delta}_i = 0.593$ and $\widehat{\widehat{\delta}}_i = 0.491$ in Panel A and Panel B respectively. Both estimates of efficiency indicate that teaching hospitals are, on average, more technically efficiency than their non-academic counterparts.

For the entire sample, Panel A reports academic hospitals operate on average 7.7 percentage points higher than non-academic hospitals whereas Panel B reports a slightly smaller difference of 7.1 percentage points. Although the average efficiency estimate for all hospitals fell between 2007 and 2012, efficiency loses were greater for non-academic hospitals. Average efficiency fell by 2.8 percentage points for teaching hospitals from $\widehat{\delta_i} = 0.689$ in 2007 to $\widehat{\delta_i} = 0.661$ in 2012. Non-teaching hospitals suffered an average efficiency drop of 4.4 percentage points from $\widehat{\delta_i} = 0.615$ in 2007 to $\widehat{\delta_i} = 0.571$ in 2012

Lastly, Table 7.1 summarizes each efficiency estimate by hospital management type. Of the four hospital management structures considered, publicly managed hospitals perform at the lowest level. Government managed hospitals, on average, operate 6 percentage points lower than all other management types, making public hospitals the least technically efficient. For the pooled sample, Panel A reports government managed hospitals having an average estimated efficiency of $\widehat{\delta_i} = 0.567$ whereas Panel B reports government efficiency estimates at $\widehat{\widehat{\delta_i}} = 0.46$. Estimating the bias-corrected efficiency estimate decreases the average efficiency estimate for government run hospitals by approximately 19%.

With the exception of government managed hospitals, it is not apparent that there are any differences in efficiency among the remaining management types. Panel A reports non-profit, for-profit, and hospitals managed by religious organizations have efficiency estimates ranging from $\widehat{\delta_i} = 0.622$, $\widehat{\delta_i} = 0.623$, and $\widehat{\delta_i} = 0.626$ respectively. Although the bias-corrected estimates $\widehat{\widehat{\delta_i}}$ in Panel B are on average lower for all management types, the differences in efficiency among non-profit, for-profit, and hospitals managed religious organizations remain small. Panel B shows the difference between the lowest and the highest estimate being less than one percentage point. That is, the lowest of the three is non-profit hospitals with an efficiency estimate of $\widehat{\widehat{\delta_i}} = 0.518$ and the best performing as church managed hospitals $\widehat{\widehat{\delta_i}} = 0.525$, a difference of 0.007. Furthermore, this implies hospitals managed by religious organizations will operate with an efficiency level that is 0.70 percentage points greater than non-profit hospitals or approximately 1.35% more efficient.

The relative differences between the panels of Table 7.1 reaffirm Simar and Wilson's assertion that the traditional non-parametric DEA estimates will always overstate efficiency. For the entire hospital sample, the bias correction decreased average efficiency by 10.4 percentage points, moving average efficiency estimate from $\widehat{\delta_i} = 0.612$ in Panel A to $\widehat{\widehat{\delta_i}} = 0.508$ in Panel B. Figure 7.1 illustrates the magnitude of the overestimation graphically.

Figure 7.1: Mean Comparison of Traditional and Bias-Corrected Technical Efficiency Estimates By Hospital Charasteristic

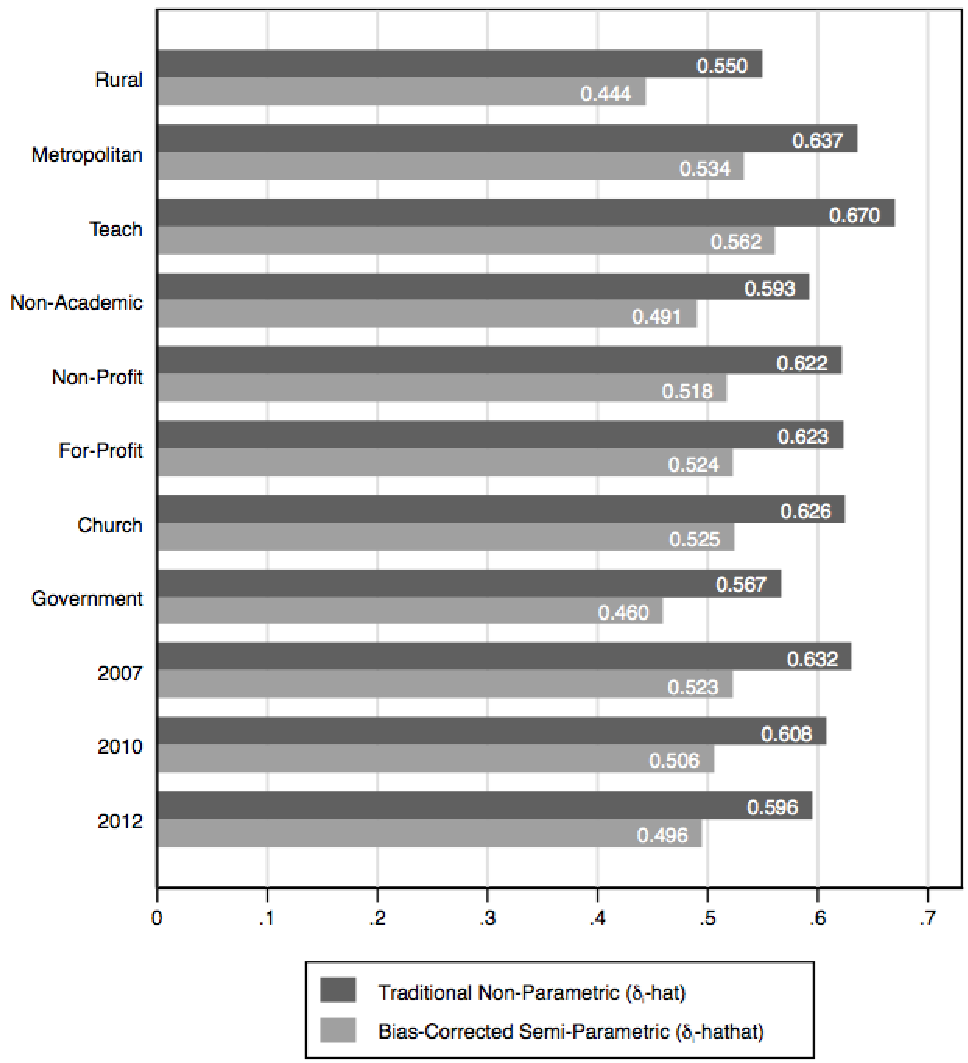
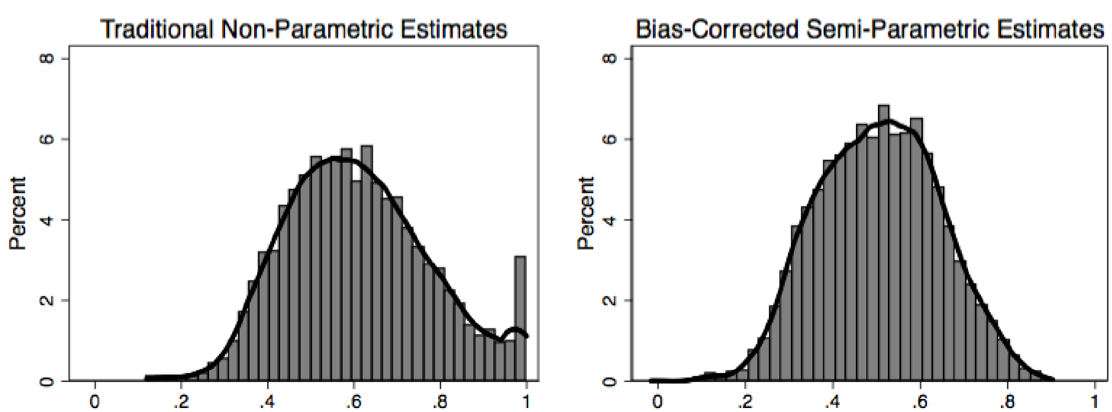


