# A Consideration of the Potential Side Effects of Health Insurance

A Dissertation

Presented for the

Doctor of Philosophy

Degree

The University of Tennessee, Knoxville

Melanie Jane Cozad

May 2012

## DEDICATION

This dissertation is dedicated to my loving husband, Kristopher Cozad, who not only believed in my dream but sacraficed to make it possible.

# Acknowledgements

I am very grateful to a number of individuals who have supported me during my graduate school career. These acknowledgments demonstrate only a portion of the gratitude I owe them for the knowledge and experience they have imparted to me during my time at the University of Tennessee.

First, I wish to extend my heartfelt appreciation to Donald Bruce for the countless hours he invested in cultivating my research and development as an economist. His natural ability to listen helped me to shape rough ideas into the essays of this dissertation. He also has been invaluable as a mentor creating opportunities for me to network with other researchers, travel to conferences, and write proposals. My professional development during these four years is largely due to his stewardship. I would also like to thank Bill Neilson for the support and guidance he provided me throughout my graduate experience. Bill Neilson is a great teacher, who excels at making difficult things easy to understand. His skill in the classroom not only frames the way I view economics but also inspires me to continually improve my own teaching skills.

Additional gratitude is extended to Paul Erwin and Nicholas Nagle for serving on my dissertation committee. Each have made contributions which has greatly improved this dissertation. I also appreciate their expertise and guidance regarding my transition to post-graduate school life. They have both provided me with an invaluable interdisciplinary perspective that I will carry throughout my career. Along the way, this research has also benefited from comments and feedback of Celeste

Carruthers, Matthew Murray, Jacob LaRiviere, and Marianne Wanamaker. A special thanks goes to my colleague and friend, Bruno Wichmann, for being a sounding board for new research ideas and providing constructive advice at ever turn. My graduate school experience has deeply benefited from having such a thoughtful and clever researcher to work alongside. I hope that we can continue our collaboration for many years to come.

On a personal note, I would also like to acknowledge the support that came from my immediate family and friends. In particular, Sandy, Ritch, Ashley, and Jane should receive special recognition. I realize that having curiosity to ask questions and utilizing the scientific process to answer them is a fundamental value passed down among the generations in our family. This dissertation is in small part my way of honoring all those who came before me and inspiration for those who are next. Bonnie Hufford deserves specific mention, because many discussions with her inspired me to focus on the importance of health care delivery issues which constitutes the subject matter of this dissertation. I hope she will continue to be as generous in sharing her time and experiences with me.

Above all else, I thank Kristopher Cozad for all that he sacrificed so that I could fulfill my dream. It takes a special person endure the rigors necessary to support this pursuit. To him, this work is dedicated and, in reward, the streams and trails of Greenville, South Carolina now lie ahead.

Finally, I also appreciate and acknowledge the financial support provided by the State Farm Dissertation Fellowship, which made timely completion of this project possible.

# Abstract

The Patient Protection and Affordable Care Act (ACA) is federal health care reform legislation that represents the most significant health insurance expansion since Medicare and Medicaid were created in 1965. In this dissertation, I focus on how health insurance expansion affects the supply side of health care markets as well as health expenditures. While health insurance expansion potentially increases the demand for care, it also creates uncertainty, thereby impacting health care utilization, delivery, and input decisions. In my first chapter, I examine whether changes in health insurance coverage rates impact state-level health care delivery efficiency. Health care providers may vary in the accuracy of their demand forecasts, which could lead to inefficient excess capacity. My analysis reveals an average state-level efficiency score of 61 percent, suggesting significant underutilized inputs. I also find that states with higher insurance coverage rates tend to be less efficient. In my second chapter, I develop a theoretical framework that explains how a health insurance mandate impacts hospital input levels. To empirically investigate the channels of the framework, I use a ten-year panel of data to compare Massachusetts hospitals with those in other surrounding states. The results suggest that the Massachusetts health insurance mandate significantly reduced the demand for emergency care but left overall demand unchanged. It also significantly increased capacity. The increase in capacity without a corresponding increase in overall demand suggests inefficiency. In my third chapter, I explore the relationship between state-level health insurance coverage rates and Medicaid expenditures. My empirical results suggest that state

Medicaid expenditures are more responsive to private health care expenditures and population aging rather than health insurance coverage rates.

# Contents

# List of Tables

# List of Figures

# Chapter 1

# Introduction

A hallmark of the recently passed U.S. health care reform legislation is the requirement that individuals purchase health insurance coverage or face a penalty beginning in 2014. This individual mandate potentially represents the most significant health insurance expansion since the Medicare and Medicaid programs were created in 1965. However, legitimate concerns regarding a large scale health insurance expansion focus on the possible ramifications of rising health care costs. In order to better understand the potential impacts of a large scale health insurance expansion, economic evaluation is a critical component of debate.

Significant attention within the literature is given to the effect of changes in health insurance coverage on consumer utilization of care and medical expenditures. Since health insurance coverage improves a consumer's access to care through a reduction in out of pocket costs, early research suggests that health insurance expansion is one of the main drivers of increases in health care expenditures (Feldstein (1973b)). However, empirical evidence from the the Rand Health Insurance Experiment (RHIE) concludes that the impact is much smaller than estimates in earlier work suggest (Newhouse (1993)). Despite the focus on consumer utilization and health expenditures, it remains uncertain how a large scale health insurance expansion affects the supply side of the market. My dissertation will fill a gap within the literature by considering how changes in health insurance coverage potentially affect U.S. states and hospital behavior. Specifically, I will focus on how changes in health insurance impact state-level health care delivery, hospital input decisions, and the funding of Medicaid expenditures.

A health insurance mandate may affect a health system's inputs through changes in the level of health insurance coverage and demand for care. A health insurance mandate likely increases health insurance coverage, which improves access to care. A large number of newly insured consumers potentially increases overall demand for medical services. However, insurance expansion that improves access to care also may decrease the demand for emergency services. Uncertainty in the magnitude of the changes in the demand for care make it difficult for a health system to predict how a health insurance mandate will affect the amount of inputs needed in order to meet demand. This uncertainty impacts health systems, because managers must decide *ex ante* whether or not to add inputs. Therefore, if a health insurance mandate affects the demand for care in ways that health care systems find hard to predict, then they could potentially choose an excessive amount of capacity that could add substantially to health care costs. This first two essays of this dissertation focus explicitly on isolating the potential impacts of insurance expansion that are working through these channels.

In my first co-authored essay (with Bruno Wichmann), we examine whether changes in health insurance coverage rates impact state-level health care system efficiency. Our analysis reveals an average state-level efficiency score of 61 percent suggesting significant underutilized inputs. We then explore the variation in efficiency of health care delivery to determine if health insurance coverage substantially impacts efficiency. Results show that a one percentage point increase in health insurance coverage decreases efficiency of health care delivery by approximately 1.3 percentage points. This implies that as health insurance expands, states add inputs into the health production process that do not necessarily improve health outcomes, thereby reducing the efficiency of health care delivery. This results suggests that health care costs may actually rise from inefficiencies stemming from health insurance expansion.

In my second essay, I consider how a health insurance expansion increases inefficiency by specifically focusing on hospital inputs. Using a theoretical framework of cost minimization, I explain how changes in health insurance coverage potentially influence a hospital's choice of input levels. Then, I empirically examine how a health insurance expansion influences hospital input levels by studying Massachusetts and neighboring states. In 2006, Massachusetts instituted health care reform legislation, which also included an individual mandate for health insurance; therefore, exploiting this change in state-level health care policy provides a unique opportunity for empirical study. By comparing Massachusetts to other states, I can empirically isolate the effects of the reform on hospital capacity and employment levels as well as utilization measures of demand for care.

The results suggest that a health insurance mandate significantly increases hospital capacity and reduces the utilization of emergency care. In addition, the health insurance mandate does not significantly affect overall utilization measures of hospital services and employment levels. Specifically, for an average hospital the effect of the health insurance mandate increases overall capacity by approximately 7 beds. The health insurance mandate also reduces the number of annual ambulance trips to the average hospital by 16%. This equates to a daily reduction of one ambulance trip for an average hospital affected by the reform relative to one that is not. These results also have important implications for health care costs. While the mandate does significantly increase hospital capacity, the magnitude of the effect suggests it is likely that the additional beds fit within the existing structure of the hospital. Therefore, the added capacity does not suggest a substantial increase in hospital expenditures from investments expanding the physical structure of a hospital. Overall, the effect of the mandate on inputs suggests minimal impacts on health care costs that are passed onto the consumer.

In my third essay, I explore the historic relationship between state-level health insurance coverage rates and Medicaid expenditures. A number of states are concerned that health care reform is an unfunded mandate, because a provision of the ACA mandates that states expand Medicaid eligibility requirements. States harbor fears that this provision of health care reform might increase their share of Medicaid expenditures on health care to unsustainable levels, when the federal government is no longer willing to provide assistance that makes the expansion possible. In this essay, I specifically examine how the growth in public and private health insurance coverage rates impacts the growth in the portion of Medicaid expenditure that the state government is responsible for. My empirical results suggest that a state's Medicaid expenditures are more responsive to private health care expenditures and population aging rather than health insurance coverage rates. These results suggest that with respect to cost containment a state should be far more concerned with changing demographics of their population rather than insurance expansion mandated by the ACA.

The following chapters of this dissertation outline the methods, results, and conclusions in more detail.

# Chapter 2

# Efficiency of Health Care Delivery: Effects of Health Insurance Coverage

## 2.1 Introduction

Health care expenditures in the United States have increased significantly in recent years. The United States spent 5.9% of its gross domestic product (GDP) on health care in 1965, by 2008 that percentage grew to 16.2% of GDP totaling 2.3 trillion dollars. The average annual growth rate of national health care expenditures over the 10 year period from 1999-2008 is approximately 7%.[1]

Understanding this rapid rise in health care costs is a growing concern. Early research examining the growth of health care expenditures (HCE) identified that GDP is positively correlated to HCE and explains a high percentage of the variation in HCE growth (see Newhouse (1977), Parkin et al. (1987), Gerdtham et al. (1992), Hitiris and Posnett (1992)). Further research refines the econometric techniques surrounding

[1] U.S. Department of Health and Human Services Centers for Medicare and Medicaid Services, http://www.cms.hhs.gov/NationalHealthExpendData/02_NationalHealthAccountsHistorical.asp (assessed on 01/06/2010).

panel unit root analysis and cointegration of GDP and HCE (see McCoskey and Selden (1998), Gerdtham and Lothgren (2000), Freeman (2003), Jewell et al. (2003), Carrion-i Silvestre (2005), Wang and Rettenmaier (2007), and Moscone and Tosetti (2010) ). Recent studies explore alternative determinants of HCE growth besides GDP, such as: physician reimbursement and the mixture of public verses private funding (see Gerdtham et al. (1992)), age and proximity to death (see Zweifel et al. (1999), Felder et al. (2000), Seshamani and Gray (2004), Matteo (2005), Werblow et al. (2007)), wage increases in excess of productivity growth (see Hartwig (2008)), and electoral motives (see Potrafke (2010)).

In this research, we take a fresh look at potential determinants of HCE by empirically investigating the impact of changes in health insurance coverage on the efficiency of health care delivery systems. In this context, technical efficiency is defined as the system's ability to minimize health care input consumption given the delivery of a certain health outcome (e.g. a target mortality rate).[2] Inefficiencies in health care systems imply under-utilization of health care inputs resulting in greater HCE. Greater HCE arises as a consequence of avoidable maintenance and opportunity costs of unused inputs. This issue is particularly salient given that the federal government recently enacted the Patient Protection and Affordable Care Act. This reform has the potential to expand health insurance coverage to 46.3 million uninsured Americans.[3] Corroborating this expectation, empirical evidence suggests that the individual health insurance mandate in Massachusetts increases health insurance coverage (see Long (2008), Long et al. (2009), Yelowitz and Cannon (2010), and Kolstad and Kowalski (2010)).

According to Nyman (1999) an increase in health insurance coverage increases the demand for health care by lowering individuals' out of pocket cost for medical services. Since health care reform potentially increases the size of health care markets, it is important to evaluate possible changes in the efficiency of health care delivery

[2]Hereafter we refer to technical efficiency as efficiency.

[3]U.S. Census Bureau; Income, Poverty, and Health Insurance Coverage in the United States: 2008, Current Population Reports, page 20, Issued September 2009.

systems. In order to choose capacity, health care systems form expectations about the sensitivity of demand to changes in health insurance coverage. Due to uncertain demand for care, the possibility remains that expanding health insurance coverage reduces the efficiency of health care delivery systems. For example, in response to a large expected influx of paying customers, systems might have incentives to add unnecessary capacity and personnel.[4]

The health care literature has examined effects of health insurance coverage on labor market outcomes (see Gruber and Madrian (1997), Royalty and Abraham (2006), Boyle and Lahey (2010)), entrepreneurship (see Holtz-Eakin et al. (1996), Fairlie et al. (2010), Heim and Lurie (2010)), precautionary saving (see Levin (1995), Chou et al. (2003)), and personal finance (see Wagstaff and Lindelow (2008), Gross and Notowidigdo (2011)). Another body of literature relates health insurance and welfare (see Feldstein (1973a), Manning et al. (1987a), Feldman and Dowd (1991),Chiu (1997), Palangkaraya et al. (2009)). Cutler and Gruber (1996) and Gruber and Simon (2008) show that public insurance expansions crowd-out private health insurance. However, despite this vast literature, empirical evidence regarding the impact of health insurance coverage on efficiency is scarce and conflicting. Chang et al. (2004) find a negative impact of health insurance coverage on hospital efficiency when Taiwan implemented a national health insurance program. Brown III (2002) finds a positive impact of managed care insurance on hospital efficiency.

As opposed to examining hospital efficiency, we investigate the relationship between health insurance coverage and health care systems, providing new insights into HCE variations. Modeling a health care system as a U.S. state, we estimate efficiency accounting for the effects of environmental factors such as health insurance coverage. Specifically, we apply the Simar and Wilson (2007) - SW hereafter - two-stage semi-parametric model of production processes to estimate the efficiency of health care delivery systems and the impact of increasing health insurance.

[4]Refer to Smet (2007) for a discussion on hospital efficiency, demand uncertainty, and standby capacity.

The estimation of the SW model involves bootstrap procedures that generate bias corrected Data Envelopment Analysis (DEA) efficiency scores.[5] This approach improves statistical efficiency of the regression of estimated efficiency on health insurance coverage. The analysis utilizes annual data from 2000 to 2007. A comparable rank order of estimated efficiency is provided.[6]

We estimate average efficiency to be 61% suggesting significant inefficiencies in the American health care sector. These inefficiencies potentially explain a portion of rising health care costs. Moreover, we estimate that a 1 percentage point increase in health insurance coverage *decreases* the efficiency of health care delivery by 1.3 percentage points. This result indicates that extraneous costs may rise as a consequence of the recently enacted health care reform. Our estimates suggest that a 1 percentage point increase in health insurance coverage potentially translates into 28.77 billion dollars in additional inefficiency cost. Traditional regression analysis ignoring the DEA bias overestimates the impact of increasing health insurance by approximately 19%.

The organization of this paper is as follows. Section 2 discusses background literature and presents the conceptual framework for a state's health care delivery. Section 3 describes the methods and characterizes the data. Section 4 presents empirical results. Section 5 provides a discussion. Section 6 offers conclusions.

## 2.2 Health Care Delivery

Research assessing efficiency within the health care sector is vast because of its ability to identify unnecessary input consumption and inform policy. Although there is a significant body of literature considering hospital efficiency, empirical

[5]For a survey of the statistical properties of DEA estimators see Simar and Wilson (2000). Section 2.3 provides additional discussion of efficiency estimation and DEA bias.

[6]DEA input-efficiency scores are bounded between 0 and 1. A health system's efficiency score of 0.80 represents 20% of unnecessary input consumption, i.e., this system can theoretically reduce its input usage by 20% without reducing output. A score of 1 represents no input waste implying an efficient system.

work concerning the efficiency of health care delivery systems is limited.[7] From the hospital's perspective the relevant efficiency question is about the ability to minimize input usage to serve a target number of patients. However, from the health care system's perspective the relevant question is about the ability to minimize input usage given the delivery of a target health outcome.

Research focusing on health care delivery systems includes Retzlaff-Roberts et al. (2004), Bhat (2005), and Spinks and Hollingsworth (2009), all of which estimate the efficiency of health care delivery for particular OECD countries using DEA. In these studies, the authors include measures of education, employment, and income as inputs into the health care delivery function. While these socio-economic variables potentially affect health outcomes, pinpointing the channels these measures operate through continues to generate discussion (see Duncan et al. (2002), Lahelma et al. (2004), and Spinks and Hollingsworth (2009)). Retzlaff-Roberts et al. (2004) argue that these types of variables fluctuate in the long run and influence health, but they are beyond the short term discretionary control of policy makers.

In this study, we view a health care delivery system as a U.S. state. Therefore, instead of focusing on health care delivery of countries, we estimate the efficiency of states in delivering health care to their population. We take a different approach from the literature in our treatment of socio-economic variables such as education, employment, and income. We view these variables not as health care inputs, but as environmental factors that may impact the systems' ability to deliver a given health outcome. This approach better fits with the perspective that these types of socio-economic variables are beyond the immediate influence of policymakers. In assessing the impact of these variables along with health insurance coverage, we utilize the SW estimation approach that specifically accounts for non-discretionary inputs.

In our framework, the state chooses capital and labor to reach a target health output. Health insurance expansion is expected to increase demand for care (see

[7] See Hollingsworth (2008) for an extensive review of the health care efficiency literature. Pilyavsky and Staat (2008), Kristensen et al. (2010), and Blank and Valdmanis (2010) provide recent research on hospital efficiency.

Nyman (1999)). Therefore, states' input decisions are based on expectations about the sensitivity of the demand to variations in health insurance coverage. The possibility remains that expanding health insurance coverage reduces states' efficiency of health care delivery. Given management heterogeneity and environmental factors, some states will do a better job forecasting demand; however, some will add more inputs than their peers (those with similar output level). These states are inefficient and impose a cost that can be measured in terms of underemployed inputs.

The main inputs to the production of health are hospital capacity and health care practitioners. We assume states utilize three health care inputs to deliver three health care outputs. Specifically, inputs are hospital beds, general practitioners, and registered nurses. Hospital beds represent a measure of physical infrastructure (capital) and the latter two represent measures of the workforce (labor). The health care outputs are survival rates, self reported health status, and population share without disabilities.

In the empirical application of our conceptual framework, the state must have mechanisms to manipulate input levels. Certificate of need (CON) policies enable states to decide whether a hospital can add extra capacity. In terms of labor, medical professionals can only legally practice medicine with a state license. States decide licensing standards, which in turn impacts the number of health care practitioners in the labor market. Therefore, states can influence the inputs to health care production through regulation. Ferrier et al. (2010) examine the efficiency of U.S. hospitals aggregated to the state level. Aggregation allows for the assessment of the impact of CON laws on efficiency. They find the hospital sector in states with active CON legislation performs better in terms of aggregate efficiency.

There are environmental factors that may influence health care delivery efficiency. In this study, environmental factors include health insurance, poverty, education, employment, income, and share of the population 65 and over. These socio-economic variables fluctuate but are viewed as outside the immediate discretionary control of state policy makers. In Appendix A, Figure **??** depicts our conceptual framework of a health care delivery system. All future figures and tables are also provided in the appropriate appendix.

While states can manipulate health care inputs through CON and licensing standards, they are subject to federal legislation. The recent enactment of the Patient Protection and Affordable Care Act will significantly change the number of insured. The main contribution of this research is to estimate the impact of health insurance coverage on health care delivery efficiency. Our analysis provides new insights into the consequences of health care reform.

## 2.3 Estimation and Data

The basic concepts of the economic theory underlying efficiency analysis are presented by Koopmans (1951), Debreu (1951), and Farrell (1957). In our research, the health care production frontier indicates the minimum inputs required by a state to deliver a given health output. Thus, it reflects the current state of technology within the health care industry. States in this industry operate either on or below the efficiency frontier (or production frontier). The best practice states are the ones whose input allocations place them on the efficiency frontier while inefficient states are the ones that operate below the frontier. Distance functions can be used to measure possible inefficiencies of the production process. The idea is to measure the distance between a particular state's production plan and the efficiency frontier. The measurement involves the proportional contraction of the input vector, given an output target. Distance function computation returns an efficiency score $\theta_i$ for each state $i$.

The health care delivery efficiency of state $i$ is evaluated by $\theta_i$. By construction $\theta_i \leq 1$. $\theta_i = 1$ indicates that state $i$ is efficient, i.e. it consumes the minimum amount of inputs necessary to produce the target output. If $\theta_i < 1$, state $i$ could reduce the consumption of *all* inputs by $(1 - \theta_i) * 100$ percent without reducing output. In this case, state $i$ utilizes more inputs than necessary and therefore is input-inefficient.

Empirically, the challenge is to obtain an estimate of the production set, thus an estimate of its closure: the efficiency frontier. Data Envelopment Analysis (DEA) is widely used to this end. The DEA approach consists of a nonparametric estimation of an industry level production set. The idea behind DEA estimation is to construct the smallest convex set containing all input and output data across production units. Once the production set is estimated, one can use distance functions to obtain measures of how far the production unit $i$ is from the estimated frontier. This yields $i$'s estimated efficiency score $\hat{\theta}_i$ .

In a typical two-stage efficiency analysis, DEA efficiency scores are computed (first-stage) and then regressed on a set of environmental variables (second-stage). Usually, tobit regressions are estimated to account for the fact that DEA efficiency scores are bounded. However, this approach is problematic. As discussed by Simar and Wilson (2007), the traditionally used DEA efficiency scores are biased estimators of efficiency.[8] In addition, these efficiency estimates are probably serially correlated in a unknown way. For these reasons, maximum likelihood estimation and the standard approaches to inference are not valid.

We model health care delivery efficiency according to the Simar and Wilson (2007) two-stage semi-parametric model of production processes. The authors provide guidance for efficiency estimation under the presence of environmental effects, addressing the econometric issues described above. Our application of the SW bootstrap procedure involves two stages. First, an initial bootstrap is used to construct bias corrected DEA measures of efficiency. We estimate robust efficiency scores for each state's delivery of health care from 2000 to 2007. Second, estimated efficiency is regressed on environmental variables. To be consistent with the SW data generating process, we utilize truncated regressions in a second bootstrap to

[8]DEA uses the smallest convex set containing all data to approximate the true unknown production set. However, the DEA set is by construction smaller or equal to the true production set, and the true production frontier could be further away from the observation $i$ than the estimated DEA frontier is. Thus, the DEA efficiency score overestimates the true efficiency.

estimate the effects of the environmental factors on efficiency.[9] We follow SW to construct 95% bootstrap confidence intervals. SW demonstrate through Monte Carlo simulations that the use of their double bootstrap improves statistical efficiency in the second-stage regression.[10]

Since the SW approach for analyzing the impact of environmental variables on efficiency is relatively new, empirical work applying their bootstrapping methods in the health care sector is limited. Pilyavsky et al. (2006) and Blank and Valdmanis (2010) use the SW approach to analyze the efficiency of hospitals. Jarvio et al. (2005) and Bernet et al. (2008) use this approach to study primary care facilities and polyclinics, respectively. Afonso and Aubyn (2005) apply the SW bootstrapping technique to estimate the efficiency of health care delivery for OECD countries. By evaluating health care delivery efficiency of U.S. states, our research adds to this growing body of empirical work using the SW approach. Comparing the estimates from OLS, Tobit, and truncated regression with estimates from the SW bootstrapping algorithm, our paper provides additional evidence for how traditional methods may lead to incorrect estimation and inference.

## Data

The empirical implementation of our efficiency analysis requires the collection of data on health care inputs, outputs, and the relevant environmental factors from 2000-2007. The number of hospital beds is obtained from the Centers for Medicare and Medicaid Services (CMS) Hospital Cost Reports. The cost reports contain micro level data for every facility that is certified by the CMS.[11] To construct our capital input measure we aggregate facilities' beds within states. The number of family and general

[9]SW define efficiency as $\theta_i = \psi(\mathbf{z_i}, \boldsymbol{\beta}) + \epsilon_\mathbf{i}$ where $\psi$ is a continuous function, $\mathbf{z_i}$ denotes environmental variables, $\boldsymbol{\beta}$ is a vector of parameters, and $\epsilon$ represents a continuous iid random variable truncated to make the input-efficiency $0 < \theta_i \leq 1$. Refer to Simar and Wilson (2007) pages 34-37 for a detailed presentation of the data generating process.

[10]For a detailed exposure on the estimation approach and the construction of the confidence intervals, refer to Simar and Wilson (2007), pages 42-43.

[11]Facilities participate in either the Medicare or Medicaid program.

practitioners and the number of registered nurses are obtained from the Bureau of Labor Statistics database. In the family and general practitioners data 12 out of the 384 observations are missing. In those instances, we use linear interpolation to replace missing data. To accommodate size differences, the three inputs are divided by the total state's population (in millions), obtained from the U.S. Census Bureau.

We use mortality rates, number of disabled, and self-reported health status to construct the output measures. We transform mortality and disability into positive health outcomes in order to estimate the efficiency of health care delivery. Size differences are also accommodated in the output measures. We construct *survival share* using mortality rate data available from the Centers for Disease Control and Prevention (CDC). We construct *able share* using data from the Social Security Administration (SSA).[12] Finally, *healthy share* is the share of the total state population that reported themselves as in "excellent", "very good" or "good" health on the CDC's Behavioral Risk Factor Surveillance System Annual Survey.

