ESSAYS ON PUBLIC POLICY AND HEALTH CARE MARKET

by

SHUYANG YANG

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ABSTRACT OF THE DISSERTATION

Essays on Public Policy and Health Care Market

By SHUYANG YANG

Dissertation Director:

Professor Carolyn Moehling

This dissertation focuses on examining the impact of public spending in health insurance and health care markets. Health care subsidies account for a fast-growing share of public expenditures in many developed and developing countries, making them an ever more important component of fiscal policy discussions. Two principle projects constitute my dissertation research. In the first project, I examine the heterogeneity in the impact of subsidized health insurance coverage on individual welfare, in the context of a Chinese public health insurance program. In the course of this research, I have also developed new econometric methods to address the empirical challenges of studying the effects of health insurance. These methods have broad applications beyond topics in health economics. In the second project, I look at the role of tax subsidies in the supply of health care. In particular, I exploit variations in state and federal level tax policies in the U.S to estimate the impact of government subsidies on ownership choice, provision of public services and the quality of hospitals.

The first chapter of the dissertation mainly assesses the effect of public health insurance on program beneficiaries' welfare, by evaluating a new national public medical insurance program in China, Urban Resident Basic Insurance (URBMI). This program, introduced in 2007 and having an annual fiscal expenditure of 30 billion RMB, aims to provide coverage to more than 200 million urban residents including elderly, children, college students and unemployed adults. I exploit the city-variation in

policy generosity as an exogenous determinant of URBMI enrollment. Using data from the Chinese Health and Nutrition Survey (CHNS), I find that URBMI increases welfare on several margins. Having insurance coverage increases health care spending while decreasing the out-of-pocket payments, providing protection from the financial risk. It also increases efficiency in medical spending by inducing the use of preventative care and reducing the probability of hospitalization. In terms of health outcomes, insurance coverage has a significant impact on subjective self-ratings in health and happiness. I also extend my examination to consider the labor market effects of URBMI. Since this program provides insurance coverage outside of employment status, it will potentially increase an individual's mobility between jobs and impact the retirement decision.

In Chapter 2, building on the results of the first chapter, I explore the heterogeneity in the impact of health insurance through a semiparametric model. Since URBMI is a national program covering a wide range of subpopulations, observed and unobserved individual characteristics may play an important role in determining the response of an individual to insurance coverage. This chapter builds a panel data model with endogenous treatment, which incorporates unobserved individual heterogeneity non-additively into the outcome. The model is estimated in the context of a semiparametric setting. I first propose a two-stage semiparametric least square (SLS) method to consistently estimate the model parameters and then conduct a localized 2SLS procedure to recover the quantile treatment effect. Identification, consistency, and root-N asymptotic normality of estimators for parameters and marginal effects are proved. The estimation results reveal substantial variation in the impact of URBMI by age, income and gender. Children, the elderly above the age of 70, and females ages 25-40 benefit the most from the program. Adult males and individuals with incomes below the median level do not respond significantly to insurance coverage. The findings of heterogeneous insurance effects have important policy implications for the cost-effectiveness of URBMI across population groups, suggesting the need for differentiated

insurance programs.

In the third chapter, another form of subsidy in health care markets is studied. This chapter focuses on assessing the effect of government subsidies on the supply side of the health care market in the U.S. An important form of government subsidies to health care providers is the tax exemption for non-profit organizations. The validity and efficiency of such practice has long been under debate. Recently, many state and federal laws have been enacted that mandate the reporting of benefits provided to the community by non-profit providers. This chapter studies the hospital sector. Given the preferential tax treatment for nonprofit hospitals, the tax rate, in conjunction with community benefit reporting requirement (CRR), determine the net subsidy provided to a nonprofit hospital compared to its for-profit counterpart. I exploit the variation in tax policy across states and over time to identify the effect of tax subsidy on the ownership choice of hospitals. I further differentiate behavior between nonprofit versus for-profit hospitals, including cost, provision of undercompensated care as well as quality. Using Center for Medicare and Medicaid Services(CMS) hospital cost report data from 1996 to 2015, I estimate a 4-6 percent increase in the probability of non-profit conversion into for-profit hospitals due to the enactment of CRR. Moreover, the effect of CRR diminishes with the tax rate. My results further show that hospitals divert community benefit spending to teaching to meet the requirement of CRR, rather than increasing provision of uncompensated care.

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Dedication

To my parents, Cangmin and Guangping, and my beloved Chen

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CHAPTER 1

INTRODUCTION

Health care subsidies account for a fast-growing share of public expenditures in many developed and developing countries, making them a more and more important component of fiscal policy discussions. My research focuses on studying the effectiveness and efficiency of public spending in health care field. In particular, empirical microeconomic methods are applied to explore the causal relationship between public health policies and the welfare of various players in the health care market. The health care industry is one of the fastest growing sectors in the United States and one of the most heavily regulated industries in the country due to its nature of imperfect competition and asymmetric information. This phenomenon also occurs in many other developed and developing countries. China, for instance, is one of those countries which are going through fast pace of expansion in health care market as well as development in regulatory environment with more effective supervision. Moreover, government intervention take different forms in this area such as subsidies to consumers, i.e. patients, subsidies or taxations to producers, i.e. health care providers, as well as other regulations that supervise the behaviors of various players in the market. The effectiveness of such public policies will greatly influence the operation of health care providers, the behavior of consumers and the interactions between them. Therefore, the prevalence and complexity of public policies in health care field leave a

lot of unanswered questions.

Two of these public health policies are focused in this dissertation: subsidized health insurance for individuals; and tax subsidies for one major type of the health care providers, hospitals. By subsidizing the consumption of health care, public medical insurance is supposed to stimulate the use of medical service while reducing the out-of-pocket expenditures for financial protection. By subsidizing hospitals through tax exemption for non-profit suppliers, it reduces the operating cost of hospitals and encourages the provision of community benefits and uncompensated care to the public. Although the two policies target different players in the health care market and through distinct fiscal policy channels, they both intend to reduce the cost of health care and encourage health care utilization, especially for the financially disadvantaged population. Comparing the effect of these two distinct approaches provides implications for reconciling fiscal resources for welfare improvement in health care market. First, I examine the impact of subsidized health insurance coverage on individual welfare in the context of a Chinese public health insurance program, using two different econometric approaches, a parametric model with panel data and a semiparametric model which further disentangles the heterogeneity in treatment effect. Later, I look at the role of tax subsidies on the supply of health care in the context of state and federal tax policies in the U.S.

In the first two following chapters, I assess the effect of public health insurance on program beneficiaries' welfare, by evaluating a new national public medical insurance program in China, Urban Resident Basic Insurance (URBMI). This program, introduced in 2007 and having an annual fiscal expenditure of 30 billion RMB, aims to provide coverage to more than 200 million urban residents including elderly, children, college students and unemployed adults. I examine the effect of Chinese URBMI by using a panel survey dataset Chinese Health and Nutrition Survey (CHNS).I have two primary objectives:1) evaluate the impact of URBMI program on both health care utilization

and health outcomes; 2) estimate the individual heterogeneity in program effects and explore the source of such heterogeneity for policy implications. First, I focus on the demand side effect of insurance coverage on program beneficiaries. Health care is a complex and multidimensional product. Therefore, a broad set of outcomes are studied to provide a thorough picture on the influence of insurance coverage. The evaluation is arranged around two main aspects of potential insurance benefits: health care utilization and health outcomes. By subsidizing the consumption of health care, public medical insurance is supposed to stimulate the usage of medical service while reducing the out-of-pocket expenditure in order to provide protection from financial risk. These are the direct program goals to be evaluated. In addition, the analysis also considers a set of outcomes measuring the consumption patterns in health care services to assess the channel of change in health care expenditures. Insurance coverage tends to alter consumer's choice of the type of health care services to adopt. For example, the insured population is more likely to consume preventative care (Ayanian et.al 2000[7]) and has more frequent contact with health care providers (Anderson et.al 2010 [5]). Ultimately, the increased consumption of health care utilization should translate into enrollees' improved health status, which is an important measure of the ultimate policy goal of improving social welfare. Hence, I also investigate the impact on health outcomes from this program.

The second objective of this research project is to assess the heterogeneity of insurance impact on individuals with different observed and unobserved characteristics. URBMI is a national policy program which covers subpopulations with distinct demographic characteristics and different needs for health care services. For instance, in low income areas, individuals are in need of basic medical care while in more developed regions, individuals with insurance may look for improving the quality of medical care they already receive. The elderly with insurance may benefit primarily from treatments for chronic diseases while children may benefit most from coverage of

preventative care. However, in terms of program coverage, URBMI subsidizes different subpopulations in a homogeneous manner, which naturally results in heterogeneous responses from individuals. Therefore, estimating such heterogeneity is crucial in the context of this program. From the perspective of econometric modeling, using regular parametric models which only estimate the average treatment effect may be misleading. I develop a new semiparametric econometric method which evaluates the heterogeneity of the treatment effect in a flexible manner. From the perspective of policy evaluation, being able to pin down the specific program effect on individuals has important implications for assessing the cost-effectiveness of URBMI and improving the design of insurance policy.