Figure 7.1 uses the pooled efficiency estimates in Table 7.1 to summarize the differences between the non-parametric $\widehat{\delta}_i$ estimates in Panel A and the bias-corrected estimates $\widehat{\widehat{\delta}}_i$ in Panel B. Figure 7.1 shows that correcting for the bias in the non-parametric estimates decreased average efficiency in every subset. For-profit hospitals experienced the smallest change with a decrease in average efficiency of 0.0995 percentage points whereas teaching hospitals experienced the largest decline in average efficiency of 0.1076 percentage points. Additionally, Figure 7.1 reveals a decline in both estimates of hospital efficiency over time. The non-parametric technical efficiency estimates of $\widehat{\delta}_i$ decreased from $\widehat{\delta}_i = 0.632$ in 2007 to $\widehat{\delta}_i = 0.596$ in 2012. During the same five year period, the bias-corrected efficiency estimates $\widehat{\widehat{\delta}}_i$ decreased from $\widehat{\widehat{\delta}}_i = 0.523$ in 2007 to $\widehat{\widehat{\delta}}_i = 0.496$ in 2012.

Figure 7.2 plots the kernel density of the traditional biased estimates $\widehat{\delta}_i$ (left) and Simar and Wilson's bias-corrected efficiency estimates $\widehat{\widehat{\delta}}_i$ (right). Although the difference is not as clear as shown in Figure 7.1, correcting $\widehat{\delta}_i$ shifts the entire distribution toward zero, reducing the mass occurring at the upper bound. Thus, both Figure 7.1 and Figure 7.2 support the argument that the lack of error term in the non-parametric DEA estimation of $\widehat{\delta}_i$ will result in an inflated measure of hospital technical efficiency, making hospitals appear more efficient.

Figure 7.2: Kernel Density of the Traditional and Bias-Corrected Efficiency Estimates



7.2 Stage 2: Estimating the Environmental Impact

The primary objective of the second-stage is to identify and understand how uncontrollable environmental factors influence hospital technical efficiency. Typically, this is achieved by regressing the estimated efficiency score obtained in the first-stage on variables considered to constrain the production process indirectly. Described in detail in Chapter 5, I follow the bootstrapping routines defined in Simar and Wilson (2007) to avoid complications plaguing conventional estimations. In a later section, I compare Simar and Wilson's bootstrapped results to the estimates produced by Tobit and OLS regressions.

Algorithm 1 is designed by Simar and Wilson (2007) to improve conventional estimation approaches without correcting for the bias in the non-parametric DEA estimate. For hospital i, in county j, in health service area s, at time t, the second-stage regression is defined such that:

$$\widehat{\delta}_{ijst} = \alpha + \eta'_{ijst}\beta_1 + \gamma'_{jt}\beta_2 + \beta_3 pcphe_{s,t-2} + \varepsilon_{ijst} \tag{7.1}$$

where $\widehat{\delta}_{ijst} \in (0, 1]$ is the biased estimator of technical efficiency produced by the traditional non-parametric DEA, η_{ijst} is a $(r \times 1)$ vector of individual hospital-level controls, γ_{jt} is a $(m \times 1)$ vector of county health and region variables, and $pcphe_{s,t-2}$ is a categorical variable indicating the level of public health spending experienced by each hospital two years prior.