The impact of health insurance coverage on efficiency is analyzed in two specifications. The first considers total health insurance coverage (*total coverage*) defined as the percentage of a state's population with any type of health insurance. The second specification considers private and public health insurance separately. *Private coverage* accounts for employer provided and directly purchased health insurance. *Public coverage* accounts for Medicare, Medicaid, and military health insurance. We obtain the health insurance coverage data from the U.S. Census Bureau.

In addition to health insurance coverage, five variables are specified in our second stage regression. The variable *poverty share* is the share of the population with income below a poverty threshold and is obtained from U.S. Census Bureau.[13] The variable *employment share* is the ratio of total employment to total population, obtained from the Bureau of Economic Analysis (BEA). The variable *state gdp*, the real per capita

[12]We formulate: *survival share* $= 1 -$ (# of deaths/population); *able share* $= 1 -$ disabled share.
[13]Average poverty threshold is \$8.28 per person, per day.

state gross domestic product (in hundreds of thousands of chained 2000 dollars), is obtained from the BEA and used as a proxy for income. The variable *diploma share*, the percentage of population with high school diploma or more, is obtained from the U.S. Census Bureau and used as a proxy for education. Finally, the variable *share 65+* represents the portion of the population 65 and over and is obtained from the U.S. Census Bureau. Detailed data sources and summary statistics for inputs, outputs, and the environmental variables are available Tables A.1-A.4 of the Appendix A.

Jarvio et al. (2005) and Pilyavsky et al. (2006) apply the approach of pooling the data in the application of the SW algorithm. In this research, we treat each state in a given year as a different decision making unit. We estimate a production frontier for the whole period which is consistent with the SW model. An advantage of pooling the data is that it increases the sample size, which is important due to the curse of dimensionality that affects all nonparametric estimation.

## 2.4 Results

### 2.4.1 First Stage: Efficiency

Over the period analyzed, we estimate that 4 states have observations defining the efficiency frontier (i.e., efficiency score equal to 1). These states are Colorado, Minnesota, New Hampshire, and Utah. These are the best practice states and these observations represent efficient health care delivery systems. Figure A.2 displays a map of the United States with efficiency rankings in 2007. The map shows the location and quantiles of the most efficient states. When considering average efficiency of the complete period, the most efficient states are Utah (0.995), Arizona (0.896), Oregon (0.894), Colorado (0.890), and California (0.849).[14] Figure A.3 displays the right-skewed estimated efficiency distribution for all analyzed years. Additional detailed efficiency information for each state is available in Table A.5 of Appendix A.

[14] Average bias corrected DEA input-efficiency score in parentheses.

Figure A.4 depicts the estimated average bias corrected DEA efficiency as well as the average traditional DEA efficiency score. While average DEA efficiency is 75% across states, the average bias corrected DEA efficiency is 61%. According to these efficiency estimates, traditional DEA efficiency is biased in the upward direction by approximately 14 percentage points. Therefore, it significantly underestimates the cost of unnecessary health care input consumption. This is evidence that traditional DEA measures can mislead policy.

There is a downward trend in average bias corrected DEA efficiency - estimated efficiency hereafter. Estimated efficiency decreases 0.4 percentage points, on average, every year. Although this decrease seems minuscule, the following back of the envelope calculation demonstrates the cost of inefficiency associated with this trend. According to the U.S. Census Bureau, U.S. health care expenditures reached 2,241 billion dollars in 2007.[15] Using this number as a proxy for health care input costs and given average efficiency in 2007 is estimated to be 60%, the cost of inefficiency in 2007 is approximately 896.4 billion dollars. Assuming annual expenditures remain unchanged, a 0.4 percentage point increase in input-inefficiency represents approximately an additional 90 billion dollars in wasted input expenditures in 2008.

### 2.4.2 Second Stage: Effects of Health Insurance Coverage

We estimate a truncated regression using the SW bootstrapping technique. We use two specifications to capture a potential difference in the effects between private and public health insurance coverage. The first includes our set of controls and total health insurance coverage. The second substitutes separate measures of private and public coverage for total coverage.

Results of these estimations are reported in Table A.6. We estimate a negative impact of total health insurance coverage on the efficiency of health care delivery. The coefficient on *total coverage* is estimated to be -1.284. Hence, we estimate that a

[15]U.S. health care expenditures obtained from the U.S. Census Bureau Statistical Abstract, 2010.

1 percentage point increase in the share of the state population with health insurance decreases efficiency by approximately 1.3 percentage points. Based on the 95% confidence interval, the marginal effect of *total coverage* on efficiency can be as high as -1.8 and is no less than -0.8. Using U.S. health care expenditures in 2007 as a proxy for input costs (2,241 billion dollars), a 1 percentage point increase in health insurance coverage potentially translates into 28.77 billion dollars in additional inefficiency cost. This amount increases to 34.33 billion dollars based upon typical two-stage efficiency analysis (as described in section 3).[16] In terms of policy implications, this overestimate from traditional methods illustrates the importance of using SW procedures.

Using the second specification, we analyze the impacts of private and public health insurance on efficiency. The 95% confidence interval on *public coverage* includes zero; therefore statistically, public health insurance coverage does not influence the efficiency of health care delivery. Corroborating this conclusion, notice that both the point estimate of the coefficient on *private coverage* and its confidence interval are close to that of *total coverage* in specification (1). We estimate that a 1 percentage point increase in private health insurance coverage decreases health care delivery efficiency by 1.113 percentage points.

For the analysis of the other covariates, we interpret the results of the second specification because it has smaller variance. The coefficient on *share 65+* is the largest (in absolute value) among all coefficients estimated, suggesting that health care delivery efficiency is more sensitive to changes in the share of the population 65 and over than it is to changes in any other environmental variable. We estimate that a 1 percentage point increase in the share of the population 65 and over decreases efficiency by 5.25 percentage points. Because a significant portion of the insured population 65 and over has public health insurance, the inclusion of *share 65+* captures most of the variation in *public coverage*, and is probably responsible for the low point estimate on its coefficient in specification (2).[17] According to the U.S.

[16] Traditional second stage regressions available in the appendix.

[17] In fact, an auxiliary regression excluding *share 65+* delivers similar coefficients for *private coverage* and *public coverage*.

Census Bureau, people 65 and over represented 12.4% of the American population in 2000. By 2030, it is projected that 19% of the population will fall into this age category.[18] This represents a 6.6 percentage point increase in *share 65+*. According to our estimates, this change in the population age distribution will, *ceteris paribus*, decrease health care delivery efficiency by approximately 34 percentage points. As the portion of population 65 and over grows, the amount of inefficient expenditures will dramatically increase. This is of particular concern given that the majority of health care expenditures by this age group are primarily funded through public health insurance, which is subsidized by state and federal governments.[19]

Poverty and education are important environmental factors impacting efficiency. The coefficient on *poverty share* is negative, and the coefficient on *diploma share* is positive. We estimate that a 1 percentage point increase in the share of the population in poverty decreases health care delivery efficiency by approximately 1.6 percentage points. As for education, our result indicates that a 1 percentage point increase in the share of the population with complete secondary education increases health care delivery efficiency by approximately 1 percentage point. While poverty and education seem to be relevant factors, employment and income do not present significant impacts on efficiency. The coefficients on *employment share* and *state gdp* have relatively wide 95% confidence intervals. The wide confidence intervals including zero are statistical evidence that health care delivery efficiency is independent of real per capita income and employment level.

## 2.5 Discussion

Empirical evidence regarding the effects of health insurance coverage on efficiency is scarce and conflicting. The existing research involves the efficiency of hospitals and

[18] U.S.Census Bureau, Population Division, Interim State Population Projections, 2005.

[19] It is important to note that efficiency scores are not indicators of the quality of health care. These measures should not be viewed as influencing individuals' migration decisions. States face these demographic projections and must consider better ways to manage health care inputs if they are to improve health care delivery efficiency.

not the efficiency of health care systems. Chang et al. (2004) use an OLS regression and find a negative impact of health insurance coverage on hospital efficiency when Taiwan implemented a national health insurance program. Brown III (2002) uses a stochastic frontier model to estimate efficiency and finds a positive impact of managed care insurance on hospital efficiency.[20]

Our main contribution to the health care literature is to estimate the effect of health insurance coverage on the efficiency of health care delivery systems. Using the SW double bootstrap procedure we estimate a negative relationship between the two variables. Using standard OLS, Tobit, and truncated regressions (with no bias correction of efficiency), we also find a negative coefficient on health insurance coverage. However, standard techniques over-estimate the impact of health insurance coverage on efficiency.[21] As a robustness check we regress bias corrected efficiency on our set of environmental variables using standard OLS, Tobit, and truncated regressions. The results of these regressions are found in Table A.7. We find that after correcting for the bias in efficiency, the results are similar to those obtained through the second SW bootstrap.

The health care literature describes phenomena that are in line with the negative relationship between health insurance coverage and efficiency. First, insurance increases access to medical care. As the demand for care increases health care outputs might increase. In this case, for inefficiency to occur, input consumption has to increase faster than health care outputs in some states. Bilodeau et al. (2002) conclude that the U.S. hospital system is overcapitalized. The authors assert that input consumption is increasing faster as new technology is being continuously adopted by providers of health care services. In the face of competition, providers find

[20] In our study, we apply a nonparametric approach to estimate efficiency. In contrast to parametric methodologies (such as Stochastic Frontier Analysis - SFA), no restriction is imposed on the shape of the production frontier. The results obtained from SFA are sensitive to the choice of the parametric functional form of the production function.

[21] OLS, Tobit, and truncated estimation results are provided in the appendix.

that the optimal decision is always to adopt newly available technology. For a given level of health care output, the increase in input consumption indicates inefficiency.

In addition, studies show that the marginal rate of substitution between labor and capital is very low in the health care sector. Jensen and Morrisey (1986) estimate the elasticity of substitution between medical staff and beds within hospitals to be approximately 0.17. The low marginal rate of technical substitution creates managerial rigidities, making it difficult to respond to changes in demand.[22] Ferrier and Valdmanis (1996) find that rural hospitals over-utilize labor relative to beds. Input mix rigidities at the state level can play an important role in determining efficiency. Health care systems may operate too deep into the decreasing returns to scale region of the production function as large amounts of certain inputs are necessary to deliver health care. In this case, systems are exposed to scale inefficiencies. Balk (2001) presents a formal framework to analyze productivity changes and input mix effects. We leave this investigation for future research.

## 2.6 Conclusions

Health care delivery input-efficiency scores are valuable because they represent a measure of underemployed medical resources. As health care expenditures rise, efficiency analysis is important for its ability to identify best practice health care systems. In this paper, we bring a new methodology from the productivity analysis literature to the health care expenditure debate. We use the Simar and Wilson (2007) model to estimate health care delivery efficiency accounting for the environment health systems face. In doing so, we are able to answer an important question: what is the impact of health insurance coverage on the efficiency of health care delivery?

Modeling an individual U.S. state as a health care system, we find that a 1 percentage point increase in health insurance coverage *decreases* health care delivery

[22] Custer and Willke (1991) and Lehner and Burgess (1995) have shown that elasticity of substitution estimates are sensitive to how physicians are defined.

efficiency by approximately 1.3 percentage points, translating to approximately 28.77 billion dollars in additional health care expenditures. Given that recently enacted health care reform potentially expands health insurance coverage, states may face serious issues regarding health care expenditures. While health insurance increases access to health care, it may reduce health care delivery efficiency, increasing unnecessary input consumption, and generating extraneous costs for society.

Research assessing the efficiency of health care delivery systems and the effects of environmental factors is scarce. Little is known about the channels through which these factors operate and how they affect productivity and the input mix within the health care industry. These insights are important in understanding how states can deliver health care more efficiently in the face of legislated insurance expansion and aging projections.

The relationship between health insurance coverage and health care expenditures is complex and operates through various channels. Our results suggest that health insurance expansions may increase health care expenditures. Nevertheless, it is important to acknowledge the empirical evidence demonstrating that increases in health insurance coverage reduce emergency room visits, which suggests lower health care expenditures. Our study is not an attempt to evaluate American health care policy. However, we shed some light on possible consequences of significant health insurance expansions. A cost-benefit analysis is needed to provide evidence that the benefits of the reform outweigh the potential costs highlighted by this research. Future work should address these issues.

# Chapter 3

# Better to Be Safe than Sorry? Impacts of a Health Insurance Mandate on Hospitals

## 3.1 Introduction

The Patient Protection and Affordable Care Act (ACA) potentially expands health insurance to over 46 million uninsured Americans. Expanding health insurance improves access to medical care through a reduction in medical costs borne by the consumer. A large number of newly insured consumers has the potential to increase overall demand for medical services. Therefore, legitimate concerns over large scale health insurance expansion focus on the possible ramifications of rising health care costs. However, large scale changes in health insurance may also influence the delivery of health care. Since one objective of the ACA is to reduce medical care costs, it is imperative to understand how a health insurance mandate impacts hospitals.

A large body of research examines the effect of changes in health insurance coverage on consumer utilization of care and medical expenditures.[1] Since health insurance coverage improves a consumer's access to care, early work suggests that health insurance expansion is one of the main drivers of increases in health care expenditures (see Feldstein (1973b) and Weisbrod (1991)). However, the Rand Health Insurance Experiment (RHIE) estimates an impact that is much smaller in magnitude than this earlier research suggests (see Newhouse (1993)). While these studies largely focus on demand for care, it remains uncertain how a large scale health insurance expansion affects the supply side of the market. Changes in hospital inputs and methods for delivering care that stem from changes in insurance coverage also potentially impact health expenditures. As the first study to focus on how health insurance coverage impacts hospitals, Finkelstein (2007) finds evidence that the introduction of Medicare is associated with an increase in expenditures that was four times larger than RHIE results would predict.

In order to better understand the nature of rising health care expenditures, it is important to examine any potential impacts that occur on the supply side of the market as a result of a legislative mandate for health insurance coverage. Massachusetts provides a rather unique opportunity for study, because, in 2006, the state enacted health care reform legislation known as Chapter 58. Major components of the reform reflect those encompassed in the ACA. The main objective of the law was to expand health insurance through a mandate that went into effect in July 2007.[2] Considering demand for hospital care, Kolstad and Kowalski (2010) use Massachusetts to examine the impact of a health insurance mandate on hospital admissions from the emergency room (ER), patients' average length of stay in the hospital, and total discharges from the hospital. They find that hospital admissions from the ER and patients' average length of stay declined, while total hospital discharges were not

[1] Manning et al. (1987b),Newhouse (1993), Card et al. (2008), Currie and Gruber (1996), Dafny and Gruber (2005), and Anderson et al. (2010) all consider different aspects of how changes in health insurance affect consumer utilization and expenditures.

[2] McDonough et al. (2006) provides a comprehensive overview of the Chapter 58 legislation.

significantly affected. Focusing on emergency outpatient care, Miller (2011) finds the reform reduced outpatient ER visits by between 2 and 8 percent.

Extending the analysis using Massachusetts to the supply side, I employ a reduced form empirical strategy to identify how a health insurance mandate affects hospitals' capacity and employment. I examine hospital utilization measures in addition to inputs, because these measures give insight into hospitals' expectations of demand, which influence their input decisions. Analyzing the supply side effects also necessitates the use of a data set which captures long run changes following the implementation of health care reform. This improves upon the existing literature exploiting the implementation of a health insurance mandate as a natural experiment by identifying any potential impacts that occur later within the post-policy period. The empirical strategy uses Centers for Medicaid and Medicare Services data from 2000 to 2009 and a difference in differences approach to test whether a health insurance mandate affects a hospital's capacity and employment levels.[3] In addition, the examination of the impact of the insurance mandate on other utilization measures such as total patient discharges, average daily census, a patient's average length of stay, and the number of ambulance trips to a hospital provides insight into a hospitals' expectation of demand. [4]

A health insurance mandate potentially affects a hospital's input through expected changes in the demand for care. Since a health insurance mandate increases health insurance coverage (see Long (2008), Long et al. (2009), Yelowitz and Cannon (2010) and Kolstad and Kowalski (2010)) and improves access to care, a large number of newly insured consumers potentially increases overall demand for hospital services. Insurance expansion that improves access to care may also decrease the demand for emergency services. However, uncertainty in the magnitude and nature in which demand for care might change as a result of the mandate make it difficult for hospitals

[3] Hospital capacity is the number of beds in the hospital.

[4] Average daily census is interpreted as how many patients are occupying beds on any given day in the hospital. Average length of stay represents the number of days an average patient spends in the hospital.

to predict the amount of inputs needed in order to meet demand. This uncertainty impacts hospitals, because managers must decide *ex ante* whether or not to add hospital capacity (see Joskow (1980), Mulligan (1985), Friedman and Pauly (1981), and Carey (1998)). Therefore, if a health insurance mandate affects the demand for care in ways that hospitals find hard to predict, then hospitals could potentially choose an excessive amount of capacity that could substantially add to health care costs. In other words, it is better for a hospital to be "safe" and have idle excess capacity rather than to be "sorry" and turn patients away. While hospitals have an easier time adjusting their levels of employment relative to capacity in order to meet changes in demand, uncertainty may also cause hospitals to substitute less skilled labor for highly skilled labor or ask existing staff to work additional hours. This stems from the fact that hospitals can add additional labor much more quickly than capacity, therefore, they may wait for expected increases in demand to be realized, and then subsequently add additional employees. However, training highly skilled specialist takes time, therefore, in the period shortly after an insurance mandate filling in with less skilled labor or existing labor is a possibility. Therefore, uncertainty in the magnitude of changes in demand may result in hospital inefficiency if capacity is added in larger amounts relative to realized increases in demand.

The results suggest that a health insurance mandate does not significantly affect demand for care on the extensive margin as measured by total discharges and average daily census. However, the reform significantly reduces patients' average length of stay by approximately 27%. The mandate also significantly reduces the utilization of the most urgent type of care provided by the hospital, the ambulance. For an average hospital the effect of the health insurance mandate reduces the number of annual ambulance trips to the average hospital by 16%. This equates to a reduction of one ambulance trip per day for an average hospital affected by the reform relative to one that is not. In terms of hospital inputs, the health insurance mandate increases overall capacity by approximately 7 beds. Since there is a decrease in the utilization of emergency care but overall utilization is not significantly impacted, the increase in hospital capacity suggests that hospitals are uncertain regarding how a health insurance mandate will affect their demand; therefore, a hospital does prefer to be "safe". One reason that changes in the demand for emergency care do not seem to decrease hospital capacity is potentially due to the fact that patients, who were previously using ambulance services and being admitted to the hospital through the emergency room, are now arriving at the "front" door to the hospital instead.

In terms of the external validity of this study, differences between Massachusetts and the nation should be kept in mind when assessing how changes in health insurance affect hospitals. Massachusetts entered the individual mandate with a higher rate of insurance coverage as compared to most states, 89% versus 84% nationally.[5] Massachusetts also had a tightly regulated insurance market prior to the implementation of Chapter 58 that makes an individual mandate more feasible compared to other states. Given the smaller changes in health insurance coverage in Massachusetts, a health insurance mandate potentially has a larger effects in states where the change in coverage is greater. Therefore, Massachusetts likely represents a lower bound estimate of the impact of the reform on utilization and hospital inputs.

The result in this chapter also have important implications for health care costs. While the health insurance mandate does significantly increase hospital capacity, the magnitude of the effect suggests it is likely that the additional beds fit within the existing structure of the hospital. Therefore, the added capacity does not suggest a substantial increase in hospital expenditures from investments expanding the physical structure of a hospital. The mandate also does not significantly affect a hospital's employment level. This utilization of inputs in the face of a health insurance mandate should have minimal impacts on health care costs that are passed onto the consumer.

This paper is organized as follows: the next section describes the theoretical framework, Section 3 outlines the empirical strategy and examines pre-reform trends, Section 4 presents results, Section 5 describes a variety of robustness checks, and Section 6 concludes.

[5]Insurance rates derived from rates of the uninsured provided by McDonough et al. (2006).

## 3.2 Theoretical Framework

A hospital faces uncertainty regarding the demand for its services as a result of the health insurance mandate. Fundamentally, prior to the changes in health insurance, the number of patients arriving at a hospital at any particular point in time is subject to large variability and a considerable portion is unpredictable (see Joskow (1980)). The unpredictable nature of demand is primarily due to emergency health care needs stemming from accidents and sudden illnesses.

A health insurance mandate expands health insurance coverage and improves access to care by reducing individuals' out of pocket costs. Therefore, a health insurance mandate may induce individuals to seek preventative care allowing for the identification and treatment of health issues before they become an emergency.[6] Many studies corroborate that increases in health insurance coverage increase the demand for preventative care (see Manning et al. (1987b), Newhouse (1993), Card et al. (2008), Currie and Gruber (1996), Dafny and Gruber (2005), and Anderson et al. (2010)). In examining Massachusetts, Kolstad and Kowalski (2010) find evidence of increases in preventive care outside of the hospital environment. If more individuals are seeking preventative care, than from a hospital's perspective the predictable portion of demand should increase as preventative care catches more illnesses and injuries early on and procedures can be scheduled in advance. A hospital should also expect that increases in health insurance coverage potentially decrease the demand for emergency care.

However, a hospital faces an additional layer of uncertainty stemming from a health insurance mandate. Uncertainty from a health insurance mandate arises because a hospital must accurately forecast changes in the magnitude of demand in order to provide health care services. A hospital must form an expectation about the

[6] It is important to note that some individuals may not be induced into this type of behavior. Gaining health insurance could cause some types of individuals to engage in more risky behavior, because they have insurance in the event of serious illness or accident. Therefore, these individuals may forgo preventative care or engage in more risky health behavior due to insurance.

magnitude of demand, because it must choose its capacity prior to the realization of demand. This stems from the fact that it takes time to build infastructure necessary to support hospital beds and services. Therefore, in order to choose its input levels, a hospital minimizes its costs in the face of the demand it expects to experience. It is generally assumed within the literature that hospitals exhibit cost minimizing behavior over profit maximization because a large fraction of hospitals are non-profits (see Joskow (1980) and Cowing and Holtmann (1983)). As depicted in Figure B.1, a hospital chooses inputs (beds and labor) to minimize its cost subject to expected demand ($Q_{expected}$). However, suppose that realized demand ($Q_{realized}$) from the health insurance mandate is in fact greater than the hospital predicts. In the short run, a hospital can potentially adjust its amount of labor to provide services in order to meet realized demand, but it cannot adjust its capacity. Because patients need an open bed in order to be admitted to the hospital, some patients have be turned away or queued for later admission. A hospital does not wish to turn patients away or queue them due to lack of capabilities. This is due to a fundamental mission to care for patients in distress or concerns over future economic loss from a reputation effect (see Joskow (1980), Mulligan (1985), Friedman and Pauly (1981)).

A hospital never wants to be in a position where realized demand is greater than expected demand, this makes a hospital's certainty in the magnitude of the change in demand very important. If a hospital faces a situation such as a health insurance mandate that makes them uncertain in their prediction of the magnitude of the change in demand, they may have an incentive to choose a higher level of inputs and be "safe" rather than have to turn patients away and be "sorry." Choosing higher levels of capacity helps ensure that hospitals avoid a situation like Figure B.1, when they are uncertain regarding the magnitude of the change in demand. This uncertainty has the potential to create inefficiency within a hospital. This inefficiency results when hospital capacity is added relatively faster than corresponding increases in realized demand. Comparing Massachusetts to other states allows for an empirical evaluation of how a health insurance mandate affects hospital inputs. Analyzing hospital utilization measures that proxy for demand provides insight into hospitals' certainty regarding realizations in demand.

## 3.3 Empirical Strategy and Data

### 3.3.1 Empirical Strategy

The empirical strategy uses annual data from 2000-2009 collected from the Centers for Medicaid and Medicare Services and a difference in differences approach to assess the impact of a health insurance mandate in Massachusetts on demand for care and hospital input levels. In this context, demand for care considers utilization measures that capture overall changes in demand for care as well as changes in demand for emergency care. Utilization measures that proxy for overall changes in demand for care include total patient discharges, average length of stay (ALS), and average daily census (ADC). The demand for emergency care is captured through the number of ambulance trips reported by the hospital. The hospital input levels are the total number of beds and total number of employees.

Determination of the effect of a mandate is based on a break in any pre-existing trend around the time of the introduction of the health reform in 2007. The counter-factual assumption allowing for identification is that, absent the mandate for health insurance, any pre-period trends continue uninterrupted. I use 7 years prior to the implementation of the mandate in Massachusetts to constitute the pre-policy trend. The counter-factual assumption also requires a group of hospitals not affected by the mandate. Since the health insurance mandate impacts all hospitals in Massachusetts this eliminates any within-state comparison groups; therefore, hospitals located in other states around Massachusetts form the comparison group. Comparison states include Maine, New Hampshire, Vermont, Connecticut, Rhode Island, New York, New Jersey, Pennsylvania, Delaware, Washington D.C., Maryland, and Virginia. The basic difference in differences specification is:

$$y_{ijt} = \alpha + \beta(MA * After)_{jt} + \gamma(MA)_i + \rho(After)_t + \delta' X_{jt} + \theta_i + \lambda_t + \nu_j + \epsilon_{ijt} \quad (3.1)$$

The dependent variable is a utilization measure or input, $y$, in hospital $i$, in state, $j$, in year $t$. The coefficient, $\beta$, gives the impact of the policy on hospital utilization and inputs. It represents the change in utilization measures and inputs after the reform relative to before the reform in Massachusetts as compared to other states. By construction, it is the interaction of the variables *MA* and *After*, where *MA* is an indicator variable equal to one if the hospital is in Massachusetts and the *After* variable represents the time period after the policy was implemented. Since annual data are used, 2007-2009 is considered as the post-policy time period in which $After = 1$. Equation 3.1 also includes a vector of time varying state variables, $X_{jt}$, to control for differences between hospitals in Massachusetts and those in other comparison states. Inclusion of these variables strengthens the assumption that there are no other factors outside the reform that affected Massachusetts relative to the other states in the post-reform period. This assumption is a critical to the validity of the difference in differences approach. These controls include factors such as population, income, poverty, education, health status, employment, and health insurance coverage. The inclusion of $\theta_i$ (an individual hospital fixed effect), $\nu_j$ (a state fixed effect), and $\lambda_t$ (year fixed effect) eliminates time invariant effects.