The main empirical challenge is addressing the endogeneity of program enrollment from the voluntary enrollment scheme of URBMI. Endogeneity bias is likely to arise both from time-varying unobserved factors such as changing attitudes towards health and demand shocks on health related consumption, as well as time-invariant individual heterogeneity, such as long run overall health conditions. Correcting for self-selection bias from multiple sources is the key effort of this paper.

In Chapter 2, I exploit city-level variation in insurance policy generosity to identify program enrollee's responses to insurance coverage. Specifically, the URBMI insurance premium, which varies by city, age-group and year, is adopted as an instrumental variable to correct for endogeneity bias in URBMI enrollment. Under IV estimation, I find that enrollment in URBMI increases total health care expenditures by 31% on average and reduces out-of-pocket expenditure by 3.5%. Examining patterns of health care utilization, the increase in health care expenditure is mainly generated by two channels: preventative care (increase of 2%) and medical services in community-level clinics (increase of 21%). URBMI does not divert enrollees to providers of higher quality such as city-level major hospitals. In terms of health outcomes, URBMI shows positive impact on some measures of chronic diseases such as high blood pressure, but the

overall impact is limited.

Further, from estimation results in Chapter 2 using linear panel data model with IV and fixed-effect, the main finding also suggests that the effect of URBMI varies largely across subpopulation with different age, income, education level and geographic region. This suggests the need for a more flexible econometric model that can incorporate individual observed and unobserved characteristics into the marginal effect function. Therefore, Chapter 3 is devoted to estimate a marginal treatment function of URBMI that changes with individual characteristics. The commonly used parametric approaches, i.e.adding interaction terms or estimating subsamples, have limitations. In particular, the marginal effect can only vary by a limited number of variables due to the restriction in sample size. Moreover, the parametric model must impose certain functional forms to the marginal effect function. However, as discussed above, due to the multidimensional nature of health care consumption, it is difficult to predict how specific individual characteristics affect individuals' responses to insurance coverage. Hence, I develop a new semiparametric panel data model with endogenous treatment, which incorporates unobserved individual heterogeneity flexibly into the outcome model as an unknown function of observed time-invariant factors.The nature of panel data allows me to handle sources of endogeneity which are unobserved but persistent over time ("fixed effect"). Departing from usual additive structure of such unobservables, such as the fixed effect specified in linear models, I consider a more general class of nonseparable models. The effect of insurance enrollment can therefore be estimated to vary by individual characteristics and individual unobserved heterogeneity.This method has broad applications beyond topics in health economics

The estimation results suggest substantial heterogeneity in URBMI's impact; the impact in fact nonlinearly changes with individual characteristics. URBMI is the most effective for children under age of 5, causing an increase in health care expenditure of 158%. Females and individuals with income level ranging from the 50th to 75th

quantile generally respond more positively to insurance coverage than the rest of the population. In contrast, individuals from lower income families benefit less from URBMI. Whether URBMI is indeed effective depends on the policy goal. If the primary policy target is to ensure accessibility of basic medical services and provide financial protection, URBMI is still short on meeting the objective. If the policy goal is simply to encourage medical care utilization, this insurance program has had some success. An important policy implication can be drawn from the results of this research: based on the individual heterogeneity estimated, the efficiency in this public insurance program can be improved by redesigning differentiated policy packages for different subgroups of the population.

The last chapter of this dissertation assess the effect of government subsidies on the supply side of the health care market in the U.S. The hospital industry is one of the few sectors in the US where different ownership types coexist. Private nonprofit hospitals (NFP), which traditionally serve as a signal of good quality in the health care market with severe asymmetric information problem, have dominated the market since the 1940s, but the number of for-profit hospitals has increased in recent years.

The underlying factors which determine the ownership choice of hospitals are not widely studied in economic literature, especially from the perspective of public policy. Due to their tax exempt status, nonprofit hospitals (NFP) are in practice heavily subsidized by federal, state and local governments. The variation in tax rates and tax policies limiting the behavior of nonprofit hospitals therefore impose different net benefit of choosing a nonprofit ownership status across state and over time. There is an ongoing policy debate on whether nonprofit hospitals should be taxed. The answer is determined by whether nonprofits are similar to their for-profit (FP) counterparts in terms of their operating behavior. The empirical literatures haven't reached consensus on this question. Recently, many state and federal laws have been enacted that mandate the reporting of benefits provided to the community by non-profit providers. These

regulations are generally referred to as community benefit reporting requirements (CRR). These regulations require non-profit providers to justify their tax exempt status by submitting detailed reports regarding their provision of community benefit mainly in three categories, teaching and education, uncompensated care and community services, and lastly undercompensated care to Medicaid and Medicare patients.

Using panel data, this study exploits the variation in tax policy across states and over time to identify the effect of tax subsidy on ownership choice of hospitals, and further the different operating behavior between nonprofit versus for-profit hospitals, including cost as well as provision of under-compensated care. A state-level fixed-effect model estimates 4-6 percentage-point increase in for-profit market share due to CRR. Moreover, the effect of CRR diminishes as the tax rate increases.Three measures of for-profit market shares are under estimation, including for-profit hospital share in number, the share of hospital beds, and the share of specific types of hospital care such as admissions, emergency room admission, inpatient days and outpatient admission. Results are consistent across various measures and indicate that tax rate and community benefit requirement laws are both important determinants of nonprofit versus for-profit market share.

To further explore the channels of such changes, I developed a behavioral model in which hospitals chooses conversion and closure decision to maximize their objective functions. NFP and FP hospitals coexist in the market with different utility functions. Driven by the behavioral model, potential determinants of ownership choice are identified. Using hospital-level data, i.e. Center for Medicare and Medicaid Services(CMS) hospital cost report data from 1996 to 2015, I empirically examine the choice of conversion and closure by NFP and FP hospitals after CRR using multinomial logit regression. CRR significantly increases the probability of conversion and closure of NFP hospitals. Lastly, the effect of CRR and tax rates on provision of community benefit is studied. It is found that NFP hospitals allocate fundings disproportionately

to different types of community benefits. Being required to provide community benefit to the society, NFP hospitals are selective in terms of the type fo benefit they increases. Teaching and education related activities receive the largest increase in funding by NFP hospitals. Although the underlying reason for this selective behavior requires further investigation, the findings in this chapter suggest that without specified clauses on the type and amount of community benefit requirement, tax-exemption and CRR, although effective to some extent, may be less efficient in subsidizing uncompensated care to the low income population.

CHAPTER 2

IS PUBLIC HEALTH INSURANCE EFFECTIVE IN CHINA?
A STUDY OF THE URBAN RESIDENT BASIC MEDICAL INSURANCE

2.1 INTRODUCTION

The provision of social medical insurance is an important functions of modern government in developed countries. Subsidizing health insurance coverage accounts for a substantial share of public expenditures. This fraction is expected to continue increasing due to aging populations and advancing technology. One of the main rationale for public health insurance lies in the rich theoretical work on the inefficiency of private insurance markets due to asymmetric information (Rothchild and Stiglitz 1976[38]). Whether such government intervention is welfare-improving is always under the scrutiny of economists.The effects of Medicare and Medicaid program on beneficiaries, for example, have been heavily studied with mixed findings depending on the outcomes examined.(e.g. Finkelstein 2010[16], Card 2004[9], Currie 1996 [12]).

In China, although less intensively studied, health care accessibility is also a key social issue. In 2006, less than 40% of Chinese citizens were enrolled in medical insurance programs of any kind, including private and public, meaning that more than 700 million people were uninsured. As a result, many households were at high risk of medical impoverishment. The Chinese government launched a health care reform

program in 2006, which aims to provide universal health insurance coverage as safety net protection to its 1.3 billion citizens. The proposed public health insurance system consists of three parts, covering three distinct populations. Rural residents are eligible for the New Rural Cooperative Medical Scheme (NCMS), which was established in 2003. For urban residents, there are two programs. Urban Employee Basic Medical Insurance (UEBMI), established in 1998, is designed for urban workers who are formally employed, while Urban Resident Basic Medical Insurance (URBMI), newly launched in 2007, is designed to cover all urban residents who are not eligible for UEBMI, including elderly, children, students and unemployed adults. For the two programs that had been established before the reform era (NCMS and UEBMI), the focus of reform is to increase program enrollment rate and raise the reimbursement rate on medical expenditures. By the end of 2012, it is estimated that 1.27 billion out of 1.34 billion of the population was covered by the three-part public insurance program.[1]

In this research project, I focus on the Urban Resident Basic Medical Insurance (URBMI). The policy target population is estimated to be over 200 million, the majority of whom were uninsured prior to the program. They are the group most vulnerable to medical impoverishment and the main target of most welfare policies. Therefore, the effectiveness of URBMI is important for improving equality in terms of medical accessibility. Around $20 billion of fiscal expenditures was dedicated to the subsidy of URBMI from 2009 to 2011 alone.[2] Despite the scale of this program, only a few studies have been conducted to evaluate its effectiveness.(Lin 2009[21]; Liu et.al 2012[34]). Moreover, URBMI has two distinct features. First, enrollment in URBMI for policy eligible population is voluntary, which results in less-than-full program take-up rate. Second, URBMI only provides partial coverage (on average 65%) for health care expenditures. The enrollment scheme and coverage structure complicates the evaluation of the program. This leaves more unanswered questions. Therefore, this

[1] Chinese Public Health Statistics Yearbook, 2012 [1]

[2] Sarah L Barber and Lan Yao, World Health Report 2010, Background Paper No.37.[8]

study places focus on the analysis of URBMI program.