Algorithm 1 estimates the second-stage using the traditional non-parametric estimate $\widehat{\delta}_i$ as the dependent variable. Because $\widehat{\delta}_i$ is a consistent estimator of δ_i, the bias in $\widehat{\delta}_i$ will disappear as $n \to \infty$. Simar and Wilson suggest that the single bootstrap routine in Algorithm 1 may be sufficient to correct for the serial correlation of the non-parametric DEA efficiency estimates. Unfortunately, the convergence of the non-parametric DEA is slow and the bias in $\widehat{\delta}_i$ will not disappear in finite samples (Simar and Wilson, 2007). As an alternative, Simar and Wilson extend Algorithm 1 with Algorithm 2 to address this problem.

Algorithm 2 uses a second bootstrapping procedure to construct a bias-corrected estimate $\widehat{\widehat{\delta}}_i$ of hospital efficiency prior to the second-stage. The dependent variable in Equation 7.1 is replaced with an the bias-corrected estimate. Hence, the second-stage estimation equation is now specified such that:

$$\widehat{\widehat{\delta}}_{ijst} = \alpha + \eta'_{ijst}\beta_1 + \gamma'_{jt}\beta_2 + \beta_3 pcphe_{s,t-2} + \varepsilon_{ijst} \tag{7.2}$$

where $\widehat{\widehat{\delta}}_{ijst} \in (0, 1]$ is the bias-corrected estimator of technical efficiency and η_{ijst}, γ_{jt}, and $pcphe_{s,t-2}$ are defined exactly as they were in Equation 7.1. The dependent variable is the sole difference between Equation 7.1 and Equation 7.2.

Table 7.2 reports the truncated regression coefficients of three models each estimated by Algorithm 1 and Algorithm 2. Significance levels are determined by the constructed percentile bootstrapped confidence intervals defined in the respective algorithm. Model 1 presents the specification defined in Chapter 5. Because public

Table 7.2: Second-Stage Semi-Parametric DEA Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Model 1		Model 2		Model 3	
	A1	A2	A1	A2	A1	A2
	$\widehat{\delta}_i$	$\widehat{\widehat{\delta}}_i$	$\widehat{\delta}_i$	$\widehat{\widehat{\delta}}_i$	$\widehat{\delta}_i$	$\widehat{\widehat{\delta}}_i$
Teach	0.0632***	0.0584***	0.0772***	0.071***	0.0648***	0.0647***
For-Profit	0.0143*	0.00855*	0.0211***	0.0149***	0.00745	0.00432
Church	0.00745	0.00527	0.00965	0.00714	-0.00212	0.00332
Govt (Non-Fed)	-0.0256***	-0.0372***	-0.0429***	-0.0521***	-0.0204**	-0.0407***
2010	-0.0171***	-0.0164***	-0.0137*	-0.013***	-0.0154*	-0.0139***
2012	-0.0342***	-0.0316***	-0.0278***	-0.0241***	-0.0285***	-0.0286***
pcphe$_{s,t-2}$ (Mid)	0.00905	0.00636	0.0106	0.00902**	0.00682	0.00634
pcphe$_{s,t-2}$ (High)	0.025***	0.0166***	0.0261***	0.0168***	0.026***	0.021***
Rural	-0.0822***	-0.0892***				
Insured	-0.000448	-0.000886***	-0.000935	-0.00148***	-0.000749	-0.00103**
Poverty	-0.00193***	-0.00174***	-0.00291***	-0.00305***	-0.001	-0.000985*
Elderly	0.00259***	0.00235***	-0.000691	-0.000915**	0.00105	0.00173***
Constant	0.651***	0.595***	0.723***	0.679***	0.685***	0.599***
σ	0.146***	0.125***	0.150***	0.129***	0.144***	0.125***
Observations	2730	5758	2730	5758	1943	4100

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

health expenditures are much lower in rural counties, I estimate Model 2 and 3 for robustness. Model 2 omits the rural dummy variable whereas Model 3 removes all rural hospitals from the estimation sample to focus on metropolitan hospitals.

The variable of interest, $pcphe_{s,t-2}$, captures the effect of public health spending on hospital technical efficiency. Recall from a previous discussion, $pcphe_{s,t-2}$ groups each hospital into one of three levels based on how much their respective health service area has spent on public health two years prior. The magnitude of spending varies by group. For example, in 2010, low-level health service areas spent, on average, \$16.19 per capita on public health. Public health spending for mid-level health services areas averaged \$36.13 per capita in 2010, ranging from \$26 per capita to \$48.44 per capita. During the same year, health service areas operating at the top of the distribution spent, on average, \$101.97 per capita on public health activities.

The results in Table 7.2 suggest that hospitals are indeed impacted by public health expenditures. Specifically, hospitals operating in health service areas with a high-level of public health spending per capita experience gains in efficiency relative to those hospitals operating in the omitted low-level group. Reported in Columns 1 and 2, Model 1 reports the mid-level public health coefficient to be $\widehat{\beta} = 0.00905$ for Algorithm 1 and $\widehat{\widehat{\beta}} = 0.00636$ for Algorithm 2. The constructed percentile bootstrapped confidence intervals of both algorithms do not show any statistical significance for the mid-level public health spending category. Although hospitals operating in mid-level public health spending areas do not experience significant gains in efficiency over those in low-level areas, hospitals operating in a high-level public health areas do.

For Model 1, Algorithm 1 estimates the high-level public health coefficient to be $\widehat{\beta} = 0.025$ with 99% confidence, whereas, Algorithm 2 reports an estimate of $\widehat{\widehat{\beta}} = 0.0166$ for high-level areas. Although the coefficient estimate decreased by approximately 33% with the bias-corrected efficiency estimate $\widehat{\widehat{\delta}}_i$, explanatory power remains the same at 99%. According to Algorithm 2 hospitals operating in a health service area with a public health spending that is roughly \$50 per capita or more will experience gains in efficiency of 1.66 percentage points relative to those in low-level areas.