A second specification captures the effect of the policy in a specific year in the post reform period. This specification includes 3 variables (*MA*Year07*, *MA*Year08*, and *MA*Year09*) in place of the *MA*After* in Equation 3.1. These variables are the interaction of *MA* and a specific year of the post-policy period. Given the long time series dimension of the data and that the treatment variable itself changes very little over time, serial correlation within the difference in differences context is common. The presence of serial correlation means that the standard error of $\hat{\beta}$ is severely understated and can lead to incorrect identification of policy impacts. To account for these issues, I use a block bootstrapping method purposed by Bertrand et al. (2004). Since Massachusetts constitutes the only treatment state, Kolstad and Kowalski (2010) suggest the implementation of the method utilizing a large number of bootstrap replications. All reported standard errors reflect 2000 bootstrap replications.

### 3.3.2 Data

Data obtained from the Centers for Medicaid and Medicare Services (CMS) hospital cost reports includes ambulance trips, total beds (excluding newborn bassinets), total employees, total inpatient days, and total patient discharges (total discharges hereafter). The utilization measure, ALS, is the number of total patient days divided by the total discharges reported by the hospital. ADC is total patient days divided by 365.[7] It is important to note that with respect to the ambulance trip data, only a limited number of hospitals report their annual number of ambulance trips. The data set is limited in sample size relative to the number of hospitals that report the other utilization measures and inputs. However, the number of hospitals from Massachusetts and the other comparison states represented within the ambulance trip data is approximately the same percentage of the number of hospitals in the larger data set suggesting that there is no sample selection of hospitals by state within the ambulance data.[8]

Summary statistics for each dependent variable in the pre-reform and post-reform policy period are in Table B.1 of Appendix B. Since the reform went into effect in July 2007, years 2000-2006 constitute the pre-policy period and 2007-2009 the post-policy period. Examining utilization measures within Massachusetts, the mean number of total discharges in Massachusetts rises from 7322 to 7851 from the pre-policy to post policy period. In all other states, the mean number of total discharges rises from 8165 to 8678. The mean ADC in Massachusetts increases from 128 to 132 from the

[7]The construction of ALS and ADC follow the American Hospital Directory definitions.

[8]The one exception is that no hospitals within Vermont report ambulance trip data.

pre-policy to the post-policy period, and in all other states it increases from 136 to 137. A patient's ALS falls in Massachusetts from 37 to 31 days, while in all other states it remains unchanged.[9] In consideration of demand for emergency care, the mean number of annual ambulance trips to hospitals in Massachusetts decreases from 2154 to 1620 trips. In all other states, the mean number of annual ambulance trips decreases from 2041 to 1932.

Examining inputs, the mean number of beds in Massachusetts increases from 173 to 179, and the mean number of employees increases from 1116 to 1298 from the pre-policy to post-policy period. In all other states, the mean number of beds decreases from 188 to 187 and the number of employees increases from 1060 to 1162. Since the difference in differences approach relies on the relative change from the pre-policy to post-policy period for a hospital in Massachusetts compared to a hospital within the group of comparison states, Figures B.2-B.7 illustrate the magnitude of change for the average of utilization measures and inputs from the pre-policy to the post-policy period. To the extent that change between the pre-policy and post-policy period is relatively larger or smaller in Massachusetts compared to all other states is preliminary evidence for the impact of a health insurance mandate on these measures. Figures B.4, B.5, and B.6 are cases where the preliminary evidence of an effect on a mandate on these variables is the strongest.

## 3.4 Examination of the Distribution of Demand and Pre-Reform Trends

### 3.4.1 Examination of Changes in the Distribution of Demand

In order to consider the impact of a health insurance mandate on the distribution of demand as discussed in Section 3.2, this subsection examines changes in the

[9] It is important to note that the data includes rehabilitation hospitals, which accounts for a longer ALS than is found with acute care hospitals.

distribution of the utilization measures between the pre and post-policy periods. Figure B.8 depicts the kernel density plots of the distributions of the demand for care as represented by total patient discharges. For Figures B.8 and B.9 only, Massachusetts is compared to a subset of the comparison states including Connecticut, New Hampshire, and Maine. The distributions for total discharges do not show a significant change between the pre-policy and post-policy period for Massachusetts or the comparison states. A Kolmogorov-Smirnov test (K-S test) of the distributions in Massachusetts fails to reject the null hypothesis that these distributions are equal at significance level of 5%. K-S tests for the other comparisons states yield the same failure to reject the null hypotheses.

Similar kernel density plots as those in Figure B.8 were constructed for other utilization measures such as ALS and ADC. These plots also demonstrate no significant difference in the distributions in the pre and post-policy period for Massachusetts and the other states.[10] K-S tests of the distributions in the pre and post-policy period for all the states including Massachusetts fail to reject the null hypothesis that the distributions are equal at a significance level of 5%. These results suggest that there is no significant difference in the distribution of demand for care in Massachusetts or the comparison states between the pre and post-policy period. Therefore, the demand for care before and after the health insurance mandate is fairly inelastic. To the extent that hospitals' predict an inelastic response in these utilization measures hospital input levels should remain largely unaffected.

Figure B.9 depicts kernel density plots of the distributions of the demand for emergency care. All the distributions display changes between the pre and post-policy periods. However, the K-S test of the distribution of the pre and post-policy periods for Massachusetts rejects the null hypothesis that the distributions are equal at a significance level of 5%. The same test fails to reject the null hypothesis for each of the comparison states. The distribution in Massachusetts displays a noticeable shift to the left. The suggests a reduction in mean of the distribution after the health

[10]These kernel density plots are available upon request.

insurance mandate was instituted. A test for the difference in means in the pre-policy and post-policy periods rejects the null hypothesis of equality of in means.

Since emergency care is the most unpredictable portion of demand that hospitals face, a change in emergency care potentially indicates that the overall variance of the distribution of demand is decreasing. To the extent that this is occurring, it can influence hospital inputs by reducing their need to hold excess inputs. Thus, the statistically significant changes in the distribution of demand for emergency care in Massachusetts provides preliminary support for the theoretical framework suggesting that a health insurance mandate potentially influences hospital input levels.

### 3.4.2 Examination of Trends

This subsection examines the trends of the dependent variables in pre and post-policy periods. For evidence of an effect of the health insurance mandate in Massachusetts, there should be a break in the pre-existing trend around the policy date. In addition, comparison states should be on similar pre-policy trajectories but not exhibit a break in trend around the implementation of the reform. Figures B.13-B.15 compare the mean of total discharges, ADC, ALS, ambulance trips, beds and employees in each year from 2000 to 2009. For the purposes of these figures only, Massachusetts is compared to Pennsylvania, New York, New Jersey, and Connecticut. Examining the breaks in pre-policy trends across all the figures, the most distinctive breaks appear around 2006. Since the health insurance mandate in Massachusetts was enacted in 2006, but not implemented until July of 2007, these graphs provide visual evidence of the importance of testing for anticipatory effects of the policy. Subsection 3.6.1 discusses this in further detail.

In terms of utilization measures that represent overall demand for care, Figure B.10 shows the mean total discharges in each year from 2000-2009 for Massachusetts and the comparison states. The comparison states are on the same pre-policy trend meaning that the relative trajectory of the trends prior to the policy are the same as in Massachusetts. Following the introduction of a health insurance mandate, there appears to be little to no break in trend suggesting that total discharges is not affected by the reform. Figure B.11 shows mean ADC for both Massachusetts and the comparison states. While the comparison states have similar pre-policy trajectories, the relative change in the post-policy trends suggests little impact of the reform. Figure B.12 shows the mean ALS. In this case, the visual evidence that the comparison states follow the same pre-policy trajectory is not as compelling. However, in analyzing Massachusetts, there is a distinctive break in the pre-policy trend suggesting that the health insurance mandate potentially reduces ALS.

Analyzing the demand for emergency care, Figure B.13 shows that Massachusetts experiences a much larger fall in the mean number of ambulance trips relative to other states in post-policy period. This provides additional visual evidence that the health insurance mandate potentially affects the demand for emergency care. In terms of hospital inputs, Figures B.14 and B.15 show the annual mean number of beds and employees from 2000-2009. In general, there seems to be very little visual evidence of a break in pre-policy trends around 2006 and 2007. This suggests that health insurance mandate may have little influence on hospital inputs.

## 3.5 Results and Discussion

Table B.2 presents the results of the overall effect of the health insurance mandate on demand for care and hospital inputs. Examining the demand for emergency care using the annual number of ambulance trips to the hospital in Column (1), the effect of the health insurance mandate is significant and generates a total reduction of approximately 326 ambulance trips. This equates to a 16% reduction in the number of annual trips from the pre-policy period. Therefore, an average hospital affected by the mandate experiences approximately one less ambulance trip per day. Since the average cost of an ambulance trip is approximately $750, this reduction saves

$274,000 dollars annually.[11] The reduction implies that the health insurance mandate induces substitution away from relying on the urgent hospital services toward more appropriate care settings. Miller (2011) finds similar evidence in her analysis of emergency room visits.

Columns (2-4) show the impact of a health insurance mandate on demand for care. One potential impact of a health insurance mandate is an increase in the demand for care resulting from a reduction in consumers' out of pocket costs. In Columns (2) and (3), the reform did not significantly impact hospital utilization measures such as total number of discharges or ADC. This reflects that on the extensive margin there was no overall change in demand for hospital services. This in conjunction with the reduction in ambulance trips suggests that a health insurance mandate changes the nature of care hospitals provide. Hospitals are seeing fewer patients arriving via ambulance needing emergency services; however, these same patients are likely entering via the "front" door, instead.

In Column (4), the health insurance mandate does significantly reduce the ALS for a patient in the hospital. Specifically, the reform reduced the ALS of a patient in a hospital in Massachusetts by approximately 10 days relative to one that is not. This represents a 27% reduction in the ALS from the pre-policy period. Kolstad and Kowalski (2010) examine a shorter period of time following the implementation of the health insurance mandate using quarterly data from the Healthcare Cost and Utilization Project National Inpatient Sample. They find that the insurance mandate results in a 1% reduction in a patient's average length of stay. The larger reduction found in this study likely stems from two factors. First, this study uses a longer time span following the health insurance mandate's implementation which allows more time for hospitals to adjust their production processes. Hospitals' adjustment of their production processes is stimulated by increasing pressures from insurance companies over reimbursement prices for hospital inpatient services. These pressures

[11] This figure was inflated to present dollars from an average cost reported in 1998 dollars from the Community Transportation Association.

likely increase with time following the mandate as the newly implemented insurance exchanges create more competition among insurance companies. As a result of increasing price pressures, hospitals make adjustments that improve their throughput of patients. Second, the CMS data used in this study include rehabilitation hospitals which in general have a longer ALS and increase the overall magnitude of the ALS estimate. Estimating the same specification and limiting the ALS to less than 5.42 days (which is the base number of days used by Kolstad and Kowalski (2010)) yields a 0.08 % reduction in ALS.[12]

Columns (5)-(6) show the impact of the health insurance mandate on hospital inputs. The reform increases hospital capacity by approximately 7 beds but does not significantly affect the number of employees. This adjustment of inputs suggests that hospitals forecasted an increase in demand as a result of a health insurance mandate. Since hospitals thought that there was potential for demand to increase in response to the mandate, they adjusted their capacity in order to be "safe" as depicted in Figure B.1. However, since the mandate did not significantly increase hospital employment, this suggests that hospitals were uncertain in their predictions. If hospitals were certain that demand was going to increase, then they also would have added additional employees. However, due to their uncertainty, hospitals did not add additional employees because adjusting labor as an input is much easier than adding capacity. In addition, hospitals also have the ability to have existing workers take on more hours to cover any initial increases in demand resulting from the mandate. Evidence that existing workers worked longer hours is supported by the impact of the health insurance mandate has on payroll expenditures. [13]

Table B.3 illustrates the timing of the impact of the health insurance mandate on hospital utilization and inputs. Since this study uses annual data, one benefit is that

[12]The estimated coefficient is not significant given the limited cluster size that occurs using hospital data from the CMS rather than individual data on hospital inpatients from the Healthcare Cost and Utilization Project National Inpatient Sample.

[13]Preliminary analysis of the data supports that the health insurance mandate increases hospital payroll expenditures.

the post-reform period is longer allowing for identification of slower moving effects of the reform.[14] The results show the effect of the health insurance mandate in each specific year (2007, 2008, and 2009) of the post-reform period.

In Column (1), the health insurance mandate significantly decreases the number of ambulance trips in 2007; however, the impact does not remain significant in 2008 and 2009. The estimated coefficient suggests that an average hospital affected by the mandate experiences a daily reduction of 1.2 ambulance trips in 2007 relative to one that is not. The timing of the effect of the mandate shows that there is a one time reduction in ambulance trips that is not sustained. This implies that the benefits from improved access to care in terms of use of the most urgent emergency services, ambulances, is short lived.

With respect to total discharges and ADC (Columns (2) and (3)), the effect of the mandate was not significant in any of the individual years of the post-reform period. These results reinforce those found in Table B.2 suggesting that the health insurance mandate does not impact the demand for hospital services. However, the health insurance mandate does have a significant impact on ALS in 2007, 2008, and 2009 (Column (4)). The magnitude of the reduction in ALS also increases in each subsequent year. In 2007, the reduction in ALS for the average hospital affected by the reform is approximately 5 days. By 2009, the magnitude of the effect is approximately 16 days. The prolonged decrease in ALS in the post-reform period implies one of two outcomes from the mandate. First, as discussed earlier, the pricing pressures from insurance companies continue to force hospitals to improve their throughput of patients in subsequent years following the mandate. Second, the insurance mandate is affecting individuals' overall health. Potentially, through better preventative care measures, individuals are getting healthier and seeking hospital services that do not

[14]From an empirical standpoint, the CMS data for 2010 is not included because the sample size of reporting hospitals is incomplete. In 2010, the number of hospitals reporting data is 2,864 hospitals as opposed to approximately 6,000 hospitals for 2000-2009. As this data becomes available, a better assessment of the timing of the effects of the mandate on utilization and inputs would include this year of data.

require as lengthy stays within the hospital as in the pre-reform period. This second explanation seems less plausible given that there should also be continued reductions regarding the use of ambulance services in conjunction with ALS.

The health insurance mandate also increases the hospital capacity in 2007 and 2008 but was not significant in 2009 (Column (5)). An average hospital affected by the mandate increases capacity by 6 beds in 2007 and 7 beds in 2008. Kolstad and Kowalski (2010) suggest that one means of improving hospital efficiency is to make smaller increases in capacity relative to demand following the reform. The addition of hospital capacity without a corresponding change in utilization suggests that hospitals are actually becoming more inefficient.[15] This inefficiency is likely due to demand uncertainty. The uncertainty is demonstrated by the fact that hospitals expected increases in demand in 2007 and 2008; therefore, they added beds in those years. However, once the corresponding realizations of demand did not occur in those years, hospitals did not continue adding anymore beds. This is supported by the fact that hospitals did not continue to increase capacity in 2009. The increase in capacity in 2007 and 2008 also suggests that it is unlikely that supply-side constraints limited total discharges that would have been driven by expanded health insurance coverage. The mandate also did not affect the total number of employees in any of the individual years in the post-reform period (Column (6)). This further suggests that increases in expected demand were not realized; therefore, the hospital did not need to adjust employment.

## 3.6 Robustness Checks

### 3.6.1 Anticipatory Effects

The examination of trends in Subsection 3.4.2 suggests breaks in the pre-policy trends potentially occur as early as 2006. Since the health insurance mandate in

[15] This is further evidence of the mechanism discussed within Chapter 2.

Massachusetts was enacted in 2006 but not fully implemented until July 2007. It is important to consider that hospitals may have expected increases in demand prior to 2007 and adjusted their inputs as early as 2006.

Table B.4 shows results of a specification that designates 2006 as part of the post-policy period along with 2007-2009. Piehl et al. (2003) point out that defining a dummy variable for the post-policy period and testing for a change in mean or other parameters can be conceptually flawed even when the start date of the program is known. This is due the fact that anticipatory effects from the health insurance mandate potentially impact the timing of the effects on hospitals. This causes the post-policy dummy variable ($After$) to not actually enter at the appropriate time for evaluating the effect of the policy. Therefore, Piehl et al. (2003) propose using a test for structural change of an unknown break point developed by Andrews (1993), as a way to consider if anticipatory effects are influencing the evaluation of a policy. They use a supremum of Wald statistics to determine where the break for the policy affect occurs. The supremum of Wald statistics is similar to a maximum F-statistic from a Chow test evaluated over all the possible breakpoints.

Table B.4 shows the same pattern of significance as those in Table B.2, when evaluated based on t-statistics. The health insurance mandate significantly reduces the number of ambulance trips to the hospital and average length of stay. These effects are significant at the 10% level. The health insurance mandate also significantly increases hospital capacity. This effect is significant at the 5% level. In each instance, the magnitude of the effect is smaller. Just as in Table B.2, the policy also does not significantly influence total discharges or the number of employees.

A comparison of the specifications in Table B.2 and Table B.4 based on the supremum Wald Statistic suggests that the break point occurred in 2006 for annual ambulance trips and hospital capacity, and in 2007 for ALS. These findings of anticipatory effects are consistent with the expected behavior of individuals and hospitals in response to the health insurance mandate. Since the health insurance mandate was enacted in 2006, individuals responded by acquiring health insurance prior to its implementation in 2007. The access in health insurance in 2006 had the immediate effect of increases individuals use of preventative care and reducing the number of ambulance trips to the hospital. Hospitals also immediately expected an increase in demand as a result of the policy and adjusted their capacity as soon as the health insurance mandate was enacted. The fact that the supremum Wald statistic selected the model where the policy begins in 2007 for ALS reinforces that the insurance companies as a result of pressures from the insurance exchange put pressure on hospitals which subsequently forced them to adjust their production processes.

### 3.6.2 Controlling for Heterogeneity in Hospital Size

Table B.5 presents results that show the effect of the policy in the post-mandate period. This specification differs from Table B.2 in that the log of the utilization measures and inputs are the dependent variable. Finkelstein (2007) suggests using the log of hospital outcomes and inputs to account for the fact that hospitals vary considerably in size. In general, the results of Table B.5 are very similar those in Table B.2 suggesting that the results are robust to heterogeneity in hospital size.

In terms of utilization measures, this specification demonstrates that the health insurance mandate significantly affects ALS but does not significantly affect total discharges and ADC. The effect of the reform on ALS is significant at the 10% level in this specification. In comparison to Table B.2, the effect of the mandate on ALS was significant at the 5% level. Kolstad and Kowalski (2010) discuss that taking the log of the ALS puts relatively more weight on shorter length of stays. Therefore, since the specification in Table B.2 has a tighter confidence interval than in this specification, the reform has more of an impact on longer length of stays. This is consistent with their findings that is based upon data with a shorter post-mandate period than the data used in this paper. In addition, this specification also shows that a health insurance mandate does not significantly reduces the annual number of ambulance trips to the hospital. This result is the only one that differs in significance as compared to Table B.2. It suggests that the annual number of ambulance trips is differentially affected by larger hospitals. This result is not necessarily surprising as larger hospitals likely have a greater fleet of ambulances. In addition, the health mandate also increases hospital capacity, but does not significantly affect hospital employment. These impacts are consistent with the findings in Table B.2.

## 3.7 Conclusion

While recent studies use Massachusetts to investigate the impacts of the health insurance mandate on insurance coverage and consumer utilization, I take a novel approach by considering the potential impacts on hospital inputs. The empirical strategy uses a difference in differences approach to assess the impacts of a health insurance mandate on hospitals' capacity and employment. Analyzing supply side effects necessitates the use of data that captures slow moving changes in these measures. This offers an additional advantage over the previous work by identifying long run impacts that occur later within the post-policy period. In addition to hospital inputs, I also examine hospital utilization measures, because they give insight into hospitals' forecasts of demand for care, which influence the choice of input levels.

The results suggest that a health insurance mandate significantly increases a hospital's capacity but does not significantly affect its employment levels. This adjustment of inputs arises because a hospital expects an increase in demand as a result of a health insurance mandate. Therefore, it adjusts its capacity in order to be "safe," rather than face being "sorry" for having to turn patients away. However, because the labor input is easier to adjust than capacity, a hospital waits to adjust its employment levels until its forecast of demand is realized.

The health insurance mandate does not significantly affect utilization of hospital services such as total discharges and ADC. Therefore, demand for hospital care remains fairly inelastic in response to the health insurance mandate. Thus, a hospital's expectation of increases in demand are never realized, and it does not adjust its employment level. The uncertainty regarding changes in demand also creates inefficiency within a hospital, because a hospital adds capacity but there is not a corresponding increase in the utilization of hospitals services.

These results also have important implications for health care costs. While a health insurance mandate significantly increases hospital capacity, the magnitude of the effect suggests it is likely that the additional beds fit within the existing structure of the hospital. Therefore, in the case of Massachusetts, the added capacity does not suggest a substantial increase in hospital expenditures from investments expanding the physical structure of a hospital. Also, the mandate does not significantly affect employment within a hospital. This use of inputs resulting from a health insurance mandate should have minimal impacts on health care costs that are passed onto the consumer. While analyzing Massachusetts provides insights into the potential impact of the ACA on the supply side of the market, the results of this study should interpreted with caution. Larger changes in health insurance coverage from an insurance mandate potentially create larger amounts of uncertainty, which may lead to larger investments in capacity. This in turn could have very different impacts on health care costs. In addition, further research is necessary to determine if over capitalization and rising expenditures are occurring through other channels such as technology.

# Chapter 4

# Bending States' Medicaid Expenditure Curves: Does Health Insurance Matter?

## 4.1 Introduction

Before the Patient Protection and Affordable Care Act (PPACA) was enacted in March, 2010, 18 state governors wrote to members of Congress concerned about the legislation's impact on state expenditures.[1] Their letters reflect a growing belief that PPACA is an unfunded mandate, because its required expansion of Medicaid might increase state expenditures on health to unsustainable levels. With the depletion of rainy day funds and depressed tax revenues stemming from the 2008-2009 recession, many states continue to face budgetary deficits making any growth in these expenditures an even more pressing issue.

With debate surrounding health care reform intensifying, significant attention is being given to the impact of changes in health insurance coverage on health care expenditures. Early research by Feldstein (1973b) suggests that expansion of heath

[1] Republican.Sentate.Gov, http://republican.senate.gov/healthcare/governors/ (accessed on 05/15/2011).

insurance coverage was a rudimentary cause of the increase in health expenditures. This is due to the fact that health insurance expansion increases the demand for medical services, because individuals' out of pocket costs are reduced. The increase in demand for services increases the overall price of medical care, when supply is less than perfectly elastic, subsequently increasing overall health expenditure. Recent studies find differing impacts of the effect of a policy driven change in health insurance on health expenditure. Using geographic variation in health insurance coverage from the implementation of Medicare, Finkelstein (2007) finds its introduction accounts for a 37% increase in real hospital expenditures for all ages. However, examining the impact of a health insurance mandate in Massachusetts, Kolstad and Kowalski (2010) find no evidence that the mandate increased the cost of hospital care.[2] In light of this research and to address budgetary pressures that states might face as a result of national health care reform, it is imperative to consider the potential impact of changes in health insurance coverage on state Medicaid expenditure.

There are a number of reasons to believe that private and public health insurance coverage could impact state Medicaid expenditure. For instance, the growth in private health insurance could increase the growth in Medicaid expenditure through a pricing channel that puts pressure on reimbursement rates. However, if reimbursement rates are largely unaffected by the private market and prices remain fixed, then growth in Medicaid expenditure is affected through those who are insured under Medicaid coverage. The effect of the growth in Medicaid coverage on Medicaid expenditure can be viewed as a quantity channel. In essence, a greater number of those with Medicaid coverage increase the demand for care because more individuals are insured. However, growth in Medicaid insurance could potentially decrease the growth of Medicaid

[2]The difference in these findings maybe driven by the fact that the Finkelstein (2007) study was a general equilibrium analysis where the Kolstad and Kowalski (2010) study was a partial equilibrium analysis. Finkelstein (2007) argues that market wide changes in health insurance alters the nature in which medical care is practiced in ways that small scale changes do not. She finds evidence that the introduction of Medicare is associated with substantial new hospital entry. It is possible that the mandate in Massachusetts was not large enough to change the nature of medical care practice, and subsequently, another reason that Kolstad and Kowalski (2010) find no evidence that cost of hospital care increased.

expenditures if better access to preventative care leads to improved health outcomes and a decrease in chronic illness meaning less expenditure. The reasons driving these effects and others are more broadly discussed in Section 2.

In this paper, I use state-level panel data from 1996-2004 to examine the impact of annual growth in private and public types of insurance coverage on the growth in Medicaid expenditure. Due to recent concerns over sustainability of these expenditures, one important contribution of this study is the focus on determinants of this specific type of expenditure rather than total health expenditures. For my study, Medicaid expenditure is considered to be state expenditure on Medicaid net of federal matching dollars. Only one other study focuses on state funded expenditure of Medicaid. Adams and Wade (2001) use data from 1984-1992 to examine the fiscal response of states to the federal matching rate and find states substitute federal funds for state generated revenues. Given research finding this substitution by states, I use more recent data to examine other potential determinants of growth in the states' portion of Medicaid expenditure.