In this chapter, I examine the effect of URBMI after four years of program implementation, i.e. until 2011. The data used in this chapter is a panel survey dataset, the Chinese Health and Nutrition Survey, which has been collected by University of North Carolina since year 1989. Only the last three waves (2006, 2009, 2011) are selected. Health care is a complex and multidimensional product. Therefore, I consider a broad set of outcomes in order to provide a thorough picture on the influence of insurance coverage. The evaluation is arranged around two main aspects of potential insurance benefits: health care utilization and health outcomes. By subsidizing the consumption of health care, public medical insurance is supposed to stimulate the usage of medical service while reducing the out-of-pocket expenditures for financial protection. These are the direct program goals to be evaluated. In addition, the analysis also considers a set of outcomes measuring the consumption pattern in health care services to assess the channel of change in health care expenditures. Insurance coverage tends to alter consumers' choices of the type of health care services to adopt. For example, the insured population is more likely to consume preventative care (Ayanian et.al 2000[7]) and they have more frequent contact with health care providers (Anderson et.al 2010 [5]). Ultimately, the increased consumption of health care utilization should translate into enrollees' improved health status, which is an important measure of the ultimate policy goal of improving social welfare. Hence, I also investigate the impact of the program on health outcomes.

The main empirical challenge is addressing the endogeneity of program enrollment due to the voluntary enrollment scheme of URBMI. Endogeneity bias is likely to arise both from time-varying unobserved factors such as changing attitudes towards health and demand shocks on health related consumption, as well as time-invariant individual heterogeneity, such as long run overall health conditions. The argument goes as follows: an individual who values health more is more likely to

enroll and at the same time, use health care services more often. On the other hand, an individual with better overall health tends to have lower demand for both health insurance and health care services. Hence, the sources of self-selection into insurance program can be multidimensional and the direction of bias is difficult to predict.

Correcting for self-selection bias from multiple sources is the key effort of this project. Two identification strategies have been adopted in this chapter. To utilize the structure of panel dataset, an individual fixed-effect model is used to capture the time invariant unobserved factors in linear model. I further correct for the bias by exploiting a quasi-experimental variation in insurance status that results from city-level differences in policy generosity. In particular, I use the city-variation of enrollment cost,which varies by city, age-group and year, as an instrument for actual URBMI enrollment status.[3] The comparison of results from OLS with IV estimation suggests significant self-selection in program enrollment. Under IV estimation, I find that enrollment in URBMI increases the total health care expenditures by 31% on average and reduces the out-of-pocket expenditures by 3.5%. Examining patterns of health care utilization, the increase in health care expenditures is mainly generated by two channels: preventative care (increase by 2%) and medical services in community-level clinics (increase by 21%). URBMI does not divert enrollees to providers with higher quality. In terms of health outcomes, URBMI has a positive impact on some measures of chronic diseases such as high blood pressure but the overall impact is limited.

[3]The dataset in city-level URBMI policy is manually collected and assembled by the author. It is the first paper that uses this information to the knowledge of the author.

2.2 BACKGROUND

2.2.1 EVOLUTION OF PUBLIC HEALTH INSURANCE SYSTEM IN URBAN CHINA

Before 1978, under a central planning economic system, universal coverage of medical services was provided to all urban residents in China. In urban area, medical insurance was offered to all urban employers working for government sectors and state-own-enterprises (SOE) [4], as well as their dependents including elderly, children and non-working relatives. Due to the relatively low quality of medical services, out-of-pocket expenditures on health care was minimal at that time.

Since the 1980s, China has been transitioning to a market economy primarily through the privatization of state-own-enterprises (SOEs). As a result, a majority of workers lost their work status as SOE employees and became ineligible for the former medical insurance program. This led to the collapse of universal coverage for urban residents. Trying to resolve this problem, the Chinese central government created the Urban Employee Basic Medical Insurance Program (UEBMI) in 1998 to replace the old employment-based urban insurance program, in order to provide public health insurance for urban residents who are employed by either state-own or private sectors. However, unlike the previous program, UEBMI doesn't provide any coverage for the dependents of urban employees. Therefore, throughout the transition period from 1998 to 2006, about 220 million urban residents were left ineligible for any public health care program. A large proportion of the uninsured were the elderly and children.

Unlike the situation in the US or other more developed countries, the market for private medical insurance is still immature and under-developed in China. Purchasing private health insurance is uncommon for a typical Chinese household. Therefore, the

[4] Employers who worked under government sectors and SOEs account for entire urban labor force

lack of medical insurance coverage, especially among vulnerable populations created heavy financial burdens for urban households. This problem was worsened by the rapidly rising cost of medical service, starting from the mid-1990s. As discussed by Yip 2009[45], due to the inefficiencies within the health care system such as distorted price schedules and high prescription drug mark-ups, the cost of health care surged and made health care unaffordable to many households. In fact, severe illness was among the top three causes of household poverty in urban China.

In order to provide safety net protection, a main component of Chinese health care reform in 2006 was to establish a new public insurance program covering uninsured urban residents, which is the newly launched Urban Resident Basic Medical Insurance (URBMI). URBMI is a government-run, voluntary enrollment public insurance program administrated at the city level. It was piloted in mid-2007 in 79 cites and additional 229 cites joined in 2008. By the end of 2009, most cities in China had adopted this program, with only a few exceptions. The target population of URBMI was estimated to be 200 million. The central government in partnership with the local levels, committed about 850 billion RMB (about 139 billion USD) to implement it health care reform plan over the three year period from 2009 to 2011. Of this, an estimated 20% was specially dedicated to subsidize URBMI.

2.2.2 THE INSTITUTIONAL SET-UP OF URBMI

The URBMI is a central government directed, and local government administered, public insurance program, similar to the institutional setting of the Medicaid program in the U.S. The role of the Chinese central government in URBMI program includes: initiating the program by offering fiscal support, mandating the implementation by passing a series of legislative acts, and supervising the details by providing policy guidelines. The detailed design and implementation of URBMI policy, however, are left

to the city governments. Therefore, URBMI policy varies considerably across different regions.

As for eligibility and enrollment, URBMI is a voluntary-based program, targeting elderly, children, adults with disabilities and other non-working urban residents. Enrollment is individual-based; i.e, within the same household, eligible household members can choose to enroll independent from the enrollment decisions of other family members. URBMI is jointly financed by the individual enrollees and the government. The average annual cost of insurance is around 250 RMB ($40 USD) for adults, and 120 RMB ($19 USD) for children. Individual enrollees contribute less than 50% of the insurance premium while the central government and local government share the rest of the cost. To ensure program implementation, the central government subsidizes at least 80 RMB ($12 USD) per enrollee annually, with extra funding for enrollees with disabilities or with income below under poverty line. Local level subsidies vary across regions but a minimum contribution is required by the central government.

Benefit packages, on the other hand, are relatively homogeneous across cities and subpopulations. However, they evolve over time. At the beginning, URBMI was only designed to pay for inpatient treatment and outpatient treatment of severe illness such as acute diseases that require surgery. As the program developed, a much broader range of medical services were included in the coverage, including preventative care. On average, the inpatient reimbursement rate is at least 65%, but differs across different levels of medical facilities. The reimbursement is less generous for treatment received in higher quality medical providers such as hospitals with triple-A rankings. For instance, if a patient is treated in community clinic, the reimbursement rate can be as high as 90%, whereas the cost can only be covered by only 65% in city-level big hospital. Moreover, the reimbursement ceiling is set to be 4 to 6 times the average annual income of urban workers, which is about 25,000-150,000 RMB ($4,100 – $24,600 USD). Detailed information on the program is summarized in Table 2.2.1.

There are three main features of URBMI that complicate the empirical analysis.