For robustness, the public health estimates of Model 1 are verified by Model 2 and 3. All models in Table 7.2 report estimates for high-level public health areas that are similar in magnitude and statistical significance. When the *Rural* indicator is omitted, Model 2 estimates the high-level coefficient to be $\widehat{\beta} = 0.0261$ for Algorithm 1 and $\widehat{\widehat{\beta}} = 0.0168$ for Algorithm 2 with 99% confidence. Similarly, Model 3 estimates the coefficient to be $\widehat{\beta} = 0.026$ and $\widehat{\widehat{\beta}} = 0.021$ for Algorithm 1 and Algorithm 2 respectively with 99% confidence. Although there are significant differences in public health spending in rural and urban areas, hospitals operating in a high-level health service area experience gains in efficiency relative to the low spending areas in both urban and rural areas.

Table 7.2 suggests hospitals have experienced significant decreases in technical efficiency since 2007. Model 1 reports the Algorithm 1 coefficient estimates for 2010 and 2012 as $\widehat{\beta} = -0.0171$ and $\widehat{\beta} = -0.0342$, respectively. Similar estimates are reported by Algorithm 2 in Column 2. For years 2010 and 2012, the Algorithm 2 estimates are $\widehat{\widehat{\beta}} = -0.0164$ and $\widehat{\widehat{\beta}} = -0.0316$ respectively. With 99% confidence, the coefficients of both algorithms show hospitals operating in 2010 and 2012 are less efficient then they were in 2007. Relative to 2007, Algorithm 2 indicates hospital technical efficiency has declined by 1.64 percentage points in 2010 and 3.16 percentage points in 2012. This result is likely a product of the downturn in the economy during this time as well asthe passing of the Affordable Care Act.

Model 1 suggests teaching hospitals unequivocally perform better than their non-academic peers. With 99% confidence, the coefficients for $Teach$ are $\widehat{\beta} = 0.0632$ for Algorithm 1 and $\widehat{\widehat{\beta}} = 0.0584$ for Algorithm 2. This implies a hospital affiliated with a medical school will operate at an efficiency level that is roughly 6 percentage points higher than a general hospital with no academic ties. Gains in efficiency with teaching hospitals are not surprising. Teaching hospitals have a wealth of resources giving them access to state of the art equipment and medical technology. Academic hospitals also employ a highly skilled labor force that is likely to be well versed on the latest medical developments.

As anticipated, government managed hospitals remain the poorest performing hospital management type. Algorithm 1 estimates the coefficient for *Govt.* as $\widehat{\beta} = -0.0256$ indicating government hospitals perform 2.56 percentage points lower than non-profit hospitals. Algorithm 2 calculates the double bootstrapped estimate of *Govt.* to be $\widehat{\widehat{\beta}} = -0.0372$. Using the bias-corrected estimate of efficiency $\widehat{\widehat{\delta_i}}$ as the dependent variable decreases the coefficient estimate for *Govt.* by 45%[1]. Moreover, Algorithm 2 suggests government managed hospitals will perform 3.72 percentage points lower than non-profits.

While the efficiency loses of government managed hospitals are expected, the relationship between the remaining hospital management types is unclear. Model 1 shows hospitals managed by religious organizations are no more or less efficient than non-profit hospitals. Model 1 also provides weak evidence supporting the conclusion that for-profit hospitals may experience efficiency gains over their non-profit counter-parts. Algorithm 1 estimates the coefficient for *For-Profit* to be $\widehat{\beta} = 0.0143$, however, it is only statistically significant at the 90% level. Column 2 reports the Algorithm 2 estimate as $\widehat{\widehat{\beta}} = 0.00855$. Although the coefficient on for-profit hospitals declined about 40%[2] in Algorithm 2, the explanatory power remains the same.

Until this point, the discussion of Models 2 and 3 has been limited as the coefficient estimates have been relatively consistent with that of Model 1. In the case of for-profit hospitals, Models 2 and 3 report unstable results. Recall, Model 2 modifies Model 1 by estimating the second-stage without the rural dummy whereas Model 3 restricts the sample size to only those hospitals operating in a metropolitan statistical area. When *Rural* is omitted, both algorithms report inflated coefficient estimates of *For-Proft* relative to Model 1. That is, Model 2 reports estimates for

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[1] Relative to the Algorithm 1 coefficient estimate of $\widehat{\beta} = -0.0256$, the Algorithm 2 coefficient estimate $\widehat{\widehat{\beta}} = -0.0372$ has changed by $\frac{-0.0372-(-0.0256)}{-0.0256} = -0.453$ or -45%.

[2] The percentage change in the coefficient estimate of *For-Profit* is calculating using the same calculation as in [1]. Relative to the Algorithm 1 the Algorithm 2 coefficient estimate has changed by $\frac{0.00855-0.0143}{0.0143} = -0.402$ or -40%.

For-Profit that are approximately 50%-75%[3] larger in magnitude relative to Model 1. Moreover, the explanatory power of *Rural* transfers to *For-Proft*, becoming statistically significant with 99% confidence in Model 2. Conversely, when the sample is restricted to only metropolitan hospitals, Model 3 shows no statistical difference between for-profit and non-profit hospitals in metropolitan areas. Relative to Model 1, the coefficient estimates of *For-Profit* shrinks by over 50%[4] for both algorithms in Model 3. This result suggests that for-profit hospitals do not experience significant gains in efficiency relative to non-profit hospitals in urban areas.