Early work by Holahan and Cohen (1986) and Buchanan et al. (1991) find states' income and physician to population ratio affect state Medicaid expenditure inclusive of federal dollars; however, these studies do not focus on growth and the impacts of private and public health insurance coverage. This study considers an exhaustive specification that focuses on many other potential determinants of state funded Medicaid expenditure growth in addition to income and physicians such as spillover effects in neighbors' spending, political ideology, socioeconomic factors affecting health status and utilization of care, as well as private and public health insurance coverage. The consideration of the growth in neighbors' spending as a potential determinant is another important contribution, because Baicker (2005b) finds evidence of spillover effects in neighbors' spending on social services which includes both Medicaid and welfare expenditures together. Further, research examining health expenditure growth primarily focuses on total national-level health care expenditure. Early work by Newhouse (1977), Leu (1986), and Parkin et al.

(1987) finds that growth in gross domestic product (GDP) is positively correlated to the growth of health care expenditures. More recently, Roberts (1999) and Gerdtham and Jonsson (2000) stress the importance of exploring other potential determinants of health care expenditure growth. Beginning this effort, Hartwig (2008) and Potrafke (2010) identify wage productivity and certain types of political ideology as important factors.

Taking the growth literature into consideration, another novel contribution of this paper is the use of growth rates to evaluate of the impact of health insurance coverage on state funded Medicaid expenditure (Medicaid expenditure hereafter). With policy discussions focused on factors that influence states' ability to bend their Medicaid expenditure curves, the examination of growth rates allows for direct application of empirical findings to inform these discussions. In addition, growth rates give insight into long term trends that drive health care costs. Analyzing trends is particularly salient because individuals who have health conditions today are likely to have the same conditions or side effects from these conditions in the future requiring additional care and subsequent expenditure. Currently, the treatment of chronic health conditions accounts for over 75% of national health care expenditures.[3]

When considering the growth of Medicaid expenditures, it is important to account for the fact that growth in the previous periods could inherently affect growth in the current time period. This inertia in health care spending may result from time trends and semi-durability of consumption that arises from chronic health conditions (Okunade and Suraratdecha (2000)). Therefore, this study also makes a contribution by using a dynamic panel specification that explicitly accounts for the inertia of health care spending. The use of a dynamic panel estimator is necessary because inclusion of previous periods of Medicaid expenditure as explanatory variables causes endogeniety problems for traditional estimation of panel data. Dynamic panel estimators provide

[3]Centers for Disease Control and Prevention: Chronic Disease Overview, http://www.cdc.gov/chronicdisease/overview/index.htm, accessed on (07/20/2011).

a consistent and efficient estimator because instruments for endogenous explanatory variables are generated from variables already specified within the model.

The results imply that although the growth in private health insurance does not have a statistically significant impact on the growth of Medicaid expenditure, growth in Medicaid insurance increases Medicaid expenditure. However, this Medicaid insurance impact is only statistically significant in static specifications that do not allow for past periods of Medicaid expenditure growth to influence the present period. In dynamic specifications that account for this trend in health care spending, the growth of Medicaid coverage does not have a statistically significant impact. These specifications potentially reflect that increases in Medicaid insurance allow individuals to become more informed regarding health and wellness which improves health outcomes reducing expenditures on chronic conditions. Alternatively, inclusion of this trend could reflect that states choose to control expenditure growth through a reduction in Medicaid benefits after experiencing budgetary pressures from growth in Medicaid expenditures in previous periods. This reduction in Medicaid benefits is equivalent to substitution at the intensive margin.

Given that health care reform is expected to expand health insurance coverage to up to 46.3 million uninsured Americans, this research sheds light on how Medicaid expenditure may be affected.[4] Since projected estimates of Medicaid insurance growth from health care reform are in line with previous growth from 1996-2004, empirical evaluation gives us an indication of whether states' fears regarding an unfunded mandate are legitimate. From a dynamic panel model perspective, evidence from this paper suggests that growth in health insurance coverage is not likely to influence the growth in Medicaid expenditures, and that aging of the population represents a more critical concern.

This paper is organized as follows: Section 2 describes a conceptual framework for the impact of health insurance and other the determinants of Medicaid expenditure,

[4]U.S. Census Bureau: Income, Poverty, and Health Insurance Coverage in the United States: 2008, Current Population Reports, page 20, issued September 2009.

Section 3 discusses the empirical strategy and data, Section 4 presents results, Section 5 offers a discussion, and Section 6 concludes.

## 4.2 Determinants of Medicaid Expenditure Growth

Regarding the literature on health care expenditure growth, research at the state-level is limited and primarily focuses on empirical techniques surrounding total health expenditure's cointegration with state gross domestic product (see Freeman (2003),Wang and Rettenmaier (2007), and Moscone and Tosetti (2010)). Due to previous emphasis on empirical methods, an investigation of a wide variety of previous literature and theory is necessary to consider the broadest possible set of determinants of Medicaid expenditure growth. Theories of government expenditure generally tend to focus on either: 1) the supply-side which deals with the government's provision of services or 2) the demand-side working through political economy mechanisms. Supply side theories suggest the government is responsible for the provision of services, while most early demand theories allow for the determination of services to depend upon the median voter (Downs (1957)). However, the public sector does not necessarily provide the level of service the median voter wants. Romer and Rosenthal (1979) explain this by demonstrating that a budget-maximizing elected official can manipulate the alternatives presented to the electorate enabling political outcomes other than those preferred by the median voter. Therefore, demand side theories suggest that variation in government expenditure is potentially a function of electoral rules, type of government, and degree of political participation.

In this paper, the framework for identifying potential determinants of Medicaid expenditure considers both supply-side and demand-driven factors. Representing the supply side are a variety of socio-economic factors inherent in the population that potentially affect the provision of services through utilization. Demand-driven factors include spillover effects from interstate competition and a measure of the political environment within a state.

### 4.2.1 Health Insurance Coverage

There are many ways in which the growth in private and public health insurance coverage potentially affects Medicaid expenditure growth. In this analysis, Medicaid, Medicare, and military health insurance represent the differing forms of public coverage. The growth in private coverage potentially works through a price channel, while changes in Medicaid coverage work through a quantity channel. The growth in military and Medicare coverage may impact Medicaid expenditure growth if changes in these programs' reimbursement rates impact Medicaid reimbursement rates. The effect of private coverage is discussed first followed by Medicaid coverage. The impacts of military and Medicare coverage are considered together.

The growth in private health insurance potentially has a positive or null effect on the growth in Medicaid expenditure. These effects work through a pricing channel, which is framed by how the private market influences the price of care. Feldstein (1973b) shows that health insurance expansion increases the demand for medical services. The increase in demand for services stems from the fact that individuals' out of pocket costs are reduced; therefore, they are only partially incurring the marginal cost for utilized care. This means that as insurance expands more individuals use more services, because previously uninsured individuals' marginal cost of care is reduced. In the case of the positive effect, this increase in demand for services is large enough to increase the overall price of medical care, when supply is less than perfectly elastic, and puts pressure on Medicaid reimbursement rates.

The pressure on Medicaid reimbursement rates comes from behavior on the part of medical practitioners. These practitioners could select to see privately insured patients over those on Medicaid, because reimbursement rates from private insurance companies more accurately reflect the increasing price of care. Previous studies find that physicians do in fact alter their behavior toward patients based upon reimbursement rates. Specifically, increases in reimbursement rates lead to an increase in the number of private physicians willing to treat Medicaid patients (Decker (2007)), an increase in the length of time spent with patients (Decker (2007)), as well as a larger portion of the practice being devoted to Medicaid patients (Baker and Royalty (2000)). Subsequently, states are potentially induced to increase their reimbursement rates, so that those with Medicaid insurance can find practitioners willing to provide them with care. Through this channel involving the price of medical services, private insurance growth potentially positively affects the growth in Medicaid expenditure.

However, private insurance could also have no impact on the growth of Medicaid expenditure. If the price of medical services does not change when more individuals gain insurance through the private market, then an increase in private coverage potentially does not affect the growth of Medicaid expenditure. This could stem from the possibility that those who have private insurance come from the healthiest segments of the population requiring very few medical services beyond preventative care. This means that demand for care may increase by only a small amount and fail to push prices up enough to exert any pressure on reimbursement rates. In this case, changes in private insurance would have no effect on changes in Medicaid expenditure growth.

Besides the effect from the private insurance, the growth in Medicaid coverage could also have a positive or null effect on the growth of Medicaid expenditure. These effects function through a quantity channel, because the growth in Medicaid insurance increases the quantity of patients potentially requiring care under Medicaid. A positive effect stems from the fact that the growth in the number of insured on Medicaid increases the demand for care, and in turn increases the growth of Medicaid expenditure. Adams and Wade (2001) find a significant positive relationship between the number of enrollees and Medicaid expenditure in levels. However, an increase in Medicaid coverage may not necessarily guarantee an increase in the growth of Medicaid expenditure. If the growth in Medicaid insurance improves access to preventative care, which in turn increases awareness regarding health and wellness issues, then health outcomes might improve leading to a reduction in expenditures on chronic conditions. Alternatively, a null effect maybe supported by the fact that states may adjust the services they choose to reimburse as eligibility expands in order to maintain costs. Howard (2010) points out it is not certain that states will maintain the health care benefits at original levels when Medicaid enrollment expands. Baicker (2005a) also finds evidence that states substitute health benefits for eligibility in order to maintain costs. In this case, if the substitution of benefits for costs generated by increased coverage is great enough, the growth in Medicaid insurance may have no effect on Medicaid expenditure growth.

Other forms of public coverage such as military and Medicare insurance also may impact the growth in Medicaid expenditure. These impacts are only likely if growth in these types of coverage influences their reimbursement rates, which in turn influences changes in Medicaid's reimbursement rates. In this study, it is not expected that the growth in these types of coverage will affect the growth of Medicaid expenditure. However, because of potential differing effects from the price and quantity channel, empirical evaluation of the effect of growth in private and Medicaid coverage on the growth of Medicaid expenditures is important.

### 4.2.2 Socioeconomic Factors

The prior literature finds that other socioeconomic factors affect the utilization of medical services and can thus influence Medicaid expenditure through channels outside of insurance. Therefore, controlling for other socio-economic factors that possibly affect expenditure is imperative. Other socioeconomic factors considered as determinants of Medicaid expenditure are: income, unemployment, health status of the population, education, age of the population, and private health care expenditure.

In general, one would expect that wealthier states with larger income growth would see a decline in Medicaid eligibility and a decrease in Medicaid expenditure growth. However, tastes for redistribution of wealth might mean that wealthier states have a greater ability to pay for Medicaid insurance within their states. Holahan and Cohen (1986) and Buchanan et al. (1991) examine variations in the levels of

Medicaid spending and find that states with income do spend more on their Medicaid programs. Holahan and Cohen (1986) proxy for income using state gross domestic product (SGDP) deflated by a gross national product price deflator. Buchanan et al. (1991) argue that this measure does not capture cross-state differences in price levels and utilize personal income per capita in their analysis. In this study, SGDP per capita will proxy for income; and cross-state differences in price levels will be captured by using a regional price deflator suggested by Matteo (2005). In light of early work, the growth in SGDP per capita is expected to have a positive impact on the growth of Medicaid expenditure.

Unemployment may also influence the growth of Medicaid expenditure, since a portion of individuals who lose their jobs and possibly their employer provided health insurance also meet Medicaid eligibility standards. While the Consolidated Omnibus Budget Reconciliation Act (COBRA) of 1986 allows workers the right to choose to continue group health benefits with their former employer provided that these individuals are willing to pay their employers' share of the insurance, it is unlikely that individuals who experience job loss and meet Medicaid eligibility standards would be able to afford this option. In some instances, Medicaid actually helps to cover COBRA premiums. Examining Medicaid enrollment, Adams and Wade (2001) find that an increase in the unemployment rate increases children's enrollment but does not affect adult enrollment. In this study, the effect of unemployment rate growth on Medicaid expenditure growth is likely to be positive but may not be statistically significant.

Health status of the population within a state also potentially influences the growth in Medicaid expenditure. Presumably, the healthier the population within a state the less utilization of medical care services is likely needed. Less utilization potentially means a decline or slowing of the growth in Medicaid expenditure. Health status of the population in practice is very difficult to measure; however, lifestyle choices likely affect the health status of a population. In general, increases in the prevalence of diseases such as cancer and heart conditions are contributing to the rise in utilization of medical services. In this study, the portion of the population that smokes will proxy for health status of the population. Smoking increases the prevalence of disease within smokers as well as non-smokers through second-hand effects. Smoking is closely linked as a cause of cancers such as: lung, oral cavity, stomach, cervical, kidney, pancreas, as well as acute myeloid leukemia.[5] Non-smokers who are exposed to second hand smoke also increase their lung cancer risk by 20% to 30%.[6] In addition to cancer, secondhand smoke exposure causes an estimated 46,000 heart disease deaths annually among adult nonsmokers in the United States. [7] Those states with less smokers potentially have populations that take better care of themselves and have lower prevalence of disease requiring less care for chronic conditions. This reduces the growth of Medicaid expenditures by reducing the demand for medical services. Thus, the growth the portion of the non-smoking portion of the population is expected to decrease the growth in Medicaid expenditure.

Along with health status, education within the state also potentially affects the growth of Medicaid expenditure. Grossman (1972) contends that individuals with more education have a better ability to care for themselves and are more efficient in the production of health. Individuals with higher levels of education may be more informed regarding health and wellness, which may lead to better health outcomes through preventative measures and less demand for care of chronic conditions. Cutler and Lleras-Muney (2006) find that education contributes to better reasoned choices regarding health related behaviors. This in turn reduces the demand for medical services and decreases Medicaid expenditure growth. Therefore, the growth in individuals with higher levels of education could decrease the growth in Medicaid

[5]Surgeon General's Report, 2004, Office on Smoking and Health, National Center for Chronic Disease Prevention and Health Promotion. pp.137, 167, 170, 183, 254, 324-325.

[6]U.S. Department of Health and Human Services. The Health Consequences of Involuntary Exposure to Tobacco Smoke: A Report of the Surgeon General. Atlanta: U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, Coordinating Center for Health Promotion, National Center for Chronic Disease Prevention and Health Promotion, Office on Smoking and Health, 2006 (accessed July 22, 2011).

[7]Centers for Disease Control and Prevention. Smoking Attributable Mortality, Years of Potential Life Lost, and Productivity Losses United States, 2000-2004, Morbidity and Mortality Weekly Report 2008; 57(45):1226-8 (July 22, 2011).

expenditures. However, in the event that individuals with higher education are confronted with an illness, they may potentially seek out more second opinions regarding a diagnosis than those with less education. In addition, these individuals may spend time searching for more innovative and costly treatments contributing to the rise in expenditures. In this study, the portion of the population with at least a bachelor's degree will proxy for educational attainment within states. It is expected that an increase in the growth of education likely decreases the growth in Medicaid expenditure.

In addition, age distribution of the population also potentially influences Medicaid expenditure growth. The portion of the population over 65 years of age has more chronic conditions requiring more medical care. In fact, 90.7% of this population have one or more chronic conditions. [8] As life expectancy of this group is increases, this portion of the population has an increased probability of developing a chronic condition and also requires longer periods of care for those conditions. A rise in the number of chronic conditions increases utilization of medical services contributing to Medicaid expenditure growth. Medicaid expenditure growth is potentially affected because even though this portion of the population qualifies for Medicare insurance, some individuals who qualify can use Medicaid benefits as supplemental insurance.[9] In addition, Medicaid also covers long term care for qualified individuals age 65 and over. Aging as an explanation for increases in total health care expenditure has been investigated within the literature yielding mixed conclusions. Zweifel et al. (1999) find evidence to support that aging is not a significant cause of the rise in total health care expenditure when age in relationship to death is controlled for. However, Werblow et al. (2007) find that age of population does matter especially with respect to long term care. Seshamani and Gray (2004) refine econometric techniques in previous studies and conclude that both aging and age in relationship to death impact

[8] Robert Wood Johnson Foundation, www.rwjf.org/files/research/50968chronic.care.chartbook.ppt, (accessed on July 22, 2010).

[9] Information found at http://www.medicaid.ms.gov/EligibilityGuides/AgedDisabledEligibility.pdf assessed on 07/11/2011.

rising hospital expenditure. In light of the relationship between this portion of the population, the prevalence of chronic conditions, and utilization of medical services, it is expected that growth in this portion of the population will increase the growth in Medicaid expenditure.

While the share of the population 65 and over will likely affect Medicaid expenditure growth, so too will the share of the portion of the population that is 17 and under. The growth in this portion of the population may either increase or decrease the growth in Medicaid expenditure. This portion of the population often requires more preventative care which is associated with an increase in utilization and expenditure. However, this portion of the population also has the lowest percentage of chronic conditions. Only 27% of children ages 0-19 have one or more chronic conditions as compared to 40% for individuals ages 20-44, 68.0% for ages 45-64, and the 90.7% of those 65 and older. [10] Since chronic conditions account for 75% of all health care spending, it is expected that the utilization for chronic care out weights that of preventative care. [11] Therefore, an increase in the portion of the population 17 and under is expected to cause a decrease in Medicaid expenditure.

One other important factor that potentially influences the growth of Medicaid expenditure is private health care expenditure. On one hand, private health expenditure could be a substitute for Medicaid expenditure. If more individuals have the ability to pay for their own care, then there is less of a need for Medicaid expenditure. In examination of determinants of public health care spending for OECD countries, Potrafke (2010) found a negative relationship between private and public health expenditure. However, increases in private health care expenditure could also have a positive effect on Medicaid expenditure through the price channel. If the growth in private health care expenditure is large enough, it could increase the price of care through increases in utilization and put pressure on government reimbursement

[10] Robert Wood Johnson Foundation, www.rwjf.org/files/research/50968chronic.care.chartbook.ppt, (accessed on July 22, 2010).

[11] Centers for Disease Control and Prevention: Chronic Disease Overview, http://www.cdc.gov/chronicdisease/overview/index.htm, accessed on (07/20/2011).

rates. In this study, it is expected that private health care expenditure will work as a substitute for Medicaid expenditure, rather than through the price channel. Thus, the expected impact of an increase in private health care expenditure growth is a decrease in Medicaid expenditure growth.

### 4.2.3 Interstate Competition

While socio-economic factors play an important role as determinants of Medicaid expenditure growth, spillover effects from interstate competition and the political environment are important demand side factors that deserve consideration. Because interstate competition likely causes spillover effects from neighboring states, it is important to acknowledge the role that these states have on expenditure. The idea of a "neighbor" state was first defined within the interstate competition literature that focused on tax competition (Case and Hines (1993), Heyndels and Vuchelen (1998), Brueckner and Saavedra (2001), Buettner (2001), and Rork (2003)) and program adoption (Brueckner (1998) and Fredriksson and Millimet (2002)).

States are potentially influenced by the spending of their neighbors for several reasons. First, states could be worried about that the benefits they offer for health care are more generous than other states. If their benefits are more generous, than individuals may have an incentive to move into that state putting an upward pressure on expenditures due to an increase in the base of individuals receiving those benefits. Potentially, states engage in a "race to the bottom" spawned by fears that excessive generosity creates unsustainable growth in Medicaid expenditure. Second, states also potentially react to actions of neighboring states because of yardstick competition. Yard stick competition occurs because voters judge how elected officials in their state are performing based on benchmark conditions from neighboring states. Baicker (2005b) suggests that voters do benchmark their state's performance against other states when considering health initiatives.

Previous studies find evidence that interstate competition affects expenditures. Specifically, Case et al. (1993) find per capita state government expenditure is positively and significantly affected by the expenditure of its neighbors. Figlio et al. (1999), Saavedra (2000), and Wheaton (2000) find spillover effects in welfare spending. Baicker (2005b) uses individual shocks to states' spending on Medicaid to isolate the influence on neighboring state spending and finds that each dollar of state spending causes an increase in neighboring states spending of approximately 90 cents. Because the literature identifies relatively large spillover effects, this study will consider the potential for interstate competition as a determinant of the growth in Medicaid expenditure. It is expected that an increase in the growth of neighbor spending increases the growth of Medicaid expenditure.

In addition to interstate competition, variation in Medicaid expenditure could be explained as a function of the political environment within a state. Potentially, the extent to which the state is run by liberals or conservatives could affect how much is spent by the state on health care. Cromwell et al. (1987) found that when other factors were held constant, Medicaid enrollment rates were higher in more liberal states. However, Buchanan et al. (1991) found that a liberal index (based on the average ratings given to each state's delegation to the U.S. House of Representatives) was not significant in explaining Medicaid expenditure. In this study, the political environment is proxied for by considering whether the majority of the state legislature is held by Democrats or Republicans. An increase in the Democratic majority within the state legislature could have a a positive effect on Medicaid expenditure; however, in light of the Buchanan et al. (1991) study, this effect is not expected to be significant.

In addition, the political environment within a state could also encompass political interest groups that may try to influence Medicaid expenditure growth. If the medical industry can lobby for less restrictive criteria and higher payments, then Medicaid expenditure growth could increase. This means that the growth in the number of physicians is also an important control variable because it proxies for the power of political interest groups within a state as well as other potential influences. It is expected that as the growth of the number of physicians within a state has a positive effect on the growth of Medicaid expenditure.

## 4.3 Empirical Specification and Data

In this paper, I use state-level panel data from 1996-2004 capitalizing on within-state variation to identify whether growth in private and public types of health insurance coverage influences Medicaid expenditure growth.[12] I choose to focus on growth rates, because growth rates give insight into long term trends that drive health care costs. Analyzing trends is also important because individuals who have health conditions today are likely to have the same conditions or side effects from these conditions in the future requiring additional care and subsequent expenditure.

The dependent variable is Medicaid expenditure growth per capita, or $Medicaidexp$. To capture, the portion of Medicaid expenditure that states fund vice the portion which is subsidized by the federal matching grants, I follow Adams and Wade (2001). Real state funded Medicaid expenditure is constructed as real Medicaid expenditures times $(1 - FMAP)$, where $FMAP$ represents the Federal Medical Assistance Percentage. This measure is divided by the total population and then a growth rate is calculated to form $Medicaidexp$. While revenues raised through special tax and donation programs were of concern during the Adams and Wade (2001) time period of study, I utilize data after the passage of the Medicaid Voluntary Contribution and Provider Specific Tax Amendments of 1991 which curtailed the use of these programs.

The main specification takes on the following form:

$$Medicaidexp_{it} = \alpha_{it} + \beta PrivateHI_{it} + \gamma PublicHI_{it} + \delta' X_{it} + \theta IComp_{-it} + \eta_i + \epsilon_t + \mu_{it}. \tag{4.1}$$

[12] DC, Alaska, and Hawaii are excluded from the analysis.

where $i = 1, ..., n$ denotes a state, and $t = 1, ..., T$, a year. $PrivateHI$, represents the growth of the share of the population with private health insurance coverage. $PublicHI$ represents 3 separate variables included in the specification: 1) the growth of the share of population with Medicaid health insurance, $MedicaidHI$, (2) the growth of the share of population with Medicare insurance, $MedicareHI$, and (3) the growth of the share of population with military insurance, $MilitaryHI$.

The term, $X_{it}$, includes the growth rates of a number of variables that proxy for the socio-economic determinants and political environment discussed in Section 2. These variables include the growth rate of: real state gross domestic product per capita (*SGDP*), the unemployment rate (*Unemployment*), share of the population that smokes (*Smoke*), share of the population with at least a bachelor's degree (*Bachelor degree*), share of the population 65 and over ($Share65$), share of the population 17 and under ($Share17$), real private health care expenditures per capita (*PrivateHCE*), and the number of physicians per capita (*Physicians*). Two dummy variables, *LowerHouse* and *UpperHouse*, proxy for the political environment within the state legislature. The variables reflect the presence of democratic control in the lower and upper house of the state legislatures in any given year. The dummy variable was constructed by assigning a value of 1 to legislatures that had a democratic majority. Otherwise, the variable took on a value of zero.

Interstate competition is captured through the term, $IComp_{-it}$. This captures the weighted average of all other states' *Medicaidexp* growth lagged one period

$$IComp_{-it} = \sum_{i \neq j} w_{ij} Medicaidexp_{j,t-1}, \tag{4.2}$$

where $w_{ij}$ are exogenously chosen weights such that $\sum_{i \neq j} w_{ij} = 1$. Brueckner (2003) suggests that the choice of weights is based upon prior judgment about the pattern of interaction.

To see if neighborhood effects matter within a growth context, I follow Baicker (2005b) and use one of her proposed weighting structures that considers geographic contiguity. For each of the 48 states, the weighting structure is as follows:

$$w_{ij} = \begin{cases} 1/n_{ij} & \text{j} \in N_i \\ 0 & \text{j} \notin N_i \end{cases} \tag{4.3}$$

such that other states that share a border become part of a set $N_i$, and $n_i = N_i$. Within the inter-state competition context, the lag of $Medicaidexp$ growth is used in this specification. Use of the lag of dependent variable in this context provides two main advantages. The first advantage is that it accurately captures the time states require to learn about changes in other states' spending and then make the necessary budgetary adjustments to affect their own expenditure. The second advantage is that it deals with an econometric issue that arises from the use of the dependent variable. Use of the dependent variable causes simultaneity bias that occurs because states compete against each other to determine levels of government spending; therefore, expenditures of one's neighbors are simultaneously determined with home state expenditures. Put another way, Tennessee's Medicaid expenditures may be affected by Medicaid policy decisions within Alabama, and in turn Alabama responds, which affects Tennessee's policy decisions. Lastly, $\eta_i$ represents any potential state fixed effect not eliminated by the growth rates, $\epsilon_t$ is a temporal effect, and $\mu_{it}$ represents the error term.