Table 2.2.1: Summary: URBMI Program Features

Characteristics	***URBMI Detail***
Administration	*City level*
Local Authority	*City has power to determined program details*
Timeline	*2007: 79 cities; 2008: 229 cities; 2009: target all*
Population	*Urban elderly, children, student, non-working adult*
Participation	*Voluntary on individual basis*
Target	*200 million*
Financing	*Individual and government equally share contribution* *Central government subsidizes at least 120 RMB/ person* *City contribution: minimum required by central gov*
Reimbursement Ceiling	*4 6 times average annual income of urban worker;* *25,000 150,000 RMB on average*
Inpatient Reimbursement	*At least 45%;* *Higher rate for lower level facilities*

Firstly, the enrollment eligibility is ambiguous for adult residents aged between 18-60 or 18-55, for males or females respectively. Although this public insurance program is designed only for adults who are unemployed or have disabilities, a considerably large proportion of working adults are also enrolled in the program. This phenomenon results from unclear eligibility policies and loose program implementation. Most cities give adults with “flexible working status” the freedom to choose between URBMI and UEBMI (employee basic insurance). However, the definition of flexible working status is ambiguous. It mainly refers to working adults employed in “private and small business”, without a clear distinction of business size. Therefore, this proportion of working population is potentially qualified for URBMI enrollment, which complicates the analysis when I define the "intent to treat" population.

Another challenge for empirical estimation comes from the design of voluntary program enrollment. As discussed above, enrollment is voluntary at the individual

level in most cities, which results in a self-selection problem in insurance enrollment. Potentially, an individual's choice of insurance enrollment could be correlated to his existing health condition, his valuation of personal health as well as unobserved health-related behavior, which are also correlated to the dependent variables under estimation and results in a biased estimation. Therefore, the self-selection bias should be the main focus when designing identification strategy.

Lastly, there exist large variations across municipalities in terms of financing and insurance premium. On one hand, the cross-city variation complicates the empirical estimation because it results in heterogeneity of treatment. In addition to estimating a single average treatment effect, the heterogeneous effect across regions should also be analyzed in order to validate the average effect. On the other hand, this cross-city policy variation is considered to be an exogenous determinant of the enrollment decision and therefore can also provide a source of identification when dealing with selection bias.

2.3 Literature Review

2.3.1 Evaluating the Effect of Public Health Insurance

The evaluation of health insurance's impact is never a single-dimensional issue. First of all, health insurance itself is a multidimensional good, which is defined by a complicated set of parameters such as insurance premium, deductible, coverage rate etc. The effect of a "pays-it-all" insurance coverage can hardly be compared to the effect of a "catastrophic-only" coverage. As discussed in Levy & Melzer (2001)[32], without a careful specification of health insurance, the evaluation of its impact can be misleading. However, this is less an important issue for a public health insurance program. In past studies, a single public health insurance program is mostly treated as a homogeneous product because the variation within a public health insurance program is very limited

compared to private insurance. Therefore, the main focues have been on comparing public insurance's impact on the insured and uninsured population, treating public insurance enrollment as a binary treatment status.[5]

Moving on to the impact, the evaluation in past studies mainly fell into two categories: health care utilization and health outcomes. The economic theory behind this is straightforward. Intuitively, health insurance reduces the price of medical services and products, and as result increases the total consumption of health care. Hundreds of studies have been conducted in this area. For example, Card et al. (2008)[9] study the impact of Medicare on health care consumption at the individual level; while Finkelstein (2007)[16] examines long term effect of Medicare expansion on aggregate health care spending. Both paper conclude that Medicare is associated with a substantial increase in health care consumption. Other studies find that not only the total consumption, but also the pattern of health care utilization is also altered by health insurance enrollment. The insured population is more likely to consume preventative care (Ayanian et.al 2000[7]) and have more frequent contact with health care provider (Anderson et.al 2010[5]). Dafny and Gruber (2005) [14]study the Medicaid program and child hospitalization. They identified two effect of health care insurance: 1)the access effect, which increases total hospitalization 2) efficiency effect, which decreases the relative utilization of inpatient treatment for avoidable diseases, because of a more frequent use of outpatient and preventative care.

Many studies have also evaluated the importance of health insurance on health outcomes. By increasing health care utilization, it is expected that individual's health conditions will be improved as a result . Hence, improving health outcomes is considered the ultimate policy goal of a public health insurance program. Nevertheless, health is also a multidimensional and complex concept, and difficult to be perfectly

[5]For example, Currie and Gruber conducted a series of research on the effect of expanding Medicaid eligibility on women and children, where they treated Medicaid eligibility as a binary status. (Currie and Gruber 2006b, Currie and Grubber 2007[2])

measured empirically (Levy et.al 2001). Past studies mainly evaluate two types of health outcomes: 1) outcomes from administrative data; and 2) self-reported health conditions. Administrative data is considered to provide a more objective and accurate measure of health. The sources of such data includes hospital discharge record and birth/death record. For example, Currie and Gruber (1996)[12] estimate the effect of Medicaid on child mortality as the only objective indicator of health. In Gruber's other study in 1996 (Gruber 1996b [13]), infant birth-weight is also included as an outcome variable. However, these objective outcome variables are sometimes considered too extreme to measure the health-related quality of life. Therefore, self-reported health conditions from survey dataset are also the commonly studied.

In this chapter, both health care utilization and health outcome variables will be examined, in order to provide a complete assessment of the effect of URBMI. The main reference paper I used in selecting outcome variables is Finkelstein's study of the Oregon health insurance experiment (Finkelstein et.al 2012[16]). Although the estimation in that study is conducted under experimental environment and not suitable for my research, I explores a wide range of outcome variables for health care utilization, financial strain and health outcomes using both administrative and survey data, which uses this study as reference for how to identify outcome variables from survey questions.

2.3.2 ENDOGENEITY IN HEALTH INSURANCE

Policy variation across region and time has been commonly used as a source of identification in previous studies (Currie and Gruber 1996b, 1996b, 1997[12], Goldman et al. 2001 [18]) The basic argument is that regional policy variation will cause difference in insurance enrollment responses but are exogenous to an individual's unobserved characteristics and his health care decisions. For instance, in a series of paper studying the effect of Medicaid expansion[12], Currie and Gruber exploit the cross-state variation

in Medicaid eligibility and expansion timing to identify the exogenous component of Medicaid enrollment and estimate a positive effect of Medicaid on health care utilization. Liu at el (2012 [34]) also study URBMI and identify the treatment effect by using city-variation in the timing of program adoption as instrument and find a 20% increase in health expenditures from URBMI enrollment. However, the timing of program adoption can only be used to examined the initial impact of the program and hence is not suitable for the evaluation of the longer panel studied in this paper.

2.3.3 PAST STUDIES ON URBMI

As mentioned, due to the short implementation period, the research conducted on URBMI is still limited. The first effort to study the effect of URBMI was by Lin et al. (2009)[33]; This study uses a household health survey for 9 cities in 2007 to estimate the impact of URBMI in terms of health care expenditures and self-reported health outcomes. It finds that enrolling in URBMI significantly decreases medical expenditures for household with low-income and individuals with previous inpatient history. Lin et.al also discovered that self-reported health conditions increase for individuals from lower income household. This study shows that URBMI is at least effective for some population group in terms of meeting its policy goal. However, I consider this study limited for two reasons. Firstly, it uses cross-sectional data from 2007, which is the year URBMI was launched. The time frame is too short for a sufficient enrollment rate and for the insurance program have significant impact on health outcomes. Secondly, the empirical methodology is simple OLS setup and does not address endogeneity issue in insurance enrollment, which may result in bias estimation.

There is another effort of studying URBMI using panel data from 2006 and 2009, which is Liu at el. (2012). It uses a difference-in-difference framework to estimate the health care utilization and medical expenditures increase due to gaining insurance

coverage. It finds a significant increase in the probability of seeking a medical provider but no impact on total medical expenditures. The authors did not consider health outcomes in the study. The Liu at el. study serves as my baseline reference because it uses the same dataset. However, I consider my research project to have possible contribution to the existing one in three ways. The first possible contribution is the methodology in addressing endogeneity. Liu at el.(2012) [34] use a difference-in-difference framework with the underlying assumption that URBMI insurance status is randomly assigned. Nevertheless, this assumption seems to be violated because the demographic characteristics differ significantly between controlled and treatment groups. Therefore, improvement can be made on identification strategy. Secondly, I provide a more comprehensive assessment of URBMI by including more dependent variables into the analysis. In particular, different measures of health care utilization as well as health outcomes will be under examination. Lastly, I am able to use an updated dataset to include 2011 survey wave, allowing for the examination of longer-term effects, reducing the ambiguity in policy implementation.