The inconsistency between the models makes it unclear whether for-profit hospitals operate with significant efficiency gains over non-profits hospitals. Although the lack of distinction between the two hospital types may appear counterintuitive, it is consistent with the research examining the behavior of non-profit hospitals. Several studies examining the behavior of non-profit hospitals have shown them to behave no differently than for-profit hospitals (Sloan, 2000; Duggan, 2000, 2002). That is, non-profit hospitals make decisions similar to that of for-profits who aim to minimize costs rather then maximizing patient welfare.

Lastly, at the county-level, population demographics have varying effects on hospital efficiency. Model 1 shows hospital efficiency is adversely affected by increases in the county indigent population share. With a coefficient estimate on *Poverty* equal to $\widehat{\beta} = -0.00193$, a one percent increase in the county poverty rate will translate into a 0.193 percentage point decrease in hospital efficiency. The coefficient estimate for poverty rate falls slightly in Algorithm 2 to $\widehat{\widehat{\beta}} = -0.00174$, however, it remains statistically significant with 99% confidence.

The percentage of the county population under 65 with health insurance is

[3] Comparing the estimates of *For-Profit* between Model 1 and Model 2 yields a percentage change of $\frac{0.0211-0.0143}{0.0143} = 0.4755$ or 48% for Algorithm 1 and a percentage change of $\frac{0.0149-0.00855}{0.00855} - 0.743$ or 74% for Algorithm 2.

[4] Performing the same comparison of the estimates for *For-Profit* using Model 1 and Model 3 yields a percentage change of $\frac{0.00745-0.0143}{0.0143} = -0.479$ or -48% for Algorithm 1 and a percentage change of $\frac{0.00432-0.00855}{0.00855} = -0.495$ or -50% for Algorithm 2.

represented by $Insured$. According to previous research, increases in the share of the population with health insurance negatively impacts the technical efficiency of state health care delivery systems (Cozad and Wichmann, 2013). Because hospitals play a critical role in the delivery of medical care, I expect to find similar results. Column 1 reports a coefficient estimate on $Insured$ as $\widehat{\beta} = -0.000448$, however, it is statistically insignificant. Additionally, Algorithm 1 reports insignificant coefficient estimates for $Insured$ in both Model 2 and Model 3.

Although Algorithm 1 failed to identify the county insurance rate as a significant determinant of hospital efficiency, Algorithm 2 provides a conclusion similar to that found in previous research. After constructing the bias-corrected efficiency measure $\widehat{\widehat{\delta}}_i$, Algorithm 2 shows $Insured$ has a significant influence on hospital efficiency. Column 2 reports the bias-corrected estimate of $Insured$ to be $\widehat{\widehat{\beta}} = -0.000886$ with 99% confidence. Moreover, a one percent increase in county insurance rate will result in an efficiency loss for hospitals of approximately 0.09 percentage points.

The results in Table 7.2 are unclear regarding the effect that the elderly population size has on hospital efficiency. In Column 1, Algorithm 1 estimates the coefficient of $Elderly$ to be $\widehat{\beta} = 0.00259$ with 99% confidence. Similarly in Column 2, Algorithm 2 reports a 99% statistically significant estimate of $Elderly$ as $\widehat{\widehat{\beta}} = 0.00235$. This implies that a one percent increase in the county elderly population share will result in an increase in hospital efficiency by approximately 0.259 and 0.235 percentage points for Algorithm 1 and Algorithm 2 respectively.

Model 1 suggests hospitals will clearly operate more efficiently as the county population gets older. However, extending the discussion to Model 2 and 3 reduces clarity. Model 2 produces the opposite results when the rural indicator is omitted. Column 4 reports a coefficient estimate for $Elderly$ equal to $\widehat{\widehat{\beta}} = -0.000915$ with 95% confidence. Alternatively, the results of Model 1 are confirmed by Model 3 when the sample is restricted to only metropolitan hospitals. Column 6 reports the Algorithm 2 estimate of $Elderly$ to be $\widehat{\widehat{\beta}} = 0.00173$ with 99% significance. Previous research supports both claims. Pilyavsky et al. (2006) argue that older populations fill up beds more often resulting in better capital efficiency while the results of Bernet et al. (2008) show otherwise.

7.3 Conventional Empirical Estimation Comparison

Simar and Wilson (2007, 2014) cite the vast majority of two-stage efficiency studies estimate the second-stage using $\widehat{\delta}_i$ as the dependent variable in an OLS or Tobit framework. They criticize these studies for ignoring the statistical properties of the non-parametric DEA estimates, arguing it is unclear what is actually being estimated. The authors present two algorithms to consistently estimate the second-stage, however, implementing these algorithms comes with a significant computational burden over conventional econometric approaches. The focus of this section is to compare Simar and Wilson's bootstrapping approaches to traditional econometric methods to see if undertaking the computational burden results in significant differences.

Table 7.3 compares the second-stage results produced by estimating Model 1 by OLS and Tobit with the bootstrapped results of Algorithm 1 and Algorithm 2. Column 1 and 2 report the OLS and Tobit results, respectively. Here, I ignore the statistical properties of the non-parametric DEA efficiency estimate $\widehat{\delta}_i$ and proceed to the second-stage using $\widehat{\delta}_i$ as the dependent variable over the entire sample.

Column 3 reports the truncated regression estimates produced by Algorithm 1. Recall from a previous discussion, Algorithm 1 is designed to improve statistical inference of the second-stage without accounting for the bias of the non-parametric DEA estimates (Simar and Wilson, 2007). Thus, using $\widehat{\delta}_i$ as the dependent variable, Algorithm 1 consistently estimates the second-stage using a single bootstrapping algorithm on a randomly selected number of observations.[5] Lastly, Column 4 lists the previously

[5] For consistent estimation of the best-practice frontier, the bootstrapping routine must be completed using the same number of m randomly selected observations (Simar and Wilson, 2000, 2007, 2014). Simar and Wilson (2007, 2014) argue that estimating the best-practice frontier using the typical bootstrap process, which specifies resampling with replacement, is inconsistent due to the unknown boundary of the production function.