In identifying the impact of the growth in private and public health insurance coverage on the growth in Medicaid expenditure, I explore random effects, fixed effects, and two different dynamic panel estimators proposed by Arellano and Bond (1991) and Arellano and Bover (1995). These specifications eliminate any unobservable time-invariant state effects and temporal effects that may systematically affect Medicaid expenditure growth. I consider dynamic panel estimators because growth rates of Medicaid expenditure in the current period are potentially related to the growth rates of Medicaid expenditure in the previous periods. This is due to the fact that individuals who have health conditions today are likely to have chronic effects from these conditions tomorrow requiring additional care and subsequent expenditure. In their examination of total health care expenditure, Okunade and Suraratdecha (2000) include the lag of the dependent variable as an explanatory variable to account for inertia. They believe this inertia may result from time trends and semi-durability of consumption of health spending. Further, Buchanan et al. (1991) notes that traditional budgetary theory dictates that the level of Medicaid spending in the prior year should affect the level of spending in the current year.

In the dynamic panel specifications, two additional terms, $Medicaidexp_{it-1}$ and $Medicaidexp_{it-2}$ , are included in Equation (1). Inclusion of these lags of the dependent variable causes endogeneity issues for the within estimator used by fixed and random effects specifications, because these terms introduce correlations with $\eta_i$, the state fixed effect. Dynamic panel estimators deal with these issues by using the first difference to eliminate the state fixed effect. The Arellano-Bond estimator instruments for the lag of the dependent variable in the first difference model with other lagged levels of the dependent variable or other variables already specified within the model to obtain consistent estimates. As a robustness check, I use the Arellano-Bover estimator for the second dynamic panel specification. The Arellano-Bover estimator is the same in all respects to the Arellano-Bond estimator except that it allows lagged differences of the dependent variable to also be utilized as instruments for the lagged levels of the dependent variable. I follow Potrafke (2010) in the choice to use dynamic panel estimators in combination with growth rates.

Data sources are outlined in Table C.1 of Appendix C. *PrivateHCE* was constructed for each state and year by subtracting reported expenditures on Medicaid and expenditures on Medicare from total health care expenditure. All expenditure variables by state and year were deflated using a regional consumer price index (CPI). All real variables were calculated with 1995 as the base year. Following Matteo (2005), states were divided into the following regions: New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains, and Far West. A regional CPI was matched to each region. Table C.2 shows the state-region classifications for each CPI. Annual growth rates were constructed for all variables.[13]

Figure C.1 shows the average annual growth rates across states for private health insurance coverage, Medicaid coverage, and Medicaid expenditures from 1996-2004. The growth in private health insurance coverage shows a steady increase until 1999, and then declines until 2002. Over the entire time period, the largest average annual growth in private health insurance coverage across states is around 1.8%.

In contrast, the average annual growth in Medicaid coverage shows an initial decline but then increases until almost the end of the period. Average growth ranged from a low of -8.1% in 1997 to a high of 7.5% in 2002. To address concerns regarding external validity, these estimates are in line with projected annual growth in Medicaid coverage expected from recent health care reform. Under a standard participation scenario that assumes moderate levels of participation among those newly eligible for coverage, Holahan and Headen (2010) project that Medicaid coverage across states is likely to increase 27.4% from 2014 to 2019. This equates to an average growth rate of 4.9% per year which falls in the range of annual Medicaid insurance growth during this study. The growth in Medicaid expenditures across states is always positive over the time period, and ranges from a low of 1.3% in 1998 to a high of 8.5% in 2002.

Panel summary statistics as well as those for specific years (1996, 2000, and 2004) are included in Table C.3 of Appendix C.

## 4.4 Results

Table C.4 presents regression results for the the growth in expenditure on Medicaid. Due to time trends and semi-durability of health consumption, the dynamic specifications in columns (1) and (2), more accurately capture the underlying data generating process by allowing for lags of the dependent variable to be considered as explanatory variables within the model. In each specification, two lags of

[13] In the case of missing data, linear interpolation is used for the education and smoking variables.

the dependent variable were necessary in order to remove higher orders of serial correlation. In these specifications, test statistics for second order autocorrelation and higher fail to reject the null hypothesis meaning that there is no serial correlation in the original error as desired. Further, in these specifications, the number of instruments exceeds the number of endogenous variables meaning that these models are over-identified. A test for over-identifying restrictions confirms that the population moment conditions are correctly specified. [14]

The Arellano-Bond specification in Column(1) is the main specification for the discussion of results. The Arellano-Bover specification offers a robustness check to the main specification. A fixed effects model is presented as a static model which serves as a baseline for comparison of the dynamic panel estimators. In addition, the random effects specification is included because a Hausman test of fixed verses random effects fails to reject the null hypothesis in which the random effects estimator is consistent and efficient. The coefficients and standard errors for all model specifications appear in Columns (1)-(4).

In Column (1), the growth in private coverage does not have a statistically significant impact on the growth of Medicaid spending. The Arellano-Bover specification provides similar evidence regarding the statistical significance of this impact. The growth in Medicaid coverage also does not have a statistically significant impact on the growth of Medicaid expenditures in both dynamic specifications. In the static models, this effect is statistically significant. The difference between the dynamic and static specifications further highlights how failure to capture time trends within health care spending potentially leads to incorrect inference. Other forms of public and private health insurance growth do not have a statistically significant

[14]The number of instruments and p-values of the test for over-identification are reported in Table C.4. It is important to note that these test statistics do not yield a value close to one. Roodman (2006) cautions when the tests statistics yield a p-value close to one, this is a sign that the model contains too many instruments. Including too many instruments within the specification can over-fit the endogenous variables and, therefore, fail to eliminate their endogenous components. Reporting the instrument count is important because another sign of an over-fit model is when the number of instruments more than exceeds the number of cross section observations.

impact on the growth of Medicaid expenditure in the main specification as well as the robustness check in column (2).

In terms of the socio-economic factors within the main specification, only the growth in private health care expenditure, share of the population over 65, and share of the population 17 and below have a statistically significant impact on the growth of Medicaid expenditure. Private health expenditure has a negative effect. The estimated coefficient indicates that a 1 percentage point increase the growth of private health expenditure decreases the growth of Medicaid expenditure by about 0.47 percentage points. The Arellano-Bover specification yields a similar result. To put this estimate into perspective, average Medicaid expenditure across states grew in nominal terms by 6.8% from 2003 to 2004. A back-of-the-envelope calculation based on average nominal Medicaid expenditure during these years shows that this impact translates into average annual savings of approximately 12.5 million dollars for a state.

The growth in the share of the population 65 and over has a positive statistically significant impact on the growth of Medicaid expenditure. For a 1 percentage point increase in the growth of the portion of the population over 65, there is approximately a 0.86 percentage point increase in the growth of Medicaid expenditure. The result from column (2) also demonstrates evidence of this effect. Given this estimate and the nominal Medicaid expenditure discussed previously, a second back-of-the-envelope calculation suggests that growth in this demographic contributes to an average annual increase of approximately 18 million dollars in Medicaid expenditure for a state. In contrast, the growth in the share of the population that is 17 and below has a negative impact on Medicaid expenditure growth. A 1 percentage point increase in the growth rate of the share of the population 17 and below decreases the growth of Medicaid expenditure by approximately 0.48 percentage points. The other dynamic specification provides additional support for the sign and statistical significance of this result.

The growth in real state gross domestic product is not statistically significant in the main specification; however, it is in the Arellano-Bover specification. The estimated coefficient in Column (2) suggests that for a 1 percentage point increase in state gross domestic product there is approximately a 0.48 percentage point increase in the growth of Medicaid expenditure. The impacts of *Unemployment*, *Smoke*, and *Physicians* are not statistically significant in the main specification, and the robustness check from a second dynamic specification supports these results. With respect to the impacts of the political environment and the growth of neighbors' spending on the growth of Medicaid expenditure, none of these variables are statistically significant, and estimated coefficients in column(2) provide additional evidence of these results.

## 4.5 Discussion

The main contribution of this paper is to estimate the impact of growth in private and public types of health insurance on the growth of Medicaid expenditure. The results suggest that the growth in private health insurance coverage, Medicare, and military coverage do not impact the growth in Medicaid expenditure. The null effect of the growth in private health insurance coverage possibly stems from the fact that growth in this type of coverage may not be large enough to increase demand for care by enough to exert pressure on reimbursement rates through the pricing channel discussed in Section 4.2. It is also possible that those who have private insurance come from the healthiest segment of the population and require very few medical services beyond preventative care thereby minimizing the influence of the price channel.

In the dynamic specifications, the growth in Medicaid insurance coverage does not have a statistically significant impact on the growth of Medicaid expenditure. Only in the static specifications that do not account for long run trends in health care spending is the impact statistically significant. The dynamic specifications show that capturing long run trends in health care spending is important for correct inference into the effects of the growth in Medicaid coverage. One possible reason that Medicaid growth does not influence the growth in Medicaid expenditure in these specifications comes from improvements in access to care. Since the growth in Medicaid insurance improves access to care, this could allow individuals to become more informed regarding health and wellness, which in turn improves health outcomes and reduces expenditures on chronic conditions. Alternatively, inclusion of the long run trend in dynamic specifications could reflect that states choose to control Medicaid expenditure growth through a reduction in Medicaid benefits after experiencing budgetary pressures from growth in these expenditures in previous periods. This reduction in Medicaid benefits is equivalent to substitution at the intensive margin.

Focusing on the dynamic specifications, the factors that have a statistically significant impact on the growth of Medicaid expenditure are the growth in state gross domestic product, private health care expenditure, the share of the population 17 and below, and the share of population 65 and over. The positive statistically significant impact of state gross domestic product on Medicaid expenditure growth suggests that states have a taste for redistribution in that as they generate more income they spend more on their Medicaid programs. In studies of Medicaid expenditure inclusive of federal dollars, Holahan and Cohen (1986) and Buchanan et al. (1991) find similar results.

There are two impacts that have a statistically significant negative effect on the growth of Medicaid expenditure. These results merit particular attention because of their potential to bend states' Medicaid expenditure curves. First, the impact of the growth in private health care expenditure is negative. This relationship implies that private health care expenditure serves as a substitute for public expenditure. The back-of-the-envelope calculation in Section 4.4 demonstrates that a state could save on average approximately 11 million dollars from the estimated effect. Second, the growth in the share of the population 17 and below has a negative effect on the growth of Medicaid expenditure. Growth in this share of the population may reduce the growth in Medicaid expenditures because this portion of the population has the lowest percentage of chronic conditions requiring medical care. However, population projections to 2030 for this age group suggest little growth in this demographic. [15]

The most consequential impact for states is that of the growth in the share of the population 65 and over. The growth in this portion of the population has a statistically significant positive impact on the growth of Medicaid expenditure. Health care trends for this age category show that life expectancy and chronic health conditions are increasing. This increase in chronic health conditions leads to an increase in the utilization of medical services. This increase in the demand for care contributes to Medicaid expenditure growth, because even though this portion of the population qualifies for Medicare insurance, some individuals rely on Medicaid for supplemental insurance or long term care. In fact, given the estimated impact from Section 4.4, this trend in growth may represent an even more pressing concern for states regarding the sustainability of Medicaid expenditure than the growth in health insurance coverage. A back-of-the-envelope calculation demonstrates that a 1 percentage point increase in the growth of this demographic translates to 18 million dollars in additional Medicaid expenditure for an average state. Population projections demonstrate that by 2030 the portion of the population 65 and over will represent 16 percent of the total population.[16] Given that currently 90.7% of this age category experience chronic conditions, states may want to focus more on the potential effects of an aging population and changes in Medicaid expenditure resulting from their care rather than changes in health insurance coverage stemming from recent health care reform.[17]

[15]U.S. Census Bureau, U.S. Population Projections.

[16]U.S. Census Bureau, U.S. Population Projections.

[17]Robert Wood Johnson Foundation, www.rwjf.org/files/research/50968chronic.care.chartbook.ppt, (accessed on July 22, 2010).

## 4.6 Conclusion

Since PPACA expands Medicaid eligibility, many state governors are concerned that it will make state funded expenditure on Medicaid unsustainable. In light of these concerns and recent research regarding health care expenditures, this study uses state-level panel data from 1996-2004 capitalizing on within-state variation to identify whether the growth in private and other public types of health insurance coverage, namely Medicaid, impact the growth of Medicaid expenditure. The results suggest that the growth of private health insurance coverage does not affect the growth in Medicaid expenditure. Further, given that the projected growth in Medicaid coverage from PPACA is in line with growth in Medicaid coverage during the time period of this study, one important finding is that growth in Medicaid insurance coverage does not influence the growth in Medicaid expenditures when time trends and the semi-durability of health care consumption are accounted for. While the growth in health insurance coverage does not appear to matter in terms of bending states' Medicaid expenditure curves, other factors such as private health care expenditure and age distribution do. Specifically, the growth in private health care expenditures and the share of the population 17 and under represent potential avenues for reducing the growth in Medicaid expenditure, while the growth in the portion of the population 65 and over increases it. Given that the share of the population 65 and over is projected to increase into 2030 and the fact 9 out 10 individuals in this age group has one or more chronic health conditions, states may want to focus more on the potential effects of an aging population within their state rather than changes in health insurance coverage stemming from the reform. In an effort to bend Medicaid expenditure curves, the exact mechanisms through which aging affects Medicaid expenditure growth warrants further research.

# Bibliography

# Bibliography


Adams, K. E. and Wade, M. (2001). Fiscal response to a matching grant: Medicaid expenditures and enrollments 1984-1992. *Public Finance Review*, 29(1):26–48. 46, 51, 53, 59

Afonso, A. and Aubyn, M. S. (2005). Non-parametric approaches to education and health efficiency in oecd countries. *Journal of Applied Economics*, 0:227–246. 13

Anderson, M., Dobkin, C., and Gross, T. (2010). The effect of health insurance coverage on the use of medical services. Working Paper 15823, National Bureau of Economic Research. 23, 27

Andrews, D. W. K. (1993). Tests for parameter instability and structural change with unknown change point. *Econometrica*, 61(4):pp. 821–856. 40

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2):277–297. 61

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1):29 – 51. 61

Baicker, K. (2005a). Extensive or intensive generosity? the price and income effects of federal grants. *The Review of Economics and Statistics*, 87(2):371–384. 52

Baicker, K. (2005b). The spillover effects of state spending. *Journal of Public Economics*, 89(2-3):529 – 544. 46, 57, 58, 60

Baker, L. C. and Royalty, A. B. (2000). Medicaid policy, physician behavior, and health care for the low-income population. *The Journal of Human Resources*, 35(3):480–502. 51

Balk, B. M. (2001). Scale efficiency and productivity change. *Journal of Productivity Analysis*, 15:159–183. 20

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, 119(1):pp. 249–275. 31

Bhat, V. (2005). Institutional arrangements and efficiency of health care delivery systems. *The European Journal of Health Economics*, 6(3):215–222. 9

Blank, J. and Valdmanis, V. (2010). Environmental factors and productivity on dutch hospitals: a semi-parametric approach. *Health Care Management Science*, 13(1):27–34. 9, 13

Boyle, M. and Lahey, J. (2010). Health insurance and the labor supply decisions of older workers: Evidence from a us department of veterans affairs expansion. *Journal of Public Economics*, 94(7-8):467–478. 7

Brown III, H. (2002). Managed care and technical efficiency. *Health Economics*, 12(2):149–158. 7, 19

Brueckner, J. K. (1998). Testing for strategic interaction among local governments: The case of growth controls. *Journal of Urban Economics*, 44(3):438–467. 57

Brueckner, J. K. (2003). Strategic interaction among governments: An overview of empirical studies. *International Regional Science Review*, 26(2):175–188. 60

Brueckner, J. K. and Saavedra, L. A. (2001). Do local governments engage in strategic property-tax competition? *National Tax Journal*, 54(2):203–229. 57

Buchanan, R. J., Cappelleri, J. C., and Ohsfeldt, R. L. (1991). The social environment and medicaid expenditures: Factors influencing the level of state medicaid spending. *Public Administration Review*, 51(1):67–73. 46, 52, 53, 58, 62, 67

Buettner, T. (2001). Local business taxation and competition for capital: the choice of the tax rate. *Regional Science and Urban Economics*, 31(2-3):215 – 245. 57

Card, D., Dobkin, C., and Maestas, N. (2008). The impact of nearly universal insurance coverage on health care utilization: Evidence from medicare. *American Economic Review*, 98(5):2242–58. 23, 27

Carey, K. (1998). Stochastic demand for hospitals and optimizing excess bed capacity. *Journal of Regulatory Economics*, 14(2):165–87. 25

Carrion-i Silvestre, J. (2005). Health care expenditure and gdp: are they broken stationary? *Journal of Health Economics*, 24(5):839–854. 6

Case, A. and Hines, J. (1993). Interstate tax competition after tra 86. *Journal of Policy Analysis and Management*, 12(1):136–148. 57

Case, A. C., Rosen, H. S., and Hines, J. R. (1993). Budget spillovers and fiscal policy interdependence: Evidence from the states. *Journal of Public Economics*, 52(3):285 – 307. 58

Chiu, W. (1997). Health insurance and the welfare of health care consumers. *Journal of Public Economics*, 64(1):125–133. 7

Chou, S., Liu, J., and Hammitt, J. (2003). National health insurance and precautionary saving: evidence from taiwan. *Journal of Public Economics*, 87(9-10):1873–1894. 7

Cowing, T. G. and Holtmann, A. G. (1983). Multiproduct short-run hospital cost functions: Empirical evidence and policy implications from cross-section data. *Southern Economic Journal*, 49(3):pp. 637–653. 28

Cromwell, J., Hurdle, S., and Schurman, R. (1987). Decentralizing medicaid: Fair to the poor, fair to taxpayers? *Journal of Health Politicas, Policy, and Law*, 12(1):1–34. 58

Currie, J. and Gruber, J. (1996). Health insurance eligibility, utilization of medical care, and child health. *The Quarterly Journal of Economics*, 111(2):431–466. 23, 27

Custer, W. and Willke, R. (1991). Teaching hospital costs: the effects of medical staff characteristics. *Health Services Research*, 25(6):831. 20

Cutler, D. and Gruber, J. (1996). Does public insurance crowd out private insurance? *The Quarterly Journal of Economics*, 111(2):391. 7

Cutler, D. M. and Lleras-Muney, A. (2006). Education and health: Evaluating theories and evidence. Working Paper 12352, National Bureau of Economic Research. 54

Dafny, L. and Gruber, J. (2005). Public insurance and child hospitalizations: access and efficiency effects. *Journal of Public Economics*, 89(1):109 – 129. 23, 27

Debreu, G. (1951). The coefficient of resource utilization. *Econometrica: Journal of the Econometric Society*, 19(3):273–292. 11

Decker, S. (2007). Medicaid physician fees and the quality of medical care of medicaid patients in the usa. *Review of Economics of the Household*, 5:95–112. 50, 51

Downs, A. (1957). An economic theory of political action in a democracy. *The Journal of Political Economy*, 65(2):pp. 135–150. 49

Fairlie, R., Kapur, K., and Gates, S. (2010). Is employer-based health insurance a barrier to entrepreneurship? *Journal of Health Economics*. 7

Farrell, M. J. (1957). The measurement of productive efficiency. *Journal of the Royal Statistical Society. Series A (General)*, 120(3):pp. 253–290. 11

Felder, S., Meier, M., and Schmitt, H. (2000). Health care expenditure in the last months of life. *Journal of Health Economics*, 19(5):679 – 695. 6

Feldman, R. and Dowd, B. (1991). A new estimate of the welfare loss of excess health insurance. *The American economic review*, 81(1):297–301. 7

Feldstein, M. (1973a). The welfare loss of excess health insurance. *The Journal of Political Economy*, 81(2):251–280. 7

Feldstein, M. S. (1973b). The welfare loss of excess health insurance. *Journal of Political Economy*, 81(2):251–80. 1, 23, 44, 50

Ferrier, G. and Valdmanis, V. (1996). Rural hospital performance and its correlates. *Journal of Productivity Analysis*, 7(1):63–80. 20

Figlio, D. N., Kolpin, V. W., and Reid, W. E. (1999). Do states play welfare games? *Journal of Urban Economics*, 46(3):437 – 454. 58

Finkelstein, A. (2007). The aggregate effects of health insurance: Evidence from the introduction of medicare. *The Quarterly Journal of Economics*, 122(1):1–37. 23, 41, 45

Fredriksson, P. G. and Millimet, D. L. (2002). Strategic interaction and the determination of environmental policy across u.s. states. *Journal of Urban Economics*, 51(1):101 – 122. 57

Freeman, D. G. (2003). Is health care a necessity or a luxury? pooled estimates of income elasticity from us state-level data. *Applied Economics*, 35(5):495–502. 6, 49

Friedman, B. and Pauly, M. (1981). Cost functions for a service firm with variable quality and stochastic demand: The case of hospitals. *The Review of Economics and Statistics*, 63(4):620–24. 25, 28

Gerdtham, U.-G. and Jonsson, B. (2000). Chapter 1 international comparisons of health expenditure: Theory, data and econometric analysis. volume 1, Part 1 of *Handbook of Health Economics*, pages 11 – 53. Elsevier. 47

Gerdtham, U. G. and Lothgren, M. (2000). On stationarity and cointegration of international health expenditure and gdp. *Journal of Health Economics*, 19(4):461 – 475. 6

Gerdtham, U.-G., Sogaard, J., Andersson, F., and Jonsson, B. (1992). An econometric analysis of health care expenditure: A cross-section study of the oecd countries. *Journal of Health Economics*, 11(1):63 – 84. 5, 6

Gross, T. and Notowidigdo, M. (2011). Health insurance and the consumer bankruptcy decision: Evidence from expansions of medicaid. *Journal of Public Economics*. 7

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80:223–255. 54

Gruber, J. and Madrian, B. (1997). Employment separation and health insurance coverage. *Journal of Public Economics*, 66(3):349–382. 7

Gruber, J. and Simon, K. (2008). Crowd-out 10 years later: Have recent public insurance expansions crowded out private health insurance? *Journal of Health Economics*, 27(2):201–217. 7

Hartwig, J. (2008). What drives health care expenditure?–baumol's model of [']unbalanced growth' revisited. *Journal of Health Economics*, 27(3):603 – 623. 6, 47

Heim, B. and Lurie, I. (2010). The effect of self-employed health insurance subsidies on self-employment. *Journal of Public Economics*. 7

Heyndels, B. and Vuchelen, J. (1998). Tax mimicking among belgian municipalities. *National Tax Journal*, 51(1):89–101. 57

Hitiris, T. and Posnett, J. (1992). The determinants and effects of health expenditure in developed countries. *Journal of Health Economics*, 11(2):173 – 181. 5

Holahan, J. and Headen, I. (2010). Medicaid coverage and spending in health reform: National and state-by-state results for adults at or below 133% fpl. Technical report, The Urban Institute, Washington D.C. 63

Holahan, J. F. and Cohen, J. W. (1986). *Medicaid: The Trade-Off Between Cost Containment and Access to Care*. The Urban Institute, Washington D.C. 46, 52, 67

Hollingsworth, B. (2008). The measurement of efficiency and productivity of health care delivery. *Health Economics*, 17(10):1107–1128. 9

Holtz-Eakin, D., Penrod, J., and Rosen, H. (1996). Health insurance and the supply of entrepreneurs. *Journal of Public Economics*, 62(1-2):209–235. 7

Howard, L. L. (2010). Is the demand for health care generosity equal for all recipients? a longitudinal analysis of state medicaid spending, 1977-2004. *Public Finance Review*, 38(3):347–377. 52

Jensen, G. and Morrisey, M. (1986). The role of physicians in hospital production. *The Review of Economics and Statistics*, 68(3):432–442. 20

Jewell, T., Lee, J., Tieslau, M., and Strazicich, M. C. (2003). Stationarity of health expenditures and gdp: evidence from panel unit root tests with heterogeneous structural breaks. *Journal of Health Economics*, 22(2):313 – 323. 6

Joskow, P. L. (1980). The effects of competition and regulation on hospital bed supply and the reservation quality of the hospital. *Bell Journal of Economics*, 11(2):421–447. 25, 27, 28

Kolstad, J. and Kowalski, A. (2010). The impact of an individual mandate on hospital and preventative care: Evidence from massachusetts. *Working Paper*. 6, 23, 24, 27, 31, 36, 37, 39, 41, 45

Koopmans, T. (1951). Analysis of production as an efficient combination of activities. *Activity analysis of production and allocation*, 36:27–56. 11

Lehner, L. A. and Burgess, J. F. (1995). Teaching and hospital production: the use of regression estimates. *Health Economics*, 4(2):113–125. 20

Leu, R. (1986). The public-private mix and international health care costs. In *Culyer, A.J., Jonsson, B. (Eds.), Public and Private Health Care Services: Complementaries and Conflicts.* Basil Blackwell, Oxford. 46

Levin, L. (1995). Demand for health insurance and precautionary motives for savings among the elderly. *Journal of Public Economics*, 57(3):337–367. 7

Long, S. K. (2008). On the road to universal coverage: Impacts of reform in massachusetts. *Health Affairs*, 27(4):270–284. 6, 24