2.4 DATA

2.4.1 INDIVIDUAL LEVEL DATA

The dataset used in this paper is Chinese Health and Nutrition Survey (CHNS), an ongoing, open cohort survey project conducted by the Carolina Population Center at the University of North Carolina at Chapel Hill and the National Institute of Nutrition and Food Safety at the Chinese Center for Disease Control and Prevention. The survey collects rich information on individuals' and households' demographic and socioeconomic characteristics, as well as the health and nutrition status of both urban and rural population. It also include community survey to provide information on

community facilities, health care provision and public insurance enrollment etc.The survey took place over a 3-day period using a multistage, random cluster process to draw a sample of about 4,400 households with a total of 26,000 individuals in nine provinces in China, which vary substantially in geography, economic development and public resources. It also carried out community survey to provide information on community facilities, healthcare provision and public insurance enrollment etc. So far, nine waves of survey had been conducted in 1989, 1991, 1993, 1997, 2000, 2004, 2006, 2009, and 2011.

For the purpose of my research, I select the data from CHNS dataset in the following manner. First of all, only the last three waves of data, i.e. wave 2006, 2009 and 2011, are selected for analysis. Year 2006 is the year right before URBMI was introduced. Including this wave provides a baseline condition before treatment. Wave 2009 and 2011 data provides the variation after treatment.

2.4.1.1 EXPLANATORY VARIABLES

The eligible individuals in the survey sample are selected to be the URBMI target population, children under 18, elders above 55 or 60 depending on gender [6], college student and unemployed adults who are registered in urban status in Chinese Household Registration System (*"Hukou"*)[7]. The eligible sample contians 3,749 observations in 2006, 3,771 observations in 2009 and 5,990 observations in 2011. Noticing that the sample expanded in 2011 due to an expansion in survey size. In the empirical analysis, I will mainly use the eligible sample as my study sample. I referred to this as full sample below.

The key variable of interest is enrollment status for URBMI. By default, in wave

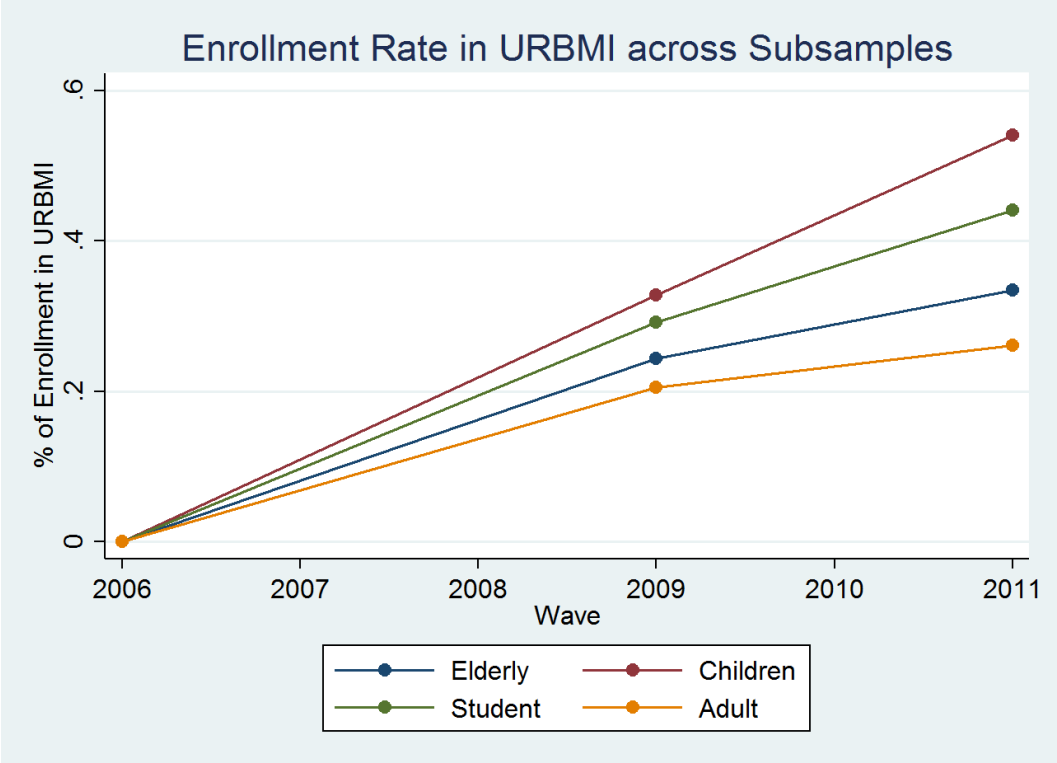
[6] The processed retirement age is 55 for females and 60 for males

[7] Adults who work for private firms with employees less than 20 people are also included in the sample. In practice, small firms are not enforced to provide employee-based insurance coverage for its workers. Hence, this population is also eligible for URBMI

2006, no observations were enrolled in URBMI. The trend of enrollment rate in various subsamples is presented in Figure 2.4.1. After it was first launched in 2007, the enrollment rate among different subsamples exhibits a rapidly increasing trend. The changing enrollment status provides a decent degree of variation to utilize for identification. The average enrollment rate reached over 30% for the full sample, among which sample of children under 18 has the highest enrollment rate of 54% in 2011, followed by college students with enrollment rate of 48%. For elderly and adult, the program take-up rate is relatively low. Although the estimation period is only four year after implementation, the enrollment rate for URBMI is far less than the policy target, of universal coverage, implying substantial self-selection issue in program adoption. In addition, the population subgroup adopt the insurance program at different rates, resulting from differentiated insurance policy.

Other explanatory variables include observable individual, household and

Figure 2.4.1: Enrollment Rate in URBMI from 2006 to 2011



community characteristics that may affect the outcome variables. There are potentially two sets of control variables. For the individual and household level controls, I include basic demographic information including gender, marital status, education level, individual income, as well as household characteristics including household size, per capita household income. I also control for individual's insurance status on other competing public or private insurance program, which includes commercial medical insurance, UEBMI program, rural cooperative public insurance and other medical subsidies by the government. The second set of controls is community characteristics including development index measures for economics, health care development, housing conditions, social service, transportation and education, which measures the economic and social development of the community.

Summary statistics of selected demographic characteristics and insurance status are presented in Table 2.4.1. The first column summarizes the mean and standard deviation of various explanatory variables of the full sample. Column (2) –(5) presents the summary statistics by waves. For wave 2009 and 2011, the comparisons between URBMI enrollee and non-enrollee are also presented, along with test result for differences in sample mean. As indicated by statistics, the characteristics of enrollees differ significantly from those who are not enrolled. Enrollees are more likely to be female, married and less educated. Moreover, URBMI enrollees have significantly lower household incomes. As for the medical insurance status, enrollees in URBMI are less likely to purchase commercial insurance and other types public medical insurance. The differential characteristics for insured and uninsured group indicate the existence of self-selection into the URBMI, which may cause biased estimation.

Table 2.4.1: Summary Statistics of Explanatory Variables

	Full Sample	Wave 2006	Wave 2009			Wave 2011		
			Non-Enrollee	Enrollee		Non-Enrollee	Enrollee	
Observation	13,510	3749	2740	1031		3695	2295	
Demographic Characteristics								
Female	0.52	0.52	0.50	0.56	***	0.51	0.57	***
Age	46.63	45.59	47.07	47.92		47.01	46.58	
Married	0.73	0.72	0.75	0.69	***	0.77	0.66	***
Education:								
Less than high school	0.59	0.61	0.60	0.71	***	0.49	0.68	***
High school	0.28	0.30	0.30	0.25	***	0.28	0.24	***
College or above	0.13	0.09	0.11	0.04	***	0.23	0.08	***
Household size	3.40	3.43	3.42	3.44		3.35	3.38	
Household income per capita	14917	8917	13965	11591	***	20389	17635	***
Health Insurance Status								
Commercial Insurance	0.06	0.05	0.07	0.03	***	0.08	0.07	**
Employee Insurance	0.13	0.13	0.15	0.07	***	0.16	0.09	***
Other Medical Subsidy	0.02	0.02	0.02	0.01	***	0.03	0.02	*

Notes: columns with asterisk reports the significance level of sample mean test result, *p<0.10, **p<0.05, ***p<0.01

2.4.1.2 OUTCOME VARIABLES

Three sets of outcomes categories are of research interest in this paper: health care expenditures, health care utilization and health outcomes. For each of the outcome category, there are multiple dependent variables measuring different aspects of the outcome in the survey. This section will briefly list the outcome variables considered in the estimation. Additional details can be found in Appendix.

For health expenditures, both total expenditures and out-of-pocket expenditures are included. Total expenditures measures the aggregate consumption level on health care expenditures while out-of-pocket payments measure the financial burden of such utilization. Within each category, three outcomes will be reported: expenditures on total medical services, expenditures on preventative care, and those on inpatient treatments.