Table 7.3: Comparison of Model 1 Results When Estimated by OLS, Tobit, and the Truncated Regressions of Algorithm 2

	(1) OLS	(2) Tobit	(3) A1	(4) A2
	$\widehat{\delta}_i$	$\widehat{\delta}_i$	$\widehat{\delta}_i$	$\widehat{\widehat{\delta}}_i$
Teach	0.0644***	0.0658***	0.0632***	0.0584***
For-Profit	0.00612	0.00635	0.0143*	0.00855*
Church	0.00192	0.00153	0.00745	0.00527
Govt (Non-Fed)	-0.0341***	-0.0346***	-0.0256***	-0.0372***
2010	-0.0229***	-0.0234***	-0.0171***	-0.0164***
2012	-0.0409***	-0.0414***	-0.0342***	-0.0316***
$\text{pcphe}_{s,t-2}$ (Mid)	0.00458	0.00465	0.00905	0.00636
$\text{pcphe}_{s,t-2}$ (High)	0.0150***	0.0153***	0.0250***	0.0166***
Rural	-0.0765***	-0.0775***	-0.0822***	-0.0892***
Insured	-0.000989**	-0.00101**	-0.000448	-0.000886***
Poverty	-0.00207***	-0.00213***	-0.00193***	-0.00174***
Elderly	0.00341***	0.00355***	0.00259***	0.00235***
Constant	0.699***	0.702***	0.651***	0.595***
σ		0.162***	0.146***	0.125***
Observations	5758	5758	2730	5758

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

discussed double bootstrapped estimates of Algorithm 2. Algorithm 2 differs from Algorithm 1 by using a bias-corrected efficiency estimate $\widehat{\widehat{\delta}}_i$ as the dependent variable in a truncated regression over the entire sample.

Overall, the various empirical approaches listed in Table 7.3 produce similar results. With minor differences, each specification produces similar conclusions regarding how each environmental factor affects hospital technical efficiency. However, there is disagreement regarding the magnitude that each environmental variable has on efficiency. In particular, the major differences regarding the size of coefficient estimates occur between the conventional econometric and bootstrapping approaches.

Comparing the results in Column 1 and 2 show little differences between the respective OLS and Tobit estimates. Both traditional econometric approaches produce nearly identical estimates of each coefficient with identical statistical significance. The largest discrepancy between the two conventional methods is with the estimated magnitude for the coefficient of $Church$. Although both OLS and Tobit do not find any statistical significance with $Church$, Column 2 reports the Tobit coefficient for $Church$ as $\widehat{\beta} = 0.00153$, approximately 20% smaller than what is estimated by OLS.

Table 7.3 shows Algorithm 1 offers little to no advantage over the OLS and Tobit estimations. In all but two cases, Algorithm 1 identifies the same factors impacting hospital efficiency. However, many of the coefficients produced by Algorithm 1 differ in magnitude relative to OLS and Tobit estimates. Algorithm 1 identifies *For-Profit* as a significant determinant of hospital efficiency, marking the sole improvement over the OLS and Tobit estimations. With 90% confidence, Algorithm 1 estimates the coefficient on *For-Profit* to be $\widehat{\beta} = 0.0143$, approximately double that of the OLS and Tobit estimates.

Algorithm 1 makes an unfavorable adjustment with the county insurance rate relative to the OLS and Tobit estimations in Table 7.3. That is, Algorithm 1 failed to identify $Insured$ as a significant factor affecting hospital efficiency. Column 1 and 2 report estimates for $Insured$ equal to $\widehat{\beta} = -0.00098$ for OLS and $\widehat{\beta} = -0.00101$ for Tobit both with 95% confidence. Column 3 shows the Algorithm 1 estimate of $Insured$ to be $\widehat{\beta} = -0.00048$, approximately 50% smaller than the OLS and Tobit estimates. Moreover, $Insured$ is no longer a significant factor influencing hospital efficiency in the Algorithm 1 estimation.

Table 7.4 reports the coefficients and 95% confidence intervals produced by OLS, Algorithm 1, and Algorithm 2 estimations.[6] In every case, the percentile bootstrapped confidence intervals reported by Algorithm 1 are wider than the 95% confidence intervals produced by OLS. The inability of Algorithm 1 to improve inferencing of the second-stage

[6] The estimates in Table 7.4 are identical to those of Table 7.3. I omit the Tobit results due to the similarity to the OLS estimates.

Table 7.4: Comparison of the OLS Confidence Intervals to the Percentile Bootstrapped Confidence Intervals Produced by Algorithm 1 & Algorithm 2