Long, S. K., Stockley, K., and Yemane, A. (2009). Another look at the impacts of health reform in massachusetts: Evidence using new data and a stronger model. *American Economic Review*, 99(2):508–11. 6, 24

Manning, W., Newhouse, J., Duan, N., Keeler, E., and Leibowitz, A. (1987a). Health insurance and the demand for medical care: evidence from a randomized experiment. *The American Economic Review*, 77(3):251–277. 7

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., and Leibowitz, A. (1987b). Health insurance and the demand for medical care: Evidence from a randomized experiment. *The American Economic Review*, 77(3):pp. 251–277. 23, 27

Matteo, L. D. (2005). The macro determinants of health expenditure in the united states and canada: assessing the impact of income, age distribution and time. *Health Policy*, 71(1):23 – 42. 6, 53, 62

McCoskey, S. K. and Selden, T. M. (1998). Health care expenditures and gdp: panel data unit root test results. *Journal of Health Economics*, 17(3):369 – 376. 6

McDonough, J., Rosman, B., Phelps, F., and Shannon, M. (2006). The third wave of massachusetts health care access reform. *Health Affairs*, 25:420–431. 23, 26

Miller, S. (2011). The effect of insurance on emergency room visits: An analysis of the 2006 massachusetts health reform. Working paper, University of Illinois-Urban Champagne. 24, 36

Moscone, F. and Tosetti, E. (2010). Health expenditure and income in the united states. *Health Economics*, 19(12):1385–1403. 6, 49

Mulligan, J. G. (1985). The stochastic determinants of hospital-bed supply. *Journal of Health Economics*, 4(2):177–181. 25, 28

Newhouse, J. (1993). *Free for All? Lessons from the RAND Health Insurance Experiment*. Harvard University Press, first edition. 1, 23, 27

Newhouse, J. P. (1977). Medical-care expenditure: A cross-national survey. *The Journal of Human Resources*, 12(1):pp. 115–125. 5, 46

Nyman, J. (1999). The value of health insurance: the access motive. *Journal of Health Economics*, 18(2):141–152. 6, 10

Okunade, A. and Suraratdecha, C. (2000). Health care expenditure inertia in the oecd countries: A heterogeneous analysis. *Health Care Management Science*, 3:31–42. 47, 62

Palangkaraya, A., Yong, J., Webster, E., and Dawkins, P. (2009). The income distributive implications of recent private health insurance policy reforms in australia. *The European Journal of Health Economics*, 10(2):135–148. 7

Parkin, D., McGuire, A., and Yule, B. (1987). Aggregate health care expenditures and national income : Is health care a luxury good? *Journal of Health Economics*, 6(2):109 – 127. 5, 46

Piehl, A. M., Cooper, S. J., Braga, A. A., and Kennedy, D. M. (2003). Testing for structural breaks in the evaluation of programs. *The Review of Economics and Statistics*, 85(3):pp. 550–558. 40

Pilyavsky, A. and Staat, M. (2008). Efficiency and productivity change in Ukrainian health care. *Journal of Productivity Analysis*, 29(2):143–154. 9

Potrafke, N. (2010). The growth of public health expenditures in oecd countries: Do government ideology and electoral motives matter? *Journal of Health Economics*, 29(6):797 – 810. 6, 47, 56, 62

Roberts, J. (1999). Sensitivity of elasticity estimates for oecd health care spending: analysis of a dynamic heterogeneous data field. *Health Economics*, 8(5):459–472. 47

Romer, T. and Rosenthal, H. (1979). Bureaucrats versus voters: On the political economy of resource allocation by direct democracy. *The Quarterly Journal of Economics*, 93(4):563–587. 49

Roodman, D. (2006). How to do xtabond2. North American Stata Users' Group Meetings 2006 8, Stata Users Group. 64

Rork, J. (2003). Coveting thy neighbors' taxation. *National Tax Journal*, 56(4):775–787. 57

Royalty, A. and Abraham, J. (2006). Health insurance and labor market outcomes: Joint decision-making within households. *Journal of Public Economics*, 90(8-9):1561–1577. 7

Saavedra, L. A. (2000). A model of welfare competition with evidence from afdc. *Journal of Urban Economics*, 47(2):248 – 279. 58

Seshamani, M. and Gray, A. (2004). Ageing and health-care expenditure: the red herring argument revisited. *Health Economics*, 13(4):303–314. 6, 55

Simar, L. and Wilson, P. (2000). Statistical inference in nonparametric frontier models: The state of the art. *Journal of Productivity Analysis*, 13(1):49–78. 8

Simar, L. and Wilson, P. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, 136(1):31–64. 7, 12, 13, 20

Smet, M. (2007). Measuring performance in the presence of stochastic demand for hospital services: an analysis of Belgian general care hospitals. *Journal of Productivity Analysis*, 27(1):13–29. 7

Spinks, J. and Hollingsworth, B. (2009). Cross-country comparisons of technical efficiency of health production: a demonstration of pitfalls. *Applied Economics*, 41(4):417–427. 9

Wagstaff, A. and Lindelow, M. (2008). Can insurance increase financial risk?:: The curious case of health insurance in china. *Journal of Health Economics*, 27(4):990–1005. 7

Wang, Z. and Rettenmaier, A. J. (2007). A note on cointegration of health expenditures and income. *Health Economics*, 16(6):559–578. 6, 49

Weisbrod, B. A. (1991). The health care quadrilemma: An essay on technological change, insurance, quality of care, and cost containment. *Journal of Economic Literature*, 29(2):523–52. 23

Werblow, A., Felder, S., and Zweifel, P. (2007). Population ageing and health care expenditure: a school of red herrings? *Health Economics*, 16(10):1109–1126. 6, 55

Wheaton, W. C. (2000). Decentralized welfare: Will there be underprovision? *Journal of Urban Economics*, 48(3):536 – 555. 58

Yelowitz, A. and Cannon, M. F. (2010). The massachusetts health plan: Much pain, little gain. *Working Paper, The Cato Institute*. 6, 24

Zweifel, P., Felder, S., and Meiers, M. (1999). Ageing of population and health care expenditure: a red herring? *Health Economics*, 8(6):485–496. 6, 55

# Appendix

# Appendix A

# Appendix

## A.1 Efficiency of Health Care Delivery Systems: Effects of Health Insurance Coverage

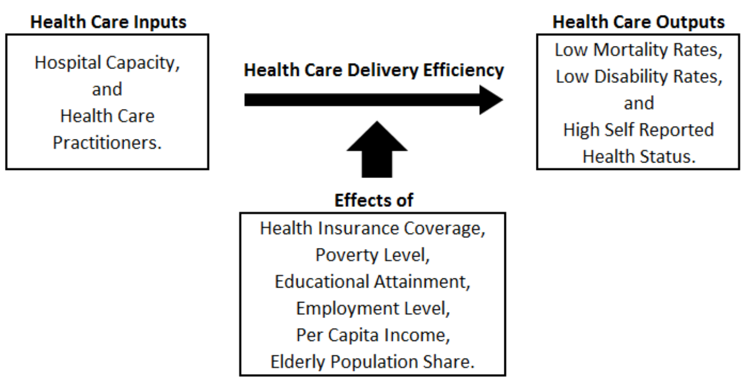


**Figure A.1:** A Health Care Delivery System

**Table A.1:** Data Sources

| Variable | Source |
|---|---|
| hospital beds | Centers for Medicare and Medicaid Services Hospital Cost Reports |
| physicians | Bureau of Labor Statistics database |
| registered nurses | Bureau of Labor Statistics database |
| population | U.S. Census Bureau, Population Division |
| health status | Centers for Disease Control and Prevention, Behavioral Risk Factor Surveillance System Annual Survey |
| disability | Social Security Administration, Disabled Beneficiaries and Dependents Master Beneficiary record file |
| mortality rate | Centers for Disease Control and Prevention, Vital Statistics of the United States; Mortality, 2001 |
| poverty | U.S. Census Bureau, Current Population Survey, 2009 Annual Social and Economic Supplements |
| employment | Bureau of Economic Analysis, State Income and Employment Summary, March 2009 |
| state gdp | Bureau of Economic Analysis, State Income and Employment Summary, March 2009 |
| high school diploma | U.S. Census Bureau, Statistical Abstract of the United States, 2010 |
| population 65+ | U.S. Census Bureau, Current Population Survey 2000-2007 |
| health insurance coverage | U.S. Census Bureau, Current Population Survey, 2009 Annual Social and Economic Supplements |

**Table A.2:** Summary Statistics - 2000

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Inputs** | | | | | |
| *hospital beds** | 48 | 2877.73 | 664.35 | 1802.37 | 4557.97 |
| *physicians** | 48 | 488.82 | 215.13 | 173.30 | 1389.71 |
| *registered nurses** | 48 | 8001.28 | 1426.66 | 5550.81 | 12018.70 |
| **Outputs** | | | | | |
| *healthy share* | 48 | 0.853 | 0.032 | 0.746 | 0.903 |
| *able share* | 48 | 0.978 | 0.006 | 0.959 | 0.989 |
| *survival share* | 48 | 0.991 | 0.001 | 0.988 | 0.994 |
| **Env. Variables** | | | | | |
| *poverty share* | 48 | 0.109 | 0.029 | 0.045 | 0.175 |
| *employment share* | 48 | 0.604 | 0.048 | 0.491 | 0.698 |
| *state gdp* † | 48 | 0.327 | 0.060 | 0.226 | 0.527 |
| *diploma share* | 48 | 0.853 | 0.040 | 0.771 | 0.918 |
| *share 65+* | 48 | 0.127 | 0.017 | 0.085 | 0.175 |
| *total coverage* | 48 | 0.876 | 0.038 | 0.763 | 0.929 |
| *private coverage* | 48 | 0.742 | 0.062 | 0.571 | 0.847 |
| *public coverage* | 48 | 0.254 | 0.037 | 0.180 | 0.327 |

* Per million of residents.
† Per resident, measured in 100 thousand dollars.

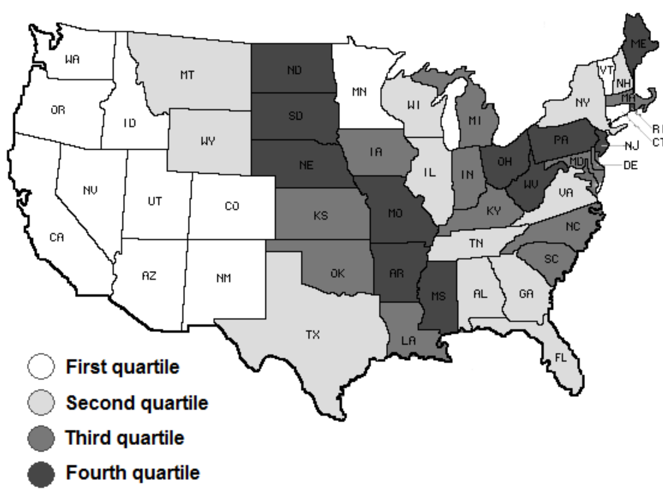


**Figure A.2:** 2007 Estimated Efficiency Map

**Table A.3:** Summary Statistics - 2004

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Inputs** | | | | | |
| *hospital beds** | 48 | 2778.33 | 648.79 | 1736.45 | 4491.93 |
| *physicians** | 48 | 386.17 | 175.22 | 127.94 | 804.55 |
| *registered nurses** | 48 | 8311.64 | 1448.88 | 5646.49 | 11659.96 |
| **Outputs** | | | | | |
| *healthy share* | 48 | 0.846 | 0.034 | 0.765 | 0.900 |
| *able share* | 48 | 0.974 | 0.008 | 0.950 | 0.987 |
| *survival share* | 48 | 0.992 | 0.001 | 0.989 | 0.994 |
| **Env. Variables** | | | | | |
| *poverty share* | 48 | 0.121 | 0.029 | 0.055 | 0.187 |
| *employment share* | 48 | 0.601 | 0.051 | 0.496 | 0.729 |
| *state gdp* † | 48 | 0.345 | 0.061 | 0.236 | 0.565 |
| *diploma share* | 48 | 0.864 | 0.037 | 0.783 | 0.923 |
| *share 65+* | 48 | 0.127 | 0.015 | 0.086 | 0.169 |
| *total coverage* | 48 | 0.863 | 0.034 | 0.758 | 0.915 |
| *private coverage* | 48 | 0.705 | 0.058 | 0.594 | 0.823 |
| *public coverage* | 48 | 0.277 | 0.044 | 0.190 | 0.372 |

* Per million of residents.

† Per resident, measured in 100 thousand dollars.

**Table A.4:** Summary Statistics - 2007

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| **Inputs** | | | | | |
| *hospital beds** | 48 | 2672.84 | 588.09 | 1627.61 | 3939.81 |
| *physicians** | 48 | 404.26 | 168.72 | 147.05 | 853.36 |
| *registered nurses** | 48 | 8609.88 | 1549.19 | 5442.74 | 12152.99 |
| **Outputs** | | | | | |
| *healthy share* | 48 | 0.844 | 0.032 | 0.769 | 0.891 |
| *able share* | 48 | 0.971 | 0.009 | 0.944 | 0.985 |
| *survival share* | 48 | 0.992 | 0.001 | 0.989 | 0.995 |
| **Env. Variables** | | | | | |
| *poverty share* | 48 | 0.119 | 0.029 | 0.058 | 0.226 |
| *employment share* | 48 | 0.619 | 0.053 | 0.509 | 0.764 |
| *state gdp* † | 48 | 0.362 | 0.066 | 0.242 | 0.581 |
| *diploma share* | 48 | 0.858 | 0.036 | 0.785 | 0.912 |
| *share 65+* | 48 | 0.129 | 0.015 | 0.089 | 0.171 |
| *total coverage* | 48 | 0.862 | 0.039 | 0.748 | 0.946 |
| *private coverage* | 48 | 0.695 | 0.062 | 0.558 | 0.799 |
| *public coverage* | 48 | 0.281 | 0.042 | 0.188 | 0.380 |

* Per million of residents.

† Per resident, measured in 100 thousand dollars.

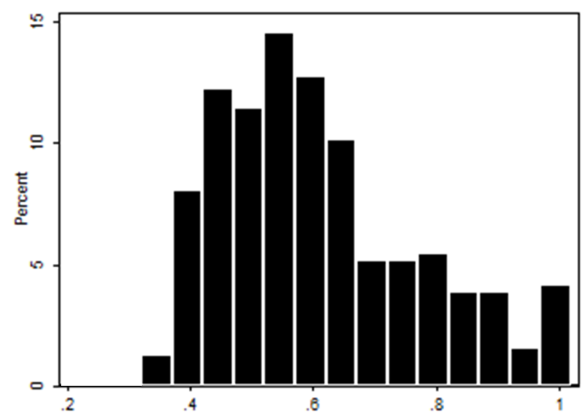


**Figure A.3:** Estimated Efficiency Histogram: 2000-2007

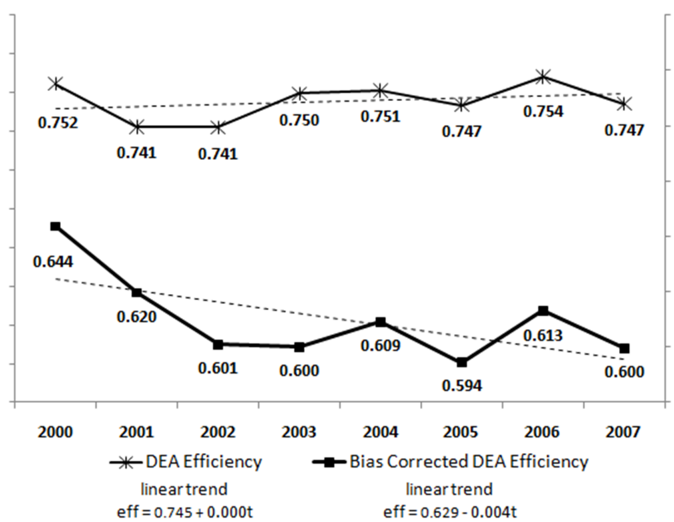


**Figure A.4:** Average Estimated Efficiency

**Table A.5:** SW Bias Corrected Efficiency

| State | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | Average |
|---|---|---|---|---|---|---|---|---|---|
| Alabama | 0.677 | 0.591 | 0.752 | 0.637 | 0.668 | 0.649 | 0.599 | 0.647 | 0.652 |
| Arizona | 0.919 | 0.945 | 0.803 | 0.830 | 0.853 | 0.921 | 0.976 | 0.926 | 0.896 |
| Arkansas | 0.797 | 0.740 | 0.719 | 0.635 | 0.562 | 0.523 | 0.548 | 0.459 | 0.623 |
| California | 0.842 | 0.856 | 0.858 | 0.890 | 0.875 | 0.817 | 0.808 | 0.844 | 0.849 |
| Colorado | 0.916 | 0.876 | 0.980 | 1.000 | 0.928 | 0.798 | 0.777 | 0.848 | 0.890 |
| Connecticut | 0.622 | 0.632 | 0.634 | 0.653 | 0.978 | 0.718 | 0.696 | 0.669 | 0.700 |
| Delaware | 0.626 | 0.660 | 0.586 | 0.589 | 0.575 | 0.545 | 0.589 | 0.524 | 0.587 |
| Florida | 0.489 | 0.536 | 0.615 | 0.583 | 0.536 | 0.498 | 0.523 | 0.562 | 0.543 |
| Georgia | 0.706 | 0.573 | 0.606 | 0.589 | 0.871 | 0.749 | 0.844 | 0.660 | 0.700 |
| Idaho | 0.770 | 0.731 | 0.713 | 0.619 | 0.805 | 0.836 | 0.876 | 0.948 | 0.787 |
| Illinois | 0.528 | 0.478 | 0.536 | 0.549 | 0.572 | 0.552 | 0.595 | 0.575 | 0.548 |
| Indiana | 0.554 | 0.535 | 0.464 | 0.467 | 0.460 | 0.477 | 0.492 | 0.463 | 0.489 |
| Iowa | 0.693 | 0.609 | 0.573 | 0.555 | 0.574 | 0.591 | 0.491 | 0.537 | 0.578 |
| Kansas | 0.674 | 0.610 | 0.554 | 0.493 | 0.493 | 0.522 | 0.516 | 0.478 | 0.542 |
| Kentucky | 0.617 | 0.609 | 0.643 | 0.642 | 0.590 | 0.639 | 0.629 | 0.541 | 0.614 |
| Louisiana | 0.471 | 0.449 | 0.601 | 0.596 | 0.536 | 0.469 | 0.495 | 0.508 | 0.516 |
| Maine | 0.539 | 0.425 | 0.486 | 0.479 | 0.423 | 0.439 | 0.523 | 0.395 | 0.464 |
| Maryland | 0.507 | 0.522 | 0.524 | 0.511 | 0.537 | 0.530 | 0.522 | 0.508 | 0.520 |
| Massachusetts | 0.373 | 0.403 | 0.392 | 0.412 | 0.470 | 0.474 | 0.444 | 0.470 | 0.430 |
| Michigan | 0.599 | 0.579 | 0.627 | 0.614 | 0.624 | 0.586 | 0.580 | 0.533 | 0.593 |
| Minnesota | 1.000 | 0.549 | 0.495 | 0.540 | 0.659 | 0.562 | 0.625 | 0.732 | 0.645 |
| Mississippi | 0.481 | 0.449 | 0.428 | 0.350 | 0.320 | 0.334 | 0.395 | 0.401 | 0.395 |
| Missouri | 0.443 | 0.386 | 0.396 | 0.387 | 0.353 | 0.373 | 0.360 | 0.372 | 0.384 |
| Montana | 0.591 | 0.486 | 0.533 | 0.544 | 0.543 | 0.513 | 0.593 | 0.591 | 0.549 |
| Nebraska | 0.502 | 0.426 | 0.437 | 0.427 | 0.414 | 0.417 | 0.427 | 0.427 | 0.434 |
| Nevada | 0.903 | 0.836 | 0.723 | 0.659 | 0.689 | 0.754 | 0.771 | 0.787 | 0.765 |
| New Hampshire | 0.750 | 1.000 | 0.555 | 0.620 | 0.747 | 0.690 | 0.810 | 0.643 | 0.727 |
| New Jersey | 0.435 | 0.439 | 0.432 | 0.466 | 0.445 | 0.399 | 0.437 | 0.414 | 0.433 |
| New Mexico | 0.789 | 0.794 | 0.733 | 0.770 | 0.609 | 0.826 | 0.761 | 0.737 | 0.752 |
| New York | 0.457 | 0.506 | 0.546 | 0.643 | 0.609 | 0.554 | 0.578 | 0.615 | 0.564 |
| North Carolina | 0.601 | 0.525 | 0.540 | 0.533 | 0.567 | 0.513 | 0.526 | 0.537 | 0.543 |
| North Dakota | 0.543 | 0.567 | 0.504 | 0.453 | 0.470 | 0.522 | 0.479 | 0.406 | 0.493 |
| Ohio | 0.515 | 0.471 | 0.485 | 0.489 | 0.498 | 0.480 | 0.457 | 0.449 | 0.481 |
| Oklahoma | 0.689 | 0.779 | 0.702 | 0.630 | 0.573 | 0.569 | 0.552 | 0.491 | 0.623 |
| Oregon | 0.867 | 0.891 | 0.810 | 0.881 | 0.912 | 0.891 | 0.914 | 0.983 | 0.894 |
| Pennsylvania | 0.514 | 0.515 | 0.419 | 0.454 | 0.425 | 0.471 | 0.445 | 0.451 | 0.462 |
| Rhode Island | 0.553 | 0.444 | 0.454 | 0.493 | 0.467 | 0.540 | 0.469 | 0.426 | 0.481 |
| South Carolina | 0.706 | 0.722 | 0.632 | 0.602 | 0.561 | 0.547 | 0.516 | 0.519 | 0.601 |
| South Dakota | 0.412 | 0.392 | 0.391 | 0.476 | 0.449 | 0.420 | 0.429 | 0.406 | 0.422 |
| Tennessee | 0.398 | 0.420 | 0.400 | 0.424 | 0.402 | 0.402 | 0.697 | 0.654 | 0.475 |
| Texas | 0.817 | 0.775 | 0.732 | 0.743 | 0.671 | 0.627 | 0.622 | 0.635 | 0.703 |
| Utah | 1.000 | 1.000 | 1.000 | 0.983 | 0.999 | 0.975 | 1.000 | 1.000 | 0.995 |
| Vermont | 0.721 | 0.725 | 0.787 | 0.863 | 0.695 | 0.750 | 0.933 | 0.981 | 0.807 |
| Virginia | 0.700 | 0.680 | 0.649 | 0.653 | 0.652 | 0.672 | 0.670 | 0.606 | 0.660 |
| Washington | 0.892 | 0.920 | 0.751 | 0.756 | 0.847 | 0.783 | 0.812 | 0.857 | 0.827 |
| West Virginia | 0.478 | 0.449 | 0.456 | 0.428 | 0.410 | 0.415 | 0.440 | 0.381 | 0.432 |
| Wisconsin | 0.619 | 0.618 | 0.591 | 0.591 | 0.685 | 0.639 | 0.637 | 0.633 | 0.626 |
| Wyoming | 0.596 | 0.619 | 0.597 | 0.598 | 0.633 | 0.564 | 0.555 | 0.547 | 0.589 |

**Table A.6:** Simar and Wilson (2007) Bootstrapping Estimation Results

| | Specification 1* | Specification 2* |
|---|---|---|
| *constant* | 1.884 | 1.655 |
| | [1.182 , 2.546] | [1.036 , 2.264] |
| *poverty share* | -1.123 | -1.607 |
| | [-1.885 , -0.294] | [-2.514 , -0.618] |
| *diploma share* | 1.054 | 1.136 |
| | [0.440 , 1.658] | [0.530 , 1.740] |
| *employment share* | -0.383 | -0.318 |
| | [-0.784 , 0.009] | [-0.721 , 0.072] |
| *state gdp* | -0.163 | -0.229 |
| | [-0.426 , 0.106] | [-0.489 , 0.040] |
| *share 65+* | -5.136 | -5.247 |
| | [-6.197 , -4.098] | [-6.456 , -4.059] |
| *total coverage* | -1.284 | |
| | [-1.768 , -0.760] | |
| *private coverage* | | -1.113 |
| | | [-1.525 , -0.671] |
| *public coverage* | | -0.361 |
| | | [-0.922 , 0.223] |
| *sigma* | .0181 | .0176 |

* SW (2007) 95% confidence intervals in parentheses.