For specific patterns of health care utilization, there are seven dependent variables identified in the survey, as listed in Table 2.A.1 below. Seeking formal medical service and receiving preventative care are the two most primary measure of health care utilization, which are both binary chose dependent variables here. The measure of the quality or intensity of treatment is represented by four variables: type of medical provider; whether receive inpatient treatment; days of hospitalization. Type of providers are categorized in three categories: city-level general hospitals, community hospitals and small clinics. The higher the category, the higher quality the hospital has in terms of the range of available treatments provided, size and physician quality. One important thing to notice is that, all of the above measures are obtained under a four-week time frame; i.e. the survey only asked respondents about their health care utilization pattern during the past four week prior to the survey. Although the short retrospect period may increase the accuracy of response, it also limits the variation in response because health care service is generally not received on a weekly or monthly basis

for the general population. Therefore, although the survey provides a wide range of health care utilization choice variables, evaluation under such survey setting tends to underestimate the effect of health care utilization, compared to other studies that measure health care utilization over long time frame. Additionally, two dependent variables concerning the treatment of certain chronic diseases are also included. These variables are not asked under the four-week time frame. It measures the utilization of long-term medical treatment for high blood pressure or diabetes.

For health outcomes, the survey includes both objective and self-reported outcomes. The objective measures of health outcome are obtained from a physical examination, which is conducted by a physician during the three-day survey period for each wave. The physical examination measures survey respondents' health conditions such as blood pressure, height, weight and observable symptoms such as goiter and angular stomatitis. Among all exam outcomes, the variables selected or constructed, are presented in Table 2.A.2. It should be noticed that the physical examination conducted in the survey was far less than a comprehensive body check that provides complete information to evaluate the overall health condition of the interviewee. However, these simple health indicators do serve as objective measures of basic aspects in respondents' health. For example, although goiter and angular stomatitis are not severe or fatal disease, they are very common in less developed regions even though they are easily treated by simple medical procedure. Therefore, these basic symptoms are related to the accessibility to the most basic medical service.

The second set of health outcome variables comes from self-reported health conditions, summarized in Table 2.A.3. General measures of wellbeing and happiness as well as self-reported symptoms and disease are included.The first variable measures the survey respondent's overall rating of wellbeing, physically or emotionally. The survey also asked questions on the psychological wellbeing of respondents. A happiness index is constructed from three happiness related question as a dependent variable for

psychological health. Other health condition variables are measures of respondents' self-reported disease or symptoms experience during the past four weeks. Again, the short time period limits the variation in response.

2.4.2 CITY-LEVEL DATA: URBMI INSURANCE POLICY

In addition to CHNS individual level dataset, city-level insurance policy variables of URBMI are also used in empirical analysis as instrumental variables. Each city determines its URBMI package for its residents. The policy variables include insurance premium, reimbursement rate for different level of medical providers and treatment type, insurance deductible for specific treatments as well as lump-sum reimbursement cap. Within a city, the insurance policy varies in four subgroups: elderly, children, college students and disadvantaged adults. In addition, the policy variables change from year to year. These policy variables can only be manually collected from local government legal documents.[8]

Among all policy variables, insurance premiums and lum-sum reimbursement caps are the two variables which summarize the variation in a single-dimension manner and hence have been selected as measures for policy generosity here.Table 2.4.2 reports the summary statistics for URBMI insurance premium and reimbursement caps. In particular the mean premium and cap is calculated for four groups of urban population: elderly, children, students and adults. In general, URBMI policy is the most generous to children and college students, subjecting them to lower enrollment cost and higher reimbursement cap. Moreover, from 2009 to 2011, the average reimbursement cap increased for all subpopulation. However, the regional pattern is harder to generalize. Comparing higher and lower income cities within a province,

[8]The main source of data is the government legal document, which can be collected from government's website or the website of municipal level human resources and social security bureau.

Table 2.4.2: Summary Statistics of URBMI Policy

	Elderly	Children	Student	Adult
Premium (in 1 RMB)				
All Cities	140.45	38.25	47.58	218.49
All Cities 2009	132.09	32.50	52.87	210.82
All Cities 2011	148.58	39.29	39.60	229.75
High Income Cities	161.89	44.55	60.91	285.23
Low Income Cities	113.02	30.88	31.67	134.69
Eastern China	206.42	49.29	61.79	318.57
Mid-China	107.69	25.31	37.71	167.17
Western China	100.50	43.50	43.50	160.50
Reimbursement Cap (in 1,000 RMB)				
All Cities	66.20	70.75	73.20	66.44
All Cities 2009	46.17	50.61	52.28	46.17
All Cities 2011	84.23	88.88	92.03	84.68
Provincial Capitals	86.90	91.30	95.95	87.35
Lower Income Cities	42.22	46.63	46.63	42.22
Eastern China	89.49	92.72	97.49	89.95
Mid-China	49.21	57.33	59.21	49.21
Western China	62.78	62.89	63.00	63.11

higher income cities tend to charge higher premiums for enrollees but on the other hand, set more generous reimbursement policy. As for geographic region, cities in Eastern China are more generous in reimbursement cap, while Middle and Western cities have relatively similar polity despite the fact that Mid-China is more economically advanced than Western part. Hence, the policy summary informally indicates that URBMI policy is exogenous to a city's characteristics. To further assess the determinants of insurance policy of URBMI policy variables, I regress the premium of URBMI on a set of city characteristics, including the urbanicity index, economics component score, population density, quality of health care score, sanitation score etc. Regression results are summarized in Table2.A.4 in Appendix. Except population density, which increases with URBMI premium, all other city characteristics are not significant predictors of insurance policy. Adding geographic indicators, population density loses significance

in affecting URBMI premium, indicating that the main difference in URBMI polity is regional differences. URBMI premium are lower for Middle and Western Chinese cities in which population densities are lower. In general, city-level URBMI policies are uncorrelated with city characteristics, especially health care related variables. Therefore, it reduces the possibility of endogenous legislation problem.

2.5 PARAMETRIC ANALYSIS: ECONOMETRIC STRATEGY

Endogeneity bias arises from omitted variables and self-selection. As discussed earlier, the source of unobserved factors is complicated, possibly including past disease history, attitude and value towards health care, health-related behavior, etc. It is difficult to predict the sign of bias because of all these concurrent factors. It should also be noticed that these unobserved effects could be either time-varying or time-invariant. As result, two methods are adopted here to address endogeneity. To better utilize the structure of panel dataset, individual fixed-effect are added into the model to control for individual's time invariant unobserved heterogeneity. As a start, consider the following linear outcome model individual i:

$$Y_{ijkt} = \beta_0 + \beta_1 URBMI_{ijkt} + \beta_2 X_{ijkt} + \beta_3 C_{jkt} + T_t + a_i + \varepsilon_{ijkt} \tag{2.5.1}$$

where Y_{ijkt} is a specific measure of health care utilization or health outcome of individual i in city j , province k at time t. $URBMI_{ijkt}$ is a dummy variable indicating whether individual i is enrolled in at time t . X_{ijkt} is a set of observed individual or household characteristics including basic demographic information, i.e. age, gender, marital status, education, household income, employment status, student status, household size, etc. Moreover, enrollment status in other commercial or public health insurance program are also included as control. C_{jkt} is the characteristics of a

surveyed community where individual i lives. Province fixed effects P_k and year fixed effect T_t are also included to control for geographic and time specific market and policy trends.

Instrumental variable approach is also added to further handle the endogeneity. The instrumental variable used here is the city-level variation in insurance policy, such as the cost of URBMI or insurance benefit coverage. Intuitively, the generosity of the URBMI program directly correlated with an individual's program take-up. A cheaper enrollment cost and a higher insurance coverage are likely to induce more eligible individual to purchase this insurance. At the same time, such policy variables only vary with the legislation environment in a certain city and certain year where the individual lives, and therefore can be considered exogenous to a particular individuals' health care related decisions.

It is worth noticing that using region-level policy variation could potentially impose threats to exclusion restriction, which is referred to as "endogenous legislation" problem by Culter and Gruber (2006). Firstly, URBMI policy could be correlated with unobserved regional factors that may potentially influence the outcome directly. For example, a wealthier city tends to impose more generous URBMI policy, while at the same time its richer citizens are likely to use more medical service and have better health conditions. However, as discussed in Session 2.4.2, URBMI premium is not significantly associated with any of the city level development factors. Secondly, it is often argued that the legislation itself could be an endogenous process, meaning that legislator designs URBMI policy specifically to deal with some perceived problem of health care utilization and health condition in the city. However, in the context of this study, I do not consider this to be a major issue because of the institutional set-up of URBMI. URBMI is a public program directed by Chinese central government. The central government sets mandatory standards and guideline for local government. Moreover, the major source of funding comes from central government instead of local fiscal resource, which limits the

freedom of "endogenous legislation" in local level. Thus, city-level policy is considered as valid instrument.

To implement the instrumental variable method, I use a modified version of 3-stage IV procedure as proposed by Woodridge (2002 [44]) for binary endogenous regressors. This procedure can be proved to produce estimator robust to misspecification in first stage.