	(1) OLS		(2) A1		(3) A2	
	$\widehat{\delta}_i$	95% CI	$\widehat{\delta}_i$	95% CI	$\widehat{\widehat{\delta}}_i$	95% CI
Teach	0.0644***	(0.0544, 0.0744)	0.0632***	(0.0497, 0.0762)	0.0584***	(0.0506, 0.0664)
For-Profit	0.00612	(-0.00612, 0.0184)	0.0143*	(-0.00262, 0.0307)	0.00855*	(-0.00173, 0.0185)
Church	0.00192	(-0.0108, 0.0147)	0.00745	(-0.00948, 0.0236)	0.00527	(-0.00521, 0.0156)
Govt (Non-Fed)	-0.0341***	(-0.0453, -0.0230)	-0.0256***	(-0.0409, -0.0103)	-0.0372***	(-0.0462, -0.0285)
2010	-0.0229***	(-0.0332, -0.0126)	-0.0171***	(-0.0310, -0.00381)	-0.0164***	(-0.0244, -0.00841)
2012	-0.0409***	(-0.0514, -0.0304)	-0.0342***	(-0.0480, -0.0201)	-0.0316***	(-0.0401, -0.0235)
$\text{pcphe}_{s,t-2}$ (Mid)	0.00458	(-0.00562, 0.0148)	0.00905	(-0.00474, 0.0224)	0.00636	(-0.00188, 0.0145)
$\text{pcphe}_{s,t-2}$ (High)	0.0150***	(0.00480, 0.0252)	0.0250***	(0.0115, 0.0397)	0.0166***	(0.00848, 0.0248)
Rural	-0.0765***	(-0.0872, -0.0659)	-0.0822***	(-0.0957, -0.0686)	-0.0892***	(-0.0980, -0.0807)
Insured	-0.000989**	(-0.00185, -0.000128)	-0.000448	(-0.00162, 0.000723)	-0.000886***	(-0.00157, -0.000276)
Poverty	-0.00207***	(-0.00310, -0.00105)	-0.00193***	(-0.00332, -0.000516)	-0.00174***	(-0.00260, -0.000958)
Elderly	0.00341***	(0.00230, 0.00452)	0.00259***	(0.00111, 0.00414)	0.00235***	(0.00152, 0.00326)
Constant	0.699***	(0.619, 0.779)	0.651***	(0.543, 0.759)	0.595***	(0.536, 0.657)
σ			0.146***	(0.142, 0.151)	0.125***	(0.123, 0.128)
Observations	5758		2730		5758	

Note: The estimates in Table 7.4 are identical to that of Table 7.3. I omit the Tobit results due to the similarity to the OLS estimates. Significance for Algorithms 1 and 2 are determined by the respective percentile bootstrapped confidence intervals.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

coefficients is similar to the results of the Monte Carlo simulation performed by Simar and Wilson (2007). The authors refer to the problem plaguing Algorithm 1 as "the curse of dimensionality" which refers to the number of inputs and outputs used to estimate technical efficiency in the first-stage. Simar and Wilson (2007) show that Algorithm 1 begins to perform worse than conventional approaches when there is more than one input and one output specified in the first-stage. They argue that increasing the number of inputs and outputs in the first-stage produces less precise estimates $\widehat{\delta_i}$, making it difficult to provide an accurate estimate.

Although the goal of Algorithm 1 is to provide better inferencing of the second-stage variables, in practice, Algorithm 1 fails to do so. Specifically, situations arise where more than one input is used to produce more than one output, making Algorithm 1 an inferior approach relative to conventional estimations. In this research, the overall conclusions of Algorithm 1 align with OLS and Tobit estimations. However, the higher first-stage dimensions[7] specified in this research resulted in wider Algorithm 1 confidence intervals relative to those produced by OLS and Tobit frameworks.

Traditional econometric approaches such as OLS and Tobit rely on the fact that the non-parametric DEA estimate for $\widehat{\delta_i}$ is a consistent estimator of δ_i. However, in finite samples, the bias value in $\widehat{\delta_i}$ is slow to disappear.Thus, ignoring the statistical properties of $\widehat{\delta_i}$ may lead to erroneous second-stage conclusions even with large sample sizes (Simar and Wilson, 2000). To get around this problem, Simar and Wilson (2007) suggest removing the bias prior to the second-stage. The authors define Algorithm 2 as an extension of Algorithm 1 to include a second bootstrapping routine. Here, the first bootstrap procedure constructs a bias-corrected estimate of efficiency $\widehat{\widehat{\delta_i}}$ prior to the second-stage by estimating the bias of $\widehat{\delta_i}$. Removing the bias value from $\widehat{\delta_i}$ should provide improved estimates of β in the second-stage.

[7] The dimensionality of the first-stage in this research is 8. That is, hospital efficiency estimates $\widehat{\delta_i}$ are obtained in the first-stage using three inputs to produce five outputs. See the discussion in Chapter 5 for a detailed description of the first-stage specification.

Overall, the double bootstrap routine specified by Algorithm 2 improves the second-stage estimation of the independent variables. In particular, constructing the bias-corrected estimate $\widehat{\widehat{\delta}}_i$ removes the bias term from the non-parametric DEA estimates and eliminates the noise arising from higher dimensions of the first-stage. Using $\widehat{\widehat{\delta}}_i$ as the dependent variable, Algorithm 2 reports coefficient estimates similar to that of the conventional estimates in Column 1 and 2 with increased precision.

Similar to Algorithm 1, Algorithm 2 identifies *For-Profit* hospitals as experiencing efficiency gains over *Non-Profit* hospitals, reporting a *For-Profit* coefficient equal to $\widehat{\widehat{\beta}} = 0.00855$ with 90% confidence. Compared to Algorithm 1, Algorithm 2 reports a less inflated coefficient on *For-Profit*, similar to what is reported by the OLS and Tobit models. Algorithm 2 reports an estimate of the coefficient for county insurance rate similar in magnitude to that of OLS and Tobit with increased significance. With 99% confidence, Algorithm 2 reports the coefficient for $Insured$ equal to $\widehat{\widehat{\beta}} = -0.000886$, marking a significant improvement over Algorithm 1 and conventional approaches.

The method proposed by Simar and Wilson (2007) to conduct a two-stage efficiency analysis appears to be superior to conventional econometric approaches, however, the improvement is marginal. Specifically, Algorithm 2 provides similar coefficient estimates with superior inferencing relative to the OLS and Tobit specifications. For every variable listed in Table 7.4, the percentile bootstrapped confidence intervals produced by Algorithm 2 are much smaller relative to the confidence intervals produced by the OLS and Tobit specifications.