**Table A.7:** Traditional Second Stage Regressions

| Variable | OLS | | Tobit | | Truncated | |
|---|---|---|---|---|---|---|
| *constant* | 2.332* | 2.042* | 2.320* | 2.034* | 2.511* | 2.167* |
| | [1.919 , 2.744] | [1.680 , 2.403] | [1.897 , 2.743] | [1.664 , 2.404] | [2.083 , 2.939] | [1.804 , 2.530] |
| *poverty share* | -1.281* | -2.322* | -1.313* | -2.345* | -1.354* | -2.387* |
| | [-1.771 , -0.790] | [-2.884 , -1.759] | [-1.816 , -0.810] | [-2.921 , -1.767] | [-1.848 , -0.858] | [-2.947 , -1.827] |
| *employment share* | -0.653* | -0.634* | -0.704* | -0.681* | -0.639* | -0.629* |
| | [-0.898 , -0.407] | [-0.869 , -0.397] | [-0.957 , -0.451] | [-0.923 , -0.437] | [-0.889 , -0.388] | [-0.865 , -0.393] |
| *state gdp* | -0.030 | -0.085 | -0.072 | -0.126 | -0.041 | -0.096 |
| | [-0.192 , 0.132] | [-0.242 , 0.0718] | [-0.239 , 0.096] | [-0.288 , 0.036] | [-0.205 , 0.123] | [-0.253 , 0.060] |
| *diploma share* | 0.981* | 1.201* | 1.117* | 1.331* | 0.840* | 1.088* |
| | [0.606 , 1.355] | [0.839 , 1.561] | [0.727 , 1.506] | [0.955 , 1.705] | [0.446 , 1.232] | [0.717 , 1.460] |
| *share 65+* | -4.352* | -4.976* | -4.711* | -5.284* | -4.574* | -5.095* |
| | [-4.964 , -3.738] | [-5.669 , -4.283] | [-5.364 , -4.056] | [-6.009 , -4.557] | [-5.272 , -3.874] | [-5.833 , -4.357] |
| *total coverage* | -1.524* | | -1.532* | | -1.555* | |
| | [-1.839 , -1.207] | | [-1.856 , -1.206] | | [-1.883 , -1.226] | |
| *private coverage* | | -1.406* | | -1.420* | | -1.418* |
| | | [-1.664 , -1.147] | | [-1.685 , -1.154] | | [-1.680 , -1.157] |
| *public coverage* | | -0.020 | | -0.046 | | -0.0145 |
| | | [-0.361 , 0.322] | | [-0.396 , 0.304] | | [-0.359 , 0.329] |
| *sigma* | .0854 | .0816 | .0875 | .0834 | .0828 | .0781 |

*Notes*. Table shows regressions of traditional DEA efficiency on environmental variables.
* Denotes significance at a 1% level. 95% confidence intervals in parentheses.

# Appendix B

# Appendix

## B.1 Is It Better to Be Safe than Sorry? The Impacts of a Health Insurance Mandate on Hospitals

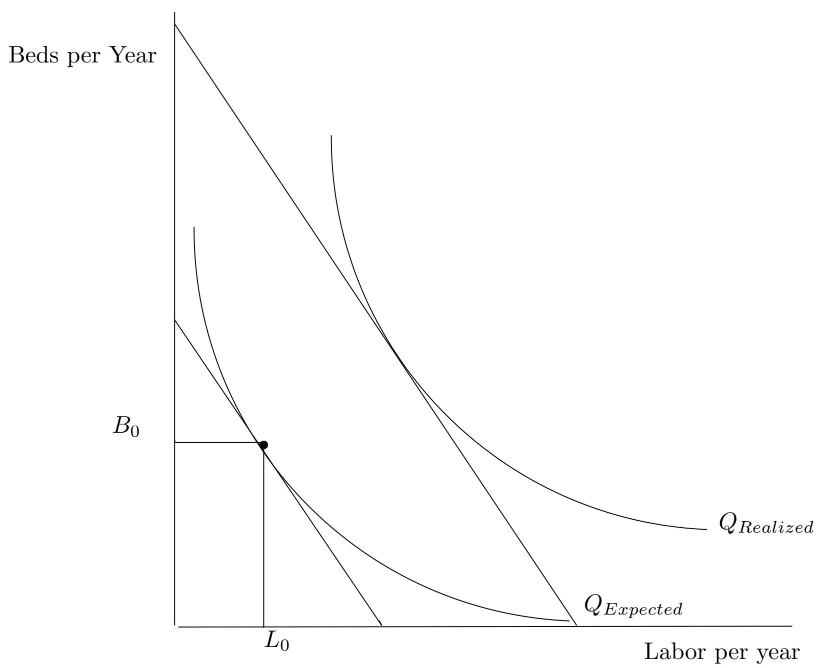


**Figure B.1:** Cost Minimization

**Table B.1:** Summary Statistics

| | Entire Panel 2000-2009 | | MA Pre-Policy | | MA Post-Policy | | Other States Pre-Policy | | Other States Post-Policy | |
|---|---|---|---|---|---|---|---|---|---|---|
| Dependent Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| **Utilization Measures** | | | | | | | | | | |
| Total Discharges | 8227 | 9844 | 7322 | 9601 | 7851 | 10297 | 8165 | 9512 | 8678 | 10596 |
| ADC | 136 | 144 | 128 | 140 | 132 | 147 | 136 | 147 | 137 | 155 |
| ALS | 33 | 205 | 37 | 122 | 31 | 81 | 32 | 198 | 32 | 248 |
| Ambulance Trips | 2010 | 2192 | 2154 | 1101 | 1620 | 634 | 2041 | 2265 | 1932 | 2174 |
| **Major Inputs** | | | | | | | | | | |
| Beds | 187 | 174 | 173 | 164 | 179 | 172 | 188 | 171 | 187 | 181 |
| Employees | 1103 | 1654 | 1116 | 1640 | 1298 | 2003 | 1060 | 1600 | 1162 | 1487 |