- Step 1: Probit model is estimated to obtain propensity score $\widehat{URBMI_{ijkt}}$

$$URBMI_{ijkt} = \begin{cases} 0, & \text{if } wave = 06 \\ 1\{\alpha_0 + \alpha_1 premium_{ijkt} + \alpha_2 Z_{ijkt} > +\mu_{ijkt}\}, & \text{otherwise} \end{cases}$$

- Step 2 and 3: Run 2SLS using estimated propensity score $\widehat{URBMI_{ijkt}}$ as an instrumental variable.

Notice that the first-stage probit regression is a two-part model. This is an inherent problem of choosing URBMI policy as IV because at wave 2006, the program has not been introduced. The enrollment probability in 2006 is zero by nature. Therefore, at first stage, if the data is from wave 2009 or 2011, URBMI enrollment status of individual i will be regressed on the instrumental variable as well as all other exogenous variables. The predicted probability of enrollment $\widehat{URBMI_{ijkt}}$ will be calculated. Zeros will be assigned to $\widehat{URBMI_{ijkt}}$ if the wave is 2006. Considering that the two-part first stage model may violate the asymptotic properties of 2SLS, bootstrapped standard error is reported.

Table 2.5.1 reports the first-stage regression results for different choices of IV and under different model specifications. Insurance premium is negatively correlated with URBMI enrollment while reimbursement cap is positively correlated with URBMI, both with statistical significance. With an increase in URBMI premium of 100 Yuans [9] ,

[9] 100 Yuans are equivalent to 14.7 USD under exchange rate in 2007

Table 2.5.1: First-Stage Regression of URBMI on Instruments (Full Sample; Wave 2009 2011)

	Linear Model			**Probit Model**				
IV Selection	Estimate		F-test	Estimate		M.E		Wald Test
Premium only								
Premium	-0.0141	***	24.82	-0.0524	**	-0.0114	**	30.39
(In 100 RMB)	(0.0037)			(0.0171)		(0.0037)		
Insurance Cap only								
Insurance Cap	0.00064	***	13.42	0.00275	***	0.0006	***	9.83
(In 1,000 RMB)	(0.0001)			(0.0006)		(0.0001		
Premium and Cap								
Premium	-0.0224	***	28.39	-0.0812	***	-0.0177	***	40.38
(In 100 RMB)	(0.0039)			(0.0179)		(0.0039)		
Cap	0.00137	***		0.00358	***	0.00078	***	
(In 100 RMB)	(0.0001)			(0.0006)		(0.0001)		

Notes: *p<0.10, **p<0.05, ***p<0.01.

the probability of enrollment decreases by about 1-2 percentage point. An increase in reimbursement cap by 1,000 Yuans is associated with an increase in URBMI enrollment by about 0.1-percentage point. The F-test for joint significance of instrumental variable is reported for each selection of IV (Wald test for Probit first stage model). For reimbursement cap, the test statistics are relatively small, indicating a weak instrument. Hence, I will only use URBMI Premium as instrument.

2.6 RESULTS

In this section, the estimation results for the effect of URBMI on health care utilization and health outcome variables will be presented. The full sample, i.e. the URBMI eligible sample, is used in estimation throughout this section. For each dependent variable, four model specifications will be analyzed: 1) pooled OLS model for comparison purpose;

2) individual fixed-effect model as the baseline model; 3) fixed-effect 2SLS model with insurance premium as IV; 4) fixed-effect 3-stage IV model with insurance premium IV, using Probit first-stage regression. Throughout this section, only the coefficients of primary interest are reported and discussed. Full regression tables are reported in appendix.

2.6.1 IMPACT ON HEALTH CARE EXPENDITURE

First, the estimation results for the effect of URBMI on health care expenditures will be presented, capturing the impact of the program on the overall utilization of health care. Full sample, i.e. the URBMI eligible sample, is used in estimation throughout this section. There are in total six dependent variables studied, among which three are before-coverage expenditures: log of total medical expenditures, log of expenditures on preventative care, log of expenditures on inpatient treatment. In addition, there are three out-of-pocket expenditures including total out-of-pocket expenditures, out-of-pocket expenditures on preventative care and out-of-pocket inpatient treatment expenditures.

Table 2.6.1 presents the parametric estimation result using the 3-stage IV method described in previous section. The parameter of interest which captures the effect of insurance is the coefficient for $URBMI$. Based on the IV estimation, URBMI has significant and positive effect on total expenditures and expenditures on preventative care. Being covered by $URBMI$ increases the total health care expenditures of the beneficiaries by 31.8% while it increases the preventative care expenditures by 2.1%. Insurance also results in a decline in out-of-pocket expenditures. Being enrolled in $URBMI$ reduces the total out-of-pocket medical cost by 3.5% and the out-of-pocket cost by 0.8%. Inpatient expenditures are not affected by insurance coverage. My findings for total expenditures are smaller compared with past studies on $URBMI$,

where Liu 2012 [34] finds a 51% to 64% increase in total expenditures depending on different sample.

Table 2.6.1 also provides the estimation results for two sets of control variables: individual characteristics and community characteristics. Among all individual characteristics, age and household income are the most significantly correlated with all measures of health care expenditures across. Consistent with past studies, college education also significantly increases total expenditures and out-of-pocket expenditures. Interestingly, marital status has a negative impact on health care spending, which contrasts many finding in comparable programs in other settings. As for community characteristics, there are five development indexes included in the estimation. In a community that is more developed in terms of per capita income and health care infrastructure, spendings on health care is significantly larger.

URBMI is estimated to have a statistically significant impact on both total and out-of-pocket expenditures, indicating that program enrollees are consuming more health care services while paying less out-of-pocket. Therefore, URBMI is effective in providing more affordable health care services to program enrollees. However, the magnitude of effects are very different. In contrast to a 31% increase in total expenditures, the decrease in out-of-pocket payment is only 3.5%, Based on the estimated magnitude, the effective reimbursement rate of URBMI is 36%, which is less than the rate specified by policy, an average of 65%. The main reason for the discrepancy in results in total utilization and financial outcomes may lies in design of insurance program coverage. Unlike more commonly known public insurance programs, URBMI only covers partial cost of medical services. Hence, it is expected that the decrease in out-of-pocket expenditures is less than proportional. However, This indicates that the average treatment effect presented in table 2.6.1 is driven by certain group of individuals whose primary objective in utilizing the benefit of URBMI is not cost-reduction. To draw insight to this question, we first explore the channels through which the increase in

expenditures occurs.

Table 2.6.1: Effect of URBMI on Health Care Expenditures

	Total Expenditure			Out-of-pocket Expenditure		
	(1)	(2)	(3)	(4)	(5)	(6)
	Medical Cost	Preventative Care	Inpatient	Medical Cost	Preventative Care	Inpatient
URBMI	0.3180***	0.0211 *	0.0147	-0.0352***	-0.0079 *	0.0144
	(0.000)	(0.034)	(0.601)	(0.000)	(0.049)	(0.587)
Other Gov Insurance	0.2630***	0.0854***	0.119***	-0.0360***	-0.0572 ***	0.1150***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Commercial insurance	0.2800*	0.1090*	-0.0389	0.0250**	0.1154***	-0.0378
	(0.013)	(0.023)	(0.476)	(0.006)	(0.000)	(0.464)
age	0.0276***	0.0033***	0.0059***	0.0239***	0.0031***	0.0056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
College Education	0.0128 ***	0.0991*	-0.0285	0.2090**	0.0733**	-0.0225
	(0.009)	(0.012)	(0.524)	(0.007)	(0.002)	(0.595)
Married	-0.1470*	-0.0493*	-0.0420	-0.0694	-0.0509***	-0.0430
	(0.011)	(0.047)	(0.137)	(0.156)	(0.001)	(0.107)
Household size	-0.1420*	-0.0144	-0.0317	0.0673	0.0299	-0.0247
	(0.024)	(0.594)	(0.300)	(0.204)	(0.068)	(0.393)
Household Income	0.0032*	0.0019**	0.0035 *	0.0056***	0.0013**	0.00038
	(0.035)	(0.003)	(0.003)	(0.000)	(0.001)	(0.585)
Community:econ	0.0341**	0.00520	0.0005	0.0115 **	0.0071*	-0.0003
	(0.010)	(0.359)	(0.938)	(0.001)	(0.040)	(0.954)
Community:health	0.0579***	0.0065	0.0059	0.0519***	0.0019	0.0059
	(0.000)	(0.144)	(0.239)	(0.000)	(0.471)	(0.218)
Community:housing	-0.0584**	-0.0123	-0.0153	-0.0037	-0.0083	-0.0144
	(0.006)	(0.177)	(0.139)	(0.837)	(0.130)	(0.140)
Community:market	-0.0016	-0.0010	-0.0012	0.0045	-0.0039	-0.0009
	(0.837)	(0.765)	(0.756)	(0.495)	(0.055)	(0.810)
Community:social service	0.0226**	0.0100***	0.0006	0.0254*	0.0026 *	0.0003
	(0.002)	(0.001)	(0.852)	(0.000)	(0.005)	(0.938)
N	13510	13510	13510	13510	13510	13510
Community FE	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
F	34.59	10.66	7.641	42.85	10.20	7.597

p-values in parentheses

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

2.6.2 CHANNELS OF EXPENDITURE GROWTH: UTILIZATION PATTERNS

To explore how URBMI enrollees allocate the increase in health care expenditures, a set of health care utilization outcomes are under estimation. Table 2.6.2 and 2.6.3 presents the estimated coefficient/marginal effect on variable of interest, URBMI enrollment status. I further categorize health care utilization into four categories: general health care utilization; intensity of treatment and treatment for chronic disease.