Unfortunately, obtaining the increased precision does not come without a cost. Implementing the double bootstrap procedure specified in Algorithm 2 involves the undertaking of a significantly greater computational burden relative to conventional econometric approaches. In the case of this research, the benefits associated with Algorithm 2's increased precision is marginal. Specifically, the only advantage Algorithm 2 reports over OLS is with the coefficient estimate of *For-Profit*. The increased precision gained with the double bootstrap routine allowed Algorithm 2 to identify *For-Profit* as a significant factor influencing hospital technical efficiency. Algorithm 2 clearly provided more precise confidence intervals for every independent variable in the second-stage. However, with the exception of *For-Profit*, the conclusions produced by OLS are virtually identical to that of Algorithm 2 without the computational burden.

Chapter 8
CONCLUSION

Growing concern surrounding rising health care costs has pushed the United States health care system onto the forefront of the debate stage. According to the Centers for Medicare and Medicaid Services (CMS), the United States spent approximately 17.42% of GDP on health care in 2014. Of the $3 trillion health care related expenditures in 2014, approximately one-third can be attributed to hospitals (CMS, 2014). The 2010 implementation of the Affordable Care Act aimed to provide affordable health insurance for all Americans and while doing so, reign in on these unsustainable health care costs. Architects of the ACA understood the easiest method to reduce health care costs is to help all Americans become more healthy. In theory, healthier individuals will demand less medical care and visit the emergency room less frequently. As a result, health care providers can reduce expenditures by allocating their costly medical resources more efficiently.

Without omnipotent power, making all Americans healthier at once is not feasible. As a consequence, policy makers must debate how to solve America's health care expenditure problem which will not occur over night. Recent research concludes that increasing the level of funds dedicated to public health will indeed result in a healthier population (Brown, 2014; Brown et al., 2014; Bailey and Goodman-Bacon, 2015). Moreover, the successful provision of public health focuses on preventing health problems from developing which will certainly make Americans healthier and potentially reduce health care expenditures in the process. Stressing public health, this research makes an attempt to identify an avenue that policy makers could exploit to reduce long-run health care expenditures, particularly those expenditures attributed to hospitals.

The primary goal of this dissertation has been to expand the understanding of the role public health plays in the U.S. health care system, particularly in affecting hospital costs. The question posed in this research asked if increases in public health funding would impact the surrounding health care providers, particularly hospitals. To answer this question I exploited the advances in efficiency analysis put forth by Simar and Wilson (2007). Specifically, I used the two-stage semi-parametric Data Envelopment Analysis (DEA) to estimate the impact of public health expenditures on the technical efficiency of U.S. hospitals. Following the bootstrapping algorithms proposed in Simar and Wilson (2007), I constructed an estimate of technical efficiency for each hospital in the first-stage. Then, using the first-stage estimate of hospital efficiency as the dependent variable in a second-stage regression, I identify several key environmental factors that might influence hospital efficiency but which are not under the control of hospitals.

There are two key findings that have come out of this research. The first key result presented here was that hospitals are indeed positively impacted by higher levels of public health spending. Relative to hospitals operating in health service areas with a low-level of per capita public health spending, hospitals operating in health service areas with a high-level of spending experience significant gains in efficiency. This suggests that increases in per capita public health will not only result in a healthier population as previous research concludes, but will increase hospital productivity and therefore lower expenditures (Ali et al., 2016).

The second key result presented in this dissertation arises from a comparison of traditional econometric estimations with the strategy proposed by Simar and Wilson (2007). Because of the problems associated with estimating the the second-stage using the traditional non-parametric DEA estimates, I used the bootstrapping algorithms proposed by Simar and Wilson (2007) to estimate the relationship between public health expenditures and hospital efficiency. For the dependent variable in the second-stage, Algorithm 2 constructs a bias-corrected estimate of hospital efficiency whereas Algorithm 1 uses the traditional non-parametric DEA estimate.

As expected by Simar and Wilson (2007), Algorithm 2 provided superior results of the two bootstrapping routines. However, the implementation of the double bootstrap routine specified in Algorithm 2 required a significantly greater computational burden over traditional econometric approaches. Therefore, I compared the bias-corrected results of Algorithm 2 to the OLS results when using the non-parametric DEA estimate as the dependent variable in an effort to understand if undertaking the computation burden results in significant differences. When the coefficient estimates of Algorithm 2 are compared to the respective estimates produced by OLS, Algorithm 2 performed marginally better. Comparing the respective confidence intervals of the two specifications supports Simar and Wilson's claim that Algorithm 2 provides more precise estimates. Nevertheless, the conclusions provided by OLS were virtually identical to Algorithm 2 without the computational burden.

There are several limitations to this research that must be considered. The first limitation to this study is the patient spillover. Using the health service area identifiers provided by the Dartmouth Atlas of Health Care, I have attempted to control for the hospital's patient market. However, it is possible that hospitals have admitted patients that reside in a neighboring health service area. Patients traveling outside of their health service area will bring any public health benefit or lack thereof with them which is not captured in this study.

The second limitation is that, this study does not account for the effectiveness of the organizations that provide public health activities and services to the community. Health departments use the funding they receive to fund public health activities that best fits the needs of the population at which they serve. Because the public health activities typically do not have an immediate measurable outcome, it is difficult to determine if the public health funds were used efficiently. Moreover, ineffective health departments may be allocating funds to unproductive services that yield little to no health benefit. Thus, simply increasing the amount of public health funding available to these inefficient health departments and public health organizations would be wasteful. Hospitals would not realize the expected gains in efficiency gains.

More research is needed to fully understand the true value that public health programs and services provide to the population. Implementing a standardized method of public health data collection is the first step in facilitating future public health research. Although the National Association of County and City Health Officers (NACCHO) collects data from local health departments, the survey is conducted on an irregular basis and has evolved over time.

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