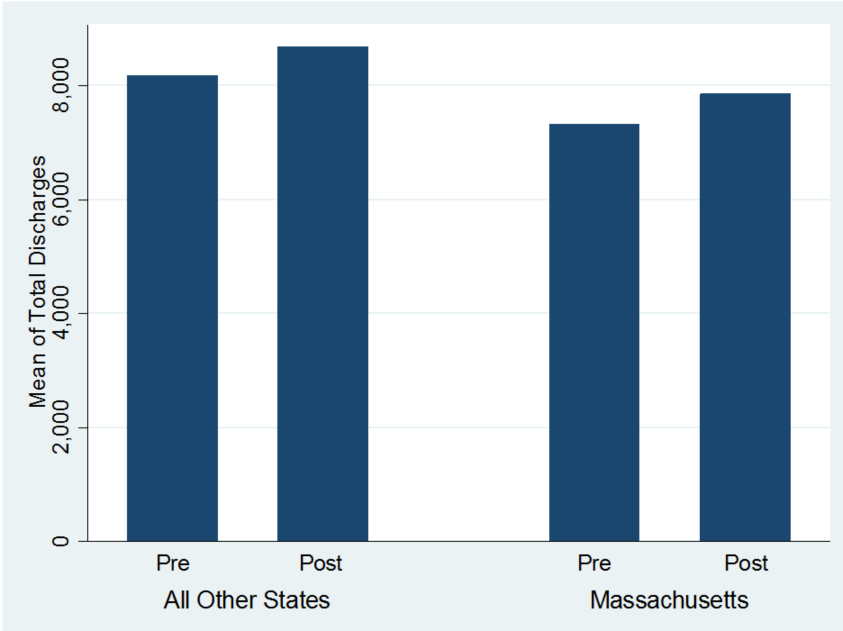


**Figure B.2:** Mean Total Discharges

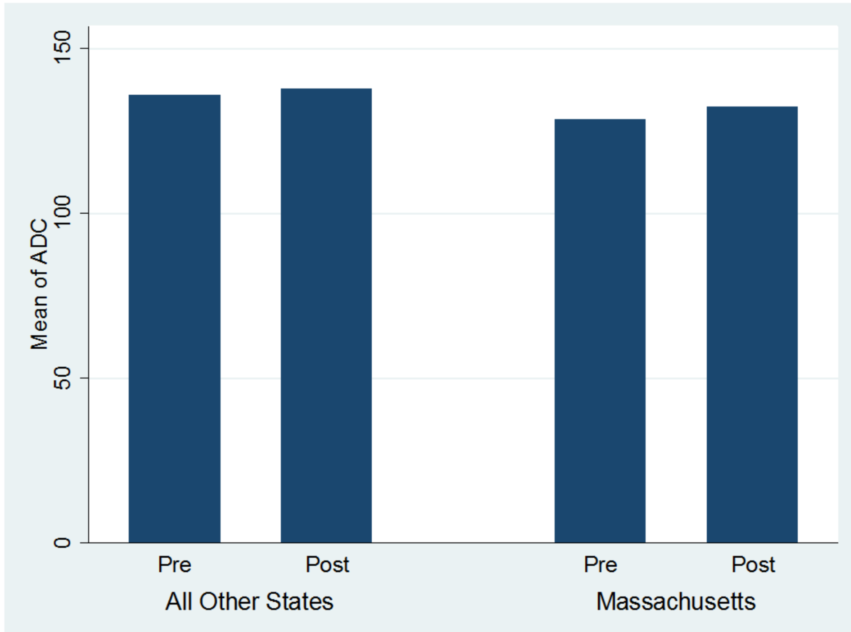


**Figure B.3:** Mean Average Daily Census

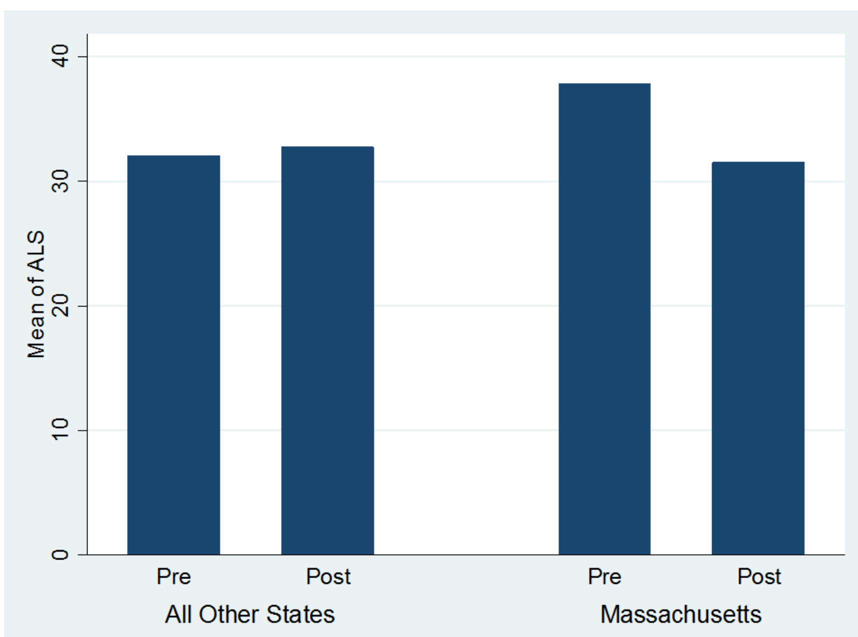


**Figure B.4:** Mean Average Length of Stay

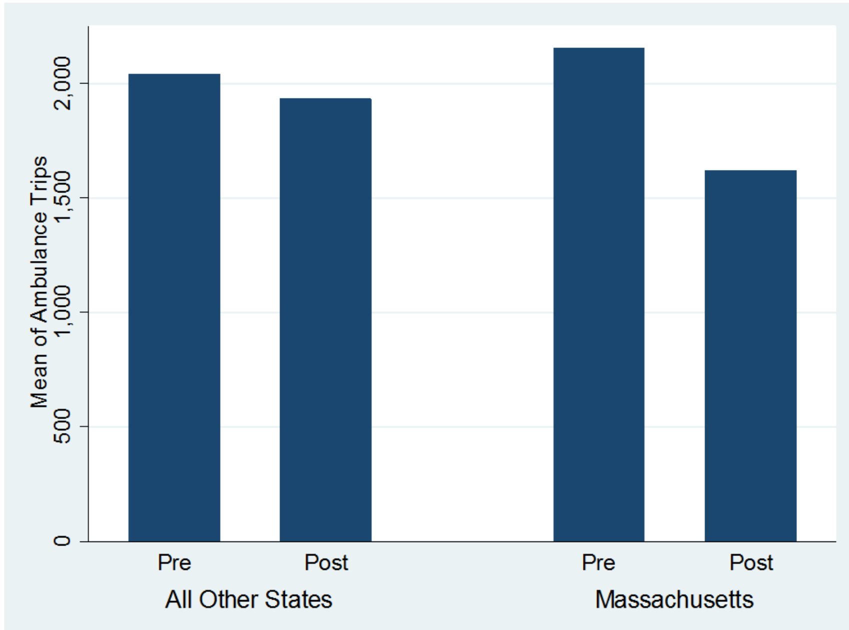


**Figure B.5:** Mean Ambulance Trips

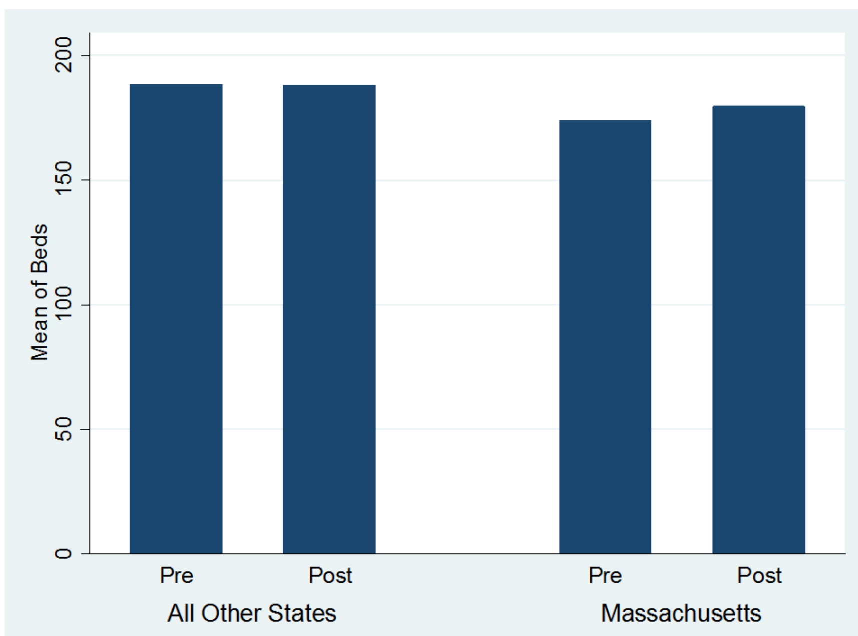


**Figure B.6:** Mean Number of Beds

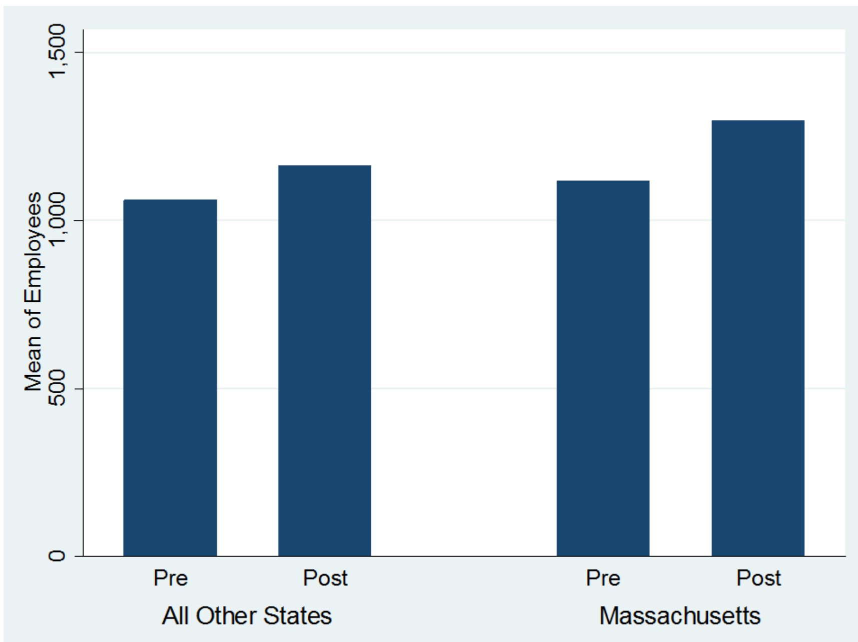


**Figure B.7:** Mean Number of Employees

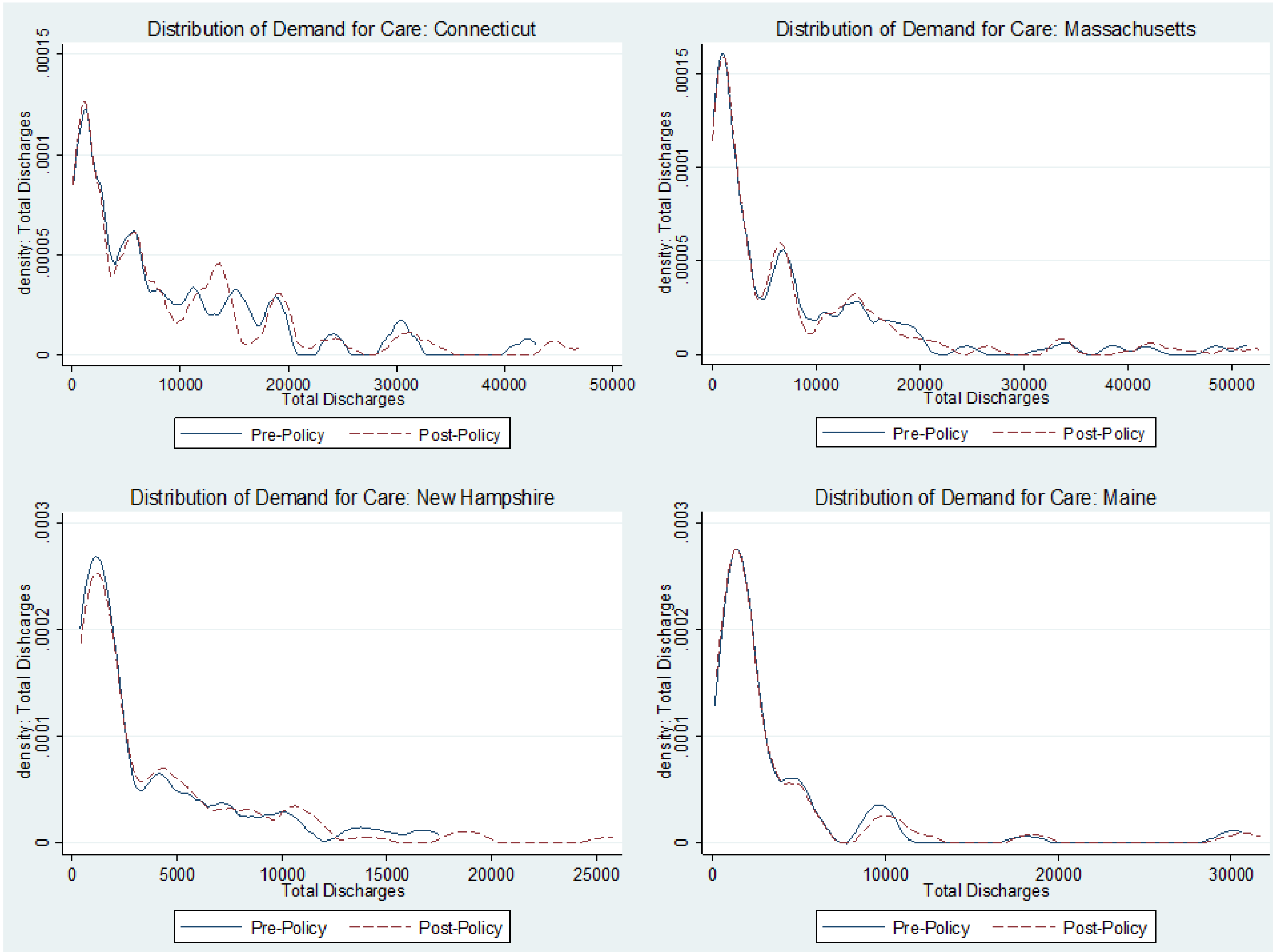


**Figure B.8:** Distribution of Demand for Care

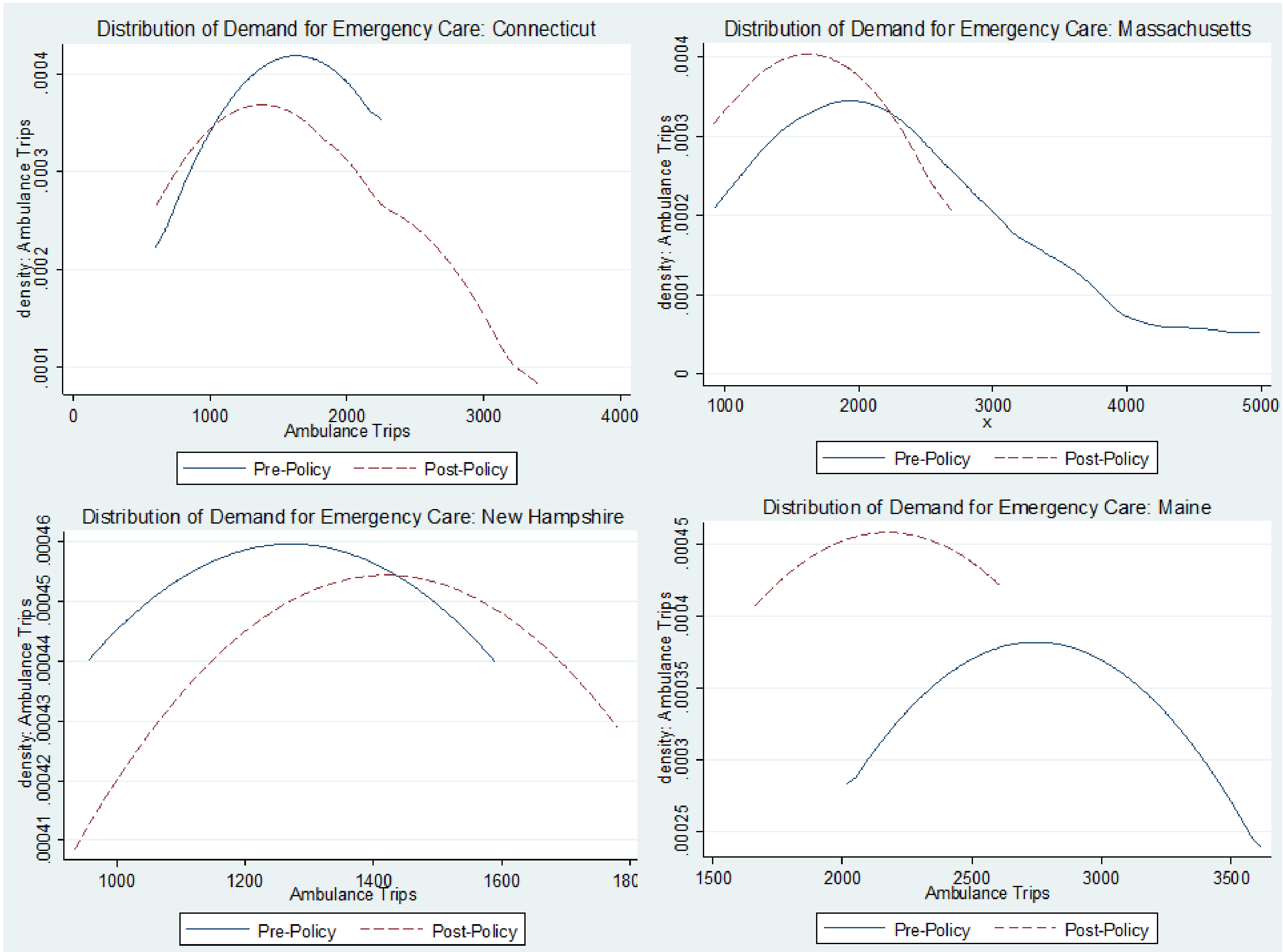


**Figure B.9:** Distribution of Demand for Emergency Care

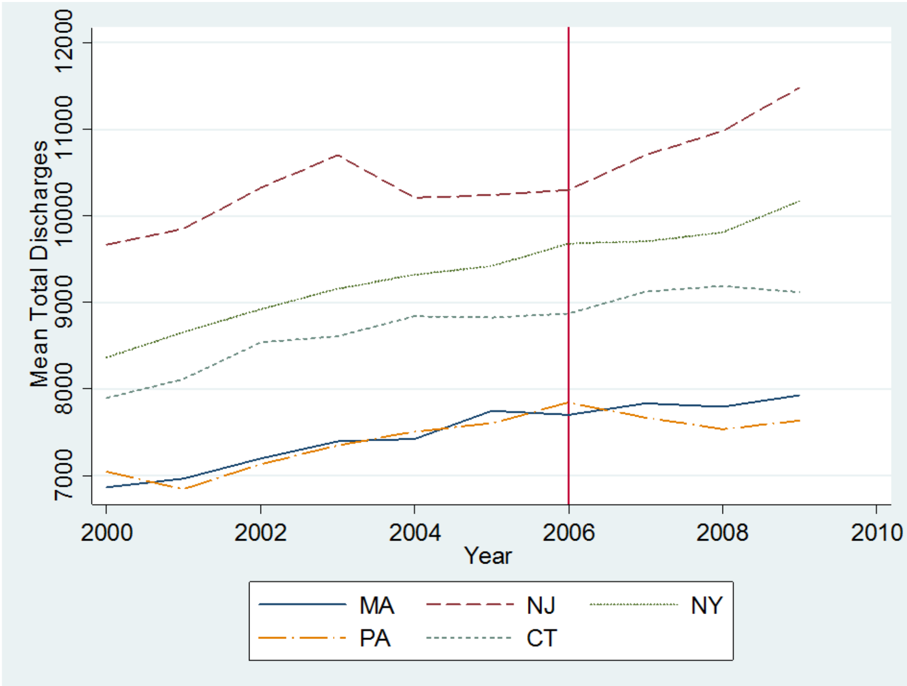


**Figure B.10:** Total Discharges Trend

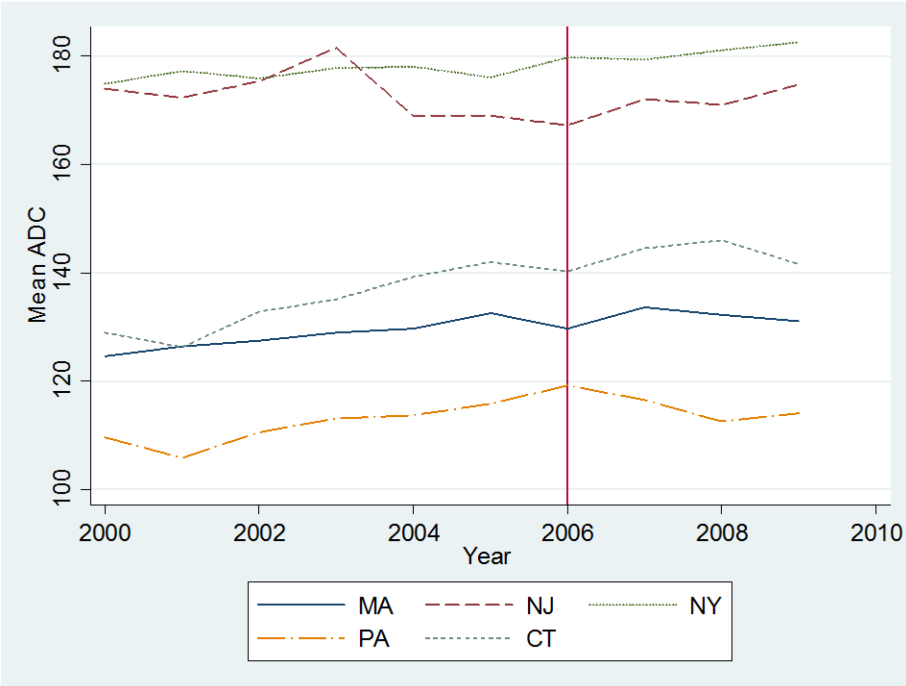


**Figure B.11:** Average Daily Census Trend

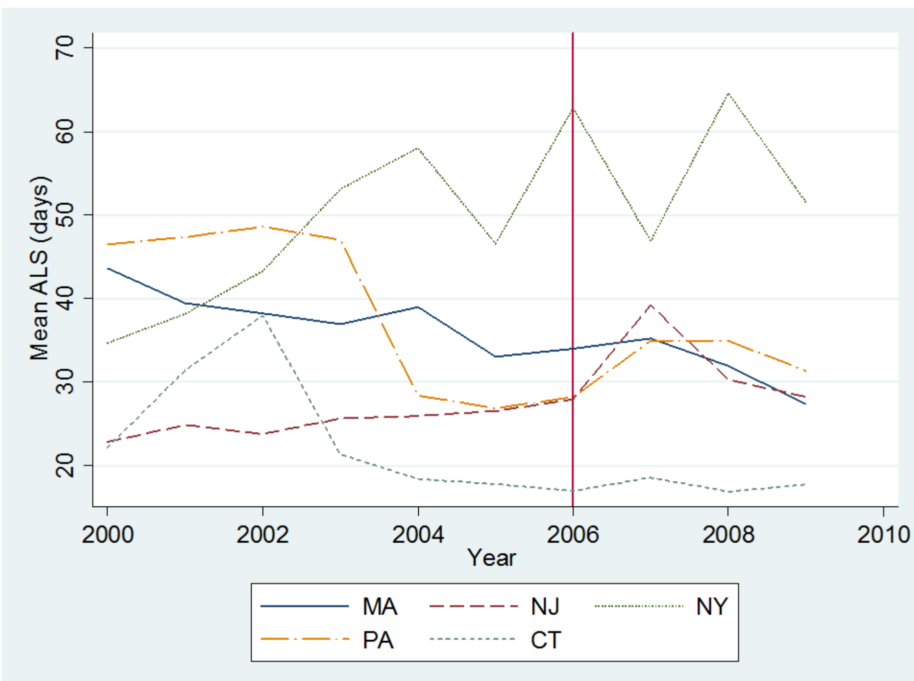


**Figure B.12:** Average Length of Stay Trend

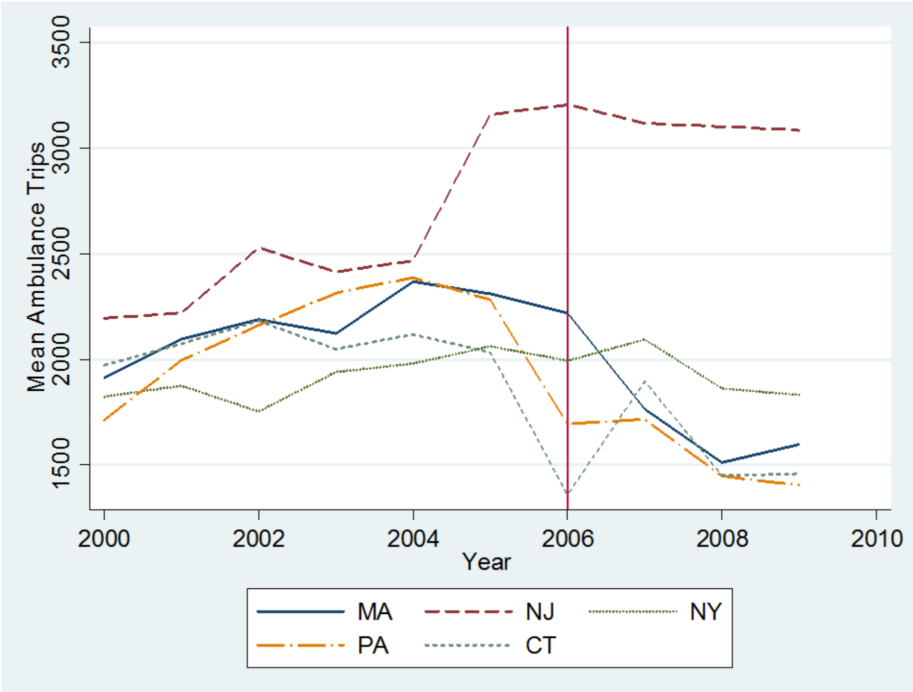


**Figure B.13:** Mean Ambulance Trips

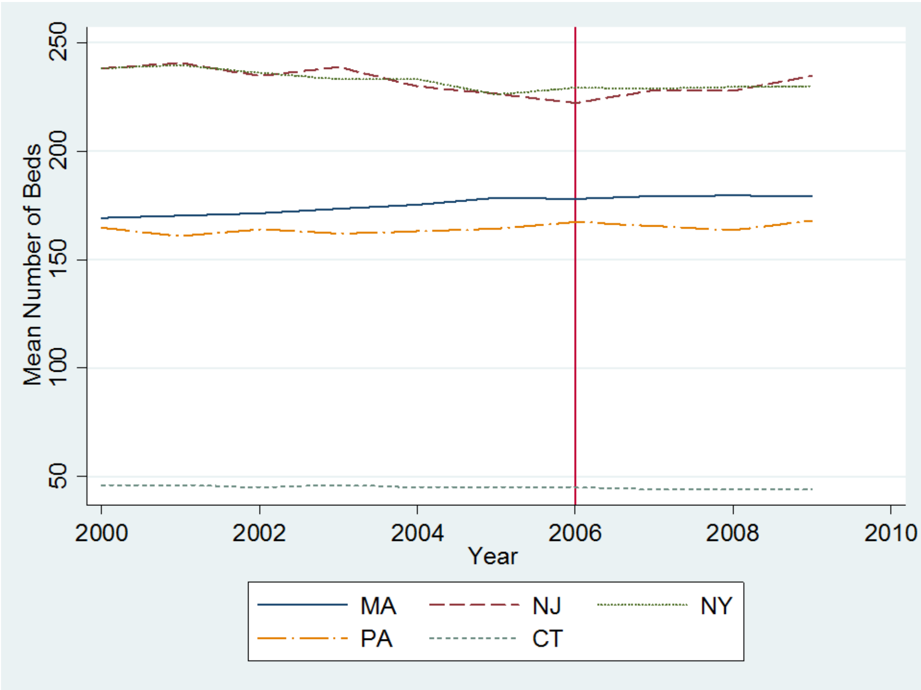


**Figure B.14:** Beds Trend

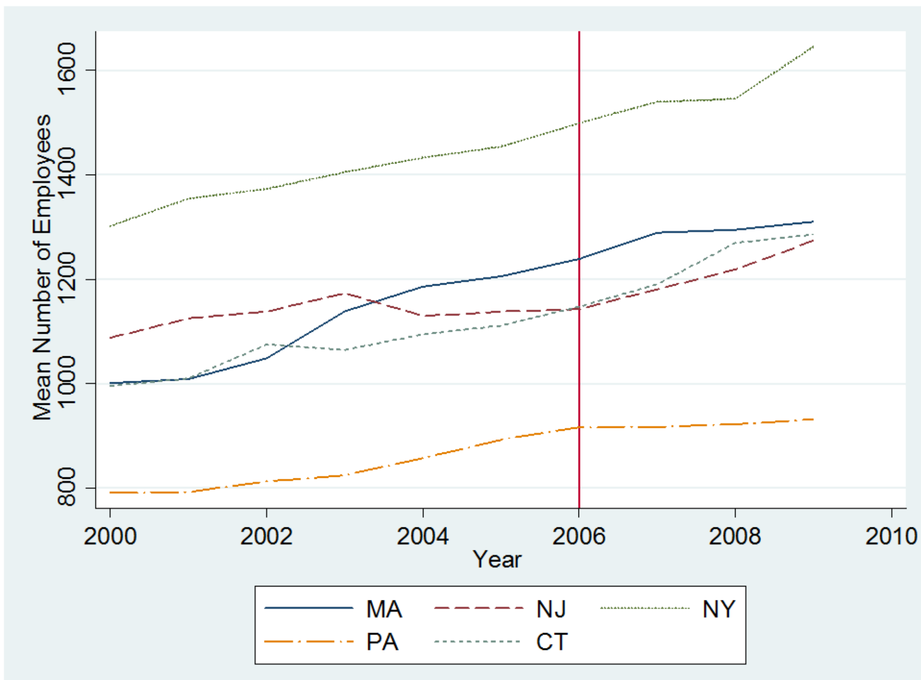


**Figure B.15:** Employees Trend

**Table B.2:** Main Specification Results-Effects of Policy in Post-Mandate Period

| Dependent Variable | (1)<br>A. Trips | (2)<br>Discharges | (3)<br>ADC | (4)<br>ALS | (5)<br>Beds | (6)<br>Employees |
|---|---|---|---|---|---|---|
| MA*After | -325.88* | 14.17 | 3.55 | -9.91** | 7.36** | 91.74 |
| | (196.50) | (137.75) | (2.73) | (4.53) | (3.76) | (100.63) |
| *N* | 1932 | 10236 | 10241 | 10236 | 10249 | 10240 |

Note 1: Block bootstrap standard errors in parentheses. * (10%) ** (5%) ***(1%) significance.

Note 2: Hospital, state, year fixed effects and time varying state controls included.

**Table B.3:** Alternative Specification Results-Effects of Policy in Different Post-Mandate Years

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable | A. Trips | Discharges | ADC | ALS | Beds | Employees |
| MA*Year07 | -441.12* | -86.64 | 2.86 | -4.57* | 6.18* | 87.78 |
| | (234.16) | (134.45) | (2.78) | (2.79) | (3.27) | (135.34) |
| MA*Year08 | -353.23 | 26.77 | 3.84 | -10.84** | 7.60 ** | 84.95 |
| | (223.35) | (138.86) | (3.06) | (5.17) | (3.74) | (149.96) |
| MA*Year09 | -163.34 | 136.39 | 4.16 | -16.03** | 8.71 | 105.35 |
| | (248.14) | (161.08) | (3.97) | (7.60) | (5.48) | (149.97) |
| $N$ | 1932 | 10236 | 10241 | 10236 | 10249 | 10240 |

Note 1: Block bootstrap standard errors in parentheses. * (10%) ** (5%) ***(1%) significance.

Note 2: Hospital, state, year fixed effects and time varying state controls included included.

**Table B.4:** Robustness Check 1-Anticipatory Effects

| Dependent Variable | (1) A. Trips | (2) Discharges | (3) ADC | (4) ALS | (5) Beds | (6) Employees |
|---|---|---|---|---|---|---|
| MA*After | -239.38* | -117.28 | 0.34 | -3.19* | 5.38** | 58.08 |
| | (135.46) | (98.87) | (1.44) | (1.75) | (2.49) | (40.11) |
| Wald Statistic Selects | Yes | NA | NA | No | Yes | NA |
| $N$ | 6963 | 10236 | 10241 | 10236 | 10249 | 10240 |

Note 1: Bootstrap standard errors in parentheses. * (10%) ** (5%) ***(1%) significance.

Note 2: Hospital, state, and year fixed effects included.

**Table B.5:** Robustness Check 2-Effects of Policy in Post-Mandate Period-Log Specification

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent Variable (in logs) | A. Trips | Discharges | ADC | ALS | Beds | Employees |
| MA*After | -.175 | -0.003 | -0.025 | -0.020* | 0.029* | 0.020 |
| | (.118) | (0.020) | (0.018) | (0.011) | (0.16) | (0.023) |
| $N$ | 6963 | 10236 | 10241 | 10236 | 10249 | 10240 |

Note 1: Bootstrap standard errors in parentheses. * (10%) ** (5%) ***(1%) significance.

Note 2: Hospital, state, and year fixed effects included.

# Appendix C

# Appendix

## C.1 Bending States' Medicaid Expenditure Curves: Does Health Insurance Matter?

**Table C.1:** Data Sources

| Variable | Description | Source |
|---|---|---|
| **Dependent Variables** | | |
| Medicaidexp | State funded Medicaid expenditure | Centers for Medicare and Medicaid Services |
| **Independent Variables** | | |
| Private HI | Private HI Coverage | U.S. Census Bureau, Current Population Survey |
| Medicaid HI | Medicaid HI Coverage | U.S. Census Bureau, Current Population Survey |
| Medicare HI | Medicare HI Coverage | U.S. Census Bureau, Current Population Survey |
| Military HI | Military HI Coverage | U.S. Census Bureau, Current Population Survey |
| SGDP | State gross domestic product | Bureau of Economic Analysis, State Income and Employment Summary |
| Unemployment | Unemployment Rate | Bureau of Labor Statistics, Local Area Unemployment Statistics |
| Smoke | Share of population that smokes | CDC, Behavioral Risk Factor Surveillance System Annual Survey |
| Bachelor Degree | Share of population with at least a bachelor's degree | U.S. Census Bureau, Statistical Abstract of the United States, |
| Share 65 | Share of population 65 and over | U.S. Census Bureau, Current Population Survey |
| Share17 | Share of population 17 and below | U.S. Census Bureau, Current Population Survey |
| Physicians | Number of Physicians per capita | Bureau of Labor Statistics |
| Lower House | Democratic majority in Lower House of state legislature | U.S. Statistical Abstract of the United States |
| Upper House | Democratic majority in Upper House of state legislature | U.S. Statistical Abstract of the United States |
| **Other Measures** | | |
| FMAP | Federal Medical Assistance Percentage | U.S. Department of Health and Human Services |
| Total Population | Total Population in thousands | U.S. Census Bureau, Current Population Survey |
| Total HCE | Total health care expenditure | Centers for Medicare and Medicaid Services |
| Medicare HCE | Medicare health care expenditure | Centers for Medicare and Medicaid Services |
| Regional CPI | Regional Consumer Price Index | Bureau of Labor Statistics |

* Numeric variables are constructed as growth rates.
** Measures used in the construction of certain variables are described in Chapter 4.

**Table C.2:** Regional CPI

| **New England** | **Mideast** | **Great Lakes** | **Plains** |
|---|---|---|---|
| CPI Boston | CPI New York, NJ | CPI Chicago | CPI Midwest Urban |
| CT | DE | IL | IA |
| ME | MD | IN | KS |
| MA | NJ | MI | MN |
| NH | NY | OH | MO |
| RI | PA | WI | NE |
| VT | | | ND |
| | | | SD |
| **Southeast** | **Southwest** | **Rocky Mountain** | **Far West** |
| CPI Atlanta | CPI Dallas Fortworth | CPI Midwest Urban | CPI San Francisco |
| AL | AZ | CO | AK |
| AR | NM | ID | CA |
| FL | OK | MT | HI |
| GA | TX | UT | NV |
| KY | | WY | OR |
| LA | | | WA |
| MS | | | |
| NC | | | |
| SC | | | |
| TN | | | |
| VA | | | |
| WV | | | |

**Table C.3:** Summary Statistics

| | 1996-2004 | | 1996 | | 2000 | | 2004 | |
|---|---|---|---|---|---|---|---|---|
| Variable | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. | Mean | Std. Dev. |
| **Dependent** | | | | | | | | |
| *Medicaid Exp* | 0 .0469 | 0.0608 | 0.0418 | 0.0879 | 0.0322 | 0.0439 | 0.0555 | 0.0524 |
| **Independent** | | | | | | | | |
| *Private HI* | -0.0035 | 0.0308 | -0.0009 | 0.0348 | -0.0015 | 0.0271 | -0.0019 | 0.0303 |
| *Medicaid HI* | 0.0251 | 0.1633 | 0.0041 | 0.1730 | 0.0587 | 0.1740 | 0.0429 | 0.1424 |
| *Medicare HI* | 0.0091 | 0.0840 | 0.0237 | 0.0932 | 0.0281 | 0.0994 | -0.0007 | 0.0681 |
| *Military HI* | 0.0438 | 0.2859 | -0.0404 | 0.2219 | 0.0681 | 0.2504 | 0.0766 | 0.2714 |
| *SGDP* | 0.0166 | 0.0335 | 0.0303 | 0.0512 | -0.0083 | 0.0227 | 0.0353 | 0.0228 |
| *Unemployment* | 0.0098 | 0.1347 | -0.0190 | 0.0650 | -0.0463 | 0.0830 | -0.0732 | 0.0572 |
| *Smoke* | -0.0049 | 0.0665 | 0.0482 | 0.0724 | -0.0088 | 0.0574 | -0.0472 | 0.0582 |
| *Bachelor Degree* | 0.0209 | 0.1099 | 0.0052 | 0.1555 | 0.0118 | 0.0769 | 0.0252 | 0.2323 |
| *Share65+* | -0.0016 | 0.0107 | 0.0023 | 0.0136 | -0.0111 | 0.0189 | 0.0026 | 0.0058 |
| *Share17-* | -0.0077 | 0.0209 | -0.0126 | 0.0303 | -0.0031 | 0.0196 | -0.0151 | 0.0142 |
| *Private HCE* | 0.0443 | 0.0281 | 0.0214 | 0.0252 | 0.0322 | 0.0266 | 0.0397 | 0.0251 |
| *Physicians* | 0.0062 | 0.0339 | 0.0193 | 0.0561 | -0.0312 | 0.0166 | -0.0111 | 0.0137 |
| *LowerHouse* | 0.5000 | 0.5006 | 0.5208 | 0.5049 | 0.4791 | 0.5049 | 0.4583 | 0.5035 |
| *UpperHouse* | 0.4514 | 0.4982 | 0.4791 | 0.5049 | 0.4375 | 0.5013 | 0.4792 | 0.5049 |
| *IComp* | 0.0476 | 0.0371 | 0.0560 | 0.0240 | 0.0570 | 0.0194 | 0.0410 | 0.0281 |

*These summary statistics represent growth rates of the variables.

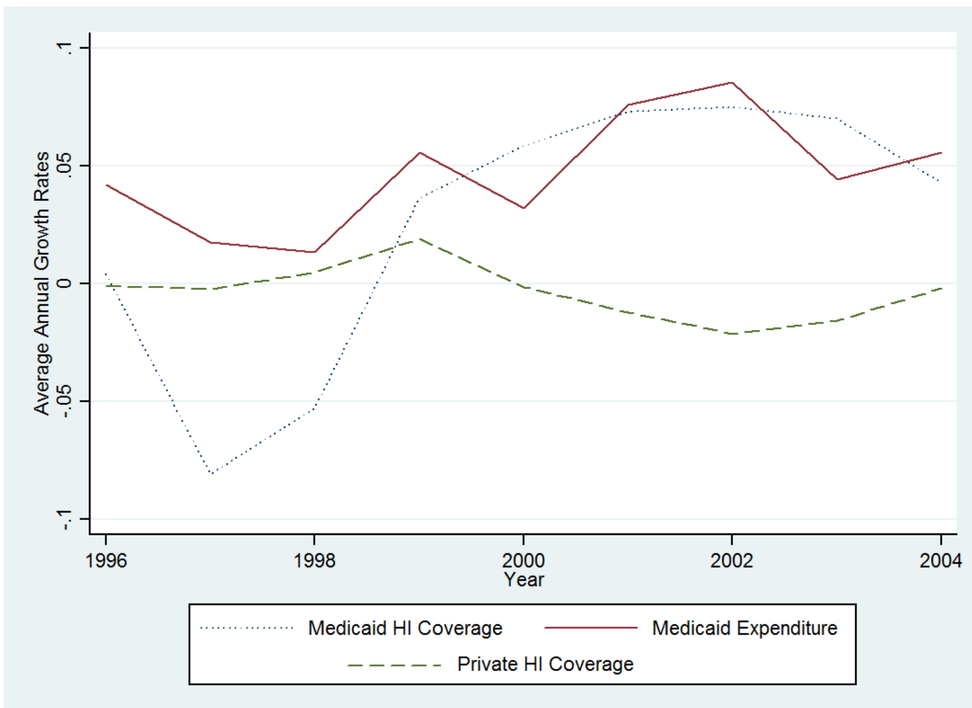


**Figure C.1:** Average Annual Growth of Health Insurance and Medicaid Expenditure

**Table C.4:** State Funded Medicaid Expenditure Growth

| | (1)<br>Main Specification<br>Arellano-Bond | (2)<br>Robustness Check<br>Arellano-Bover | (3)<br>Static Specification<br>Random Effects | (4)<br>Static Specification<br>Fixed Effects |
|---|---|---|---|---|
| PrivateHI | 0.0220 | 0.0172 | 0.0560 | 0.0485 |
| | (0.1135) | (0.1408) | (0.0834) | (0.0828) |
| MedicaidHI | 0.0161 | 0.0240 | 0.0344** | 0.0313* |
| | (0.0189) | (0.0229) | (0.0153) | (0.0160) |
| MedicareHI | -0.0344 | -0.0271 | 0.000796 | 0.00834 |
| | (0.0355) | (0.0346) | (0.0272) | (0.0283) |
| MilitaryHI | -0.00290 | -0.00207 | 0.00292 | 0.00480 |
| | (0.0128) | (0.0104) | (0.0089) | (0.0095) |
| SGDP | 0.306 | 0.484** | 0.278** | 0.245** |
| | (0.2271) | (0.1987) | (0.1098) | (0.1066) |
| Unemployment | 0.0150 | 0.0184 | 0.0175 | 0.0104 |
| | (0.0398) | (0.0491) | (0.0304) | (0.0295) |
| Smoke | 0.0359 | 0.0528 | 0.0734* | 0.0716* |
| | (0.0521) | (0.0545) | (0.0416) | (0.0423) |
| BachelorDegree | 0.00780 | -0.0186 | 0.0355 | 0.0336 |
| | (0.0358) | (0.0407) | (0.0242) | (0.0251) |
| Share65 | 0.856*** | 0.796** | 0.808*** | 0.667** |
| | (0.2642) | (0.3230) | (0.2173) | (0.2717) |
| Share17 | -0.481** | -0.339* | -0.297** | -0.243 |
| | (0.2103) | (0.1731) | (0.1474) | (0.1666) |
| PrivateHCE | -0.471*** | -0.408*** | -0.494*** | -0.606*** |
| | (0.1054) | (0.1284) | (0.1104) | (0.1147) |
| Physicians | 0.277 | 0.258 | 0.281* | 0.425** |
| | (0.1834) | (0.1642) | (0.1463) | (0.1608) |
| LowerHouse | 0.00594 | -0.00950 | -0.00856* | -0.00374 |
| | (0.0193) | (0.0176) | (0.0044) | (0.0104) |
| UpperHouse | 0.0101 | 0.0226 | 0.00740 | 0.0124 |
| | (0.0146) | (0.0156) | (0.0049) | (0.0149) |
| IComp | 0.00756 | -0.0332 | -0.00185 | -0.0384 |
| | (0.0854) | (0.0972) | (0.0823) | (0.0816) |
| _cons | 0.0632*** | 0.0603*** | 0.0647*** | 0.0694*** |
| | (0.0239) | (0.0159) | (0.0121) | (0.0136) |
| $N$ | 432 | 432 | 432 | 432 |
| Fixed Effects | Y | Y | Y | Y |
| Temporal Effects | Y | Y | Y | Y |
| Lags of Dep. Variable | 2 | 2 | 0 | 0 |
| Number of Instruments | 51 | 52 | 0 | 0 |
| P-values from test of over-identification | 0.56 | 0.29 | NA | NA |

Cluster robust standard errors in parentheses.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$
NA = Not applicable.

# Vita

Melanie Cozad was born in Harrisburg, PA, to Sandy Stock and Richard R. Yeager Jr. She attended Cumberland Valley High School in Mechanicsburg, Pennsylvania. After high school, Melanie pursued her undergraduate studies at the the United States Naval Academy where she majored in Economics. In 2002, she obtained a Bachelor of Science degree and was commissioned as a Second Lieutenant in the United States Marine Corps. While serving on active duty, Melanie enrolled in a Master's of Business Administration program at Cameron University. After serving two tours of duty in Afghanistan and completing her MBA, Melanie left the military and pursued graduate studies in economics. She accepted a graduate assistantship at The University of Tennessee, Knoxville in the Economics department. Melanie completed a Master of Arts degree in August 2010 and a Doctor of Philosophy in May 2012. She has accepted a position as an Assistant Professor of Economics at Furman University in Greenville, South Carolina.