For Category A: general health care choice, it mainly measures the probability of using medical service and general quality of service selected. In particular, it measures the probability of visiting formal medical provider, probability of seeking preventative care, and the choice of medical provider's type. Moreover, these variables are decision variables mainly based on individual's own choice, with less intervention from medical provider. As result, URBMI may have more direct impact on these variables. The regression results from Table **??** show that under pooled OLS model, URBMI enrollment shows significant effect on all of the four variables. URBMI enrollment increases the probability of seeking formal health care and the probability of seeking preventative care. It also induces enrollees to choose higher quality medical provider, by increasing the probability of visiting city-level hospital and decreasing that of community-level hospital. However, after adding individual fixed effect, URBMI only significantly influence the choice of preventative care. The coefficients of URBMI for the remaining three variables decrease in magnitude and lose significance. The parity of estimation result between pooled OLS and fixed effect model further confirms the existence of unobserved time invariant factors in error term that are correlated with variable URBMI. Under instrumental variable approach with individual fixed-effect, the impact of URBMI is significant for both the choice of seeking formal health care and the choice of preventative care. The magnitude of coefficients also largely increases. Enrollment into URBMI is estimated to increase the probability of visiting formal health care

provider by 21 percentage points, which is higher than the findings in Liu et al. (2012). Meanwhile, enrolling into URBMI will raise the chance of seeking preventative care by 4.2 percentage points. In terms of facility type, URBMI does not increase enrollee's probability in visiting city-level and community hospitals. Hence, most of the increase in expenditures occurs through community clinics. The growing use in preventative care and community clinics implies that URBMI affects health care consumption mainly through the basic outpatient care.

Comparing results from different model specification, one thing worth discussing is the sign of endogeneity bias caused by different source of unobserved factors. Noticing that by adding individual fixed-effect into the model, it decreases the size of URBMI effect, which means that time invariant factors in the model tend to bias up the coefficient. However, by using instruments that further adjust for bias from other factors, the magnitude of effect increases largely, meaning that other unobserved factors are likely to have bias down the coefficient. The channel through which these different factors affect the result should be examined with care. One possible explanation is provided as follow: The source of time invariant individual factors are likely to be values towards health, which is arguably persistent across time, while the time varying factors are more likely to capture individual's behavioral characteristics, which are considered more easily changing, especially in a fast developing environment as China. For time invariant factors, a person who values health more is more likely to purchase URBMI, while at the same time more likely to utilize health care service. Therefore, this positive chain of correlation is considered to bias up the coefficient.. As for time varying behavioral factors, it is suspected that an individual who enrolled in URBMI is more possible to engage in healthier behavior and therefore has less demand for health care utilization due to better health. This chain of connection tends to bias down the effect of URBMI. Comparing the magnitude of bias, time varying factors seems to play a more significant role in the model.

For category B, it measures the intensity of treatment received. In other words, it provides information on not only whether the individual use health care, but also how much quantity of medical service is used. Referring to Table**??**, after adjusting for endogeneity bias, URBMI enrollment only shows statistically significant effect on inpatient days, which is a small decrease for about 0.3 day. The sign of estimated coefficient is counter intuitive in some sense. However, the estimation on inpatient treatment can be imprecise due to the limited observation number in the sample. Only about 10% of individuals who seek health care service will received inpatient treatment, which limits the variation in observation. In addition to the general measurement of utilization, I also examine treatment usage for individuals with chronic diseases, as shown in Category D. In pooled OLS model, URBMI enrollment indicates a significantly higher adoption rate of treatment for both high blood pressure and diabetes. However, after adjusting for endogeneity bias, the effect disappears and even become negative in some case.

2.6.3 EFFECT OF URBMI ON HEALTH OUTCOMES

In addition to health care expenditures, the estimation result for health outcome variables is presented in this sections. Full sample, i.e. the URBMI eligible sample, is used in estimation throughout this section. For each dependent variable, four model specifications will be analyzed: 1) pooled OLS model for comparison purpose; 2) individual fixed-effect model as the baseline model; 3) fixed-effect 2SLS model with insurance premium IV; 4)Fixed-effect 3-stage model with insurance premium IV. Throughout this section, only the marginal effect of primary interest are reported and discussed.

Table 2.6.4 presents the regression results on selected physical examination

Table 2.6.2: Effect of URBMI on Healthcare Utilization

Model	Pooled OLS		Fixed Effect		FE 2SLS		FE 3-Stage IV	
Category A: General Healthcare Choice								
Seek formal medical service in past 4 weeks								
	0.0211	***	0.0064		0.1766	**	0.2176	*
Obs=13510	(0.008)		(0.012)		(0.082)		(0.118)	
Visit city-level hospital in past 4 weeks								
	0.0633	**	-0.0380		0.2911		0.0677	
Obs=2,188	(0.03)		(0.088)		(0.28)		(0.205)	
Visit community-level hospital in past 4 weeks								
	-0.1100	***	-0.0140		-0.1220		0.0394	
Obs=2,188	(0.032)		(0.106)		(0.338)		(0.244)	
Seek preventative care in past 4 weeks								
	0.0135	**	0.0257	***	0.0387	**	0.0421	*
Obs=13510	(0.006)		(0.01)		(0.01716)		(0.02418)	
Category B: Intensity of Utilization								
Inpatient treatment in past 4 week								
	0.0016		-0.0045		-0.1584		-0.1943	
Obs=13510	(0.003)		(0.005)		(0.156)		(0.202)	
Inpatient days in past 4 week								
	0.0255		-0.0357		-0.2499	**	-0.3260	*
Obs=13510	(0.037)		(0.0692)		(0.124)		(0.173)	
Ln(total medical expenditures+1)								
	0.1103		0.0118		0.3290	**	0.3180	***
Obs=13510	(0.046)		(0.076)		(0.124)		(0.003)	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

Table 2.6.3: Effect of URBMI on Healthcare Utilization (Continued)

Model	Pooled OLS		Fixed Effect	FE 2SLS		FE 3-Stage IV	
Category C: Financial Burden from Health Care Service							
Ln(out-of-pocket expense+1)							
	-0.0967	**	-0.0064	-0.0328	**	-0.0352	***
Obs=13510	(0.043)		(0.073)	(0.013)		(0.017)	
Category D: Treatment for Chronic Disease							
Receive high blood pressure treatment							
	0.0993	***	0.0290	0.0619		-0.0320	
Obs=1,221	(0.0371)		(0.0952)	(0.1830)		(0.1651)	
Receive diabetes treatment							
	0.1153	*	0.1356	-0.2940		-0.2670	
Obs=302	(0.066)		(0.448)	(0.496)		(0.860)	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

outcomes. URBMI enrollment significantly decreases the probability of getting high blood pressure test result. In particular, after correcting for bias, enrolling in URBMI is associated with about 16-percentage-points less chance of showing high blood pressure symptoms. The coefficient is considerably large in magnitude. Except for high blood pressure, URBMI enrollment does not impose sizable effect on other examination outcome variables. However, the result is consistent with expectation due to the following two reasons. Firstly, physical examination result is only available for 2009, which is only 2 years after the launce of URBMI at maximum . The effective period of URBMI is still too short for significant impact to take place. Secondly, as discussed in Section 4.1.3, the physical examination conducted in the survey is in the most basic version. The symptoms checked in the examination may not be prevailing in urban area, such as goiter. Hence, there are vary limited variation in the sample to provide a significant coefficient. However, the signs of coefficient for all these variables are negative, which gives some information about the direction of URBMI effect.

Table 2.6.4: Effect of URBMI on Physical Examination Outcomes

Model	Pooled OLS		Fixed Effect		FE 2SLS		FE 3-Stage IV	
High Blood Pressure (wave=2006,2009)								
	-0.0302	*	-0.0919	***	-0.1638	***	-0.1549	***
Obs=8935	(0.017)		(0.031)		(0.612)		(0.001)	
Obesity (wave=2006,2009)								
	-0.0236		-0.0422		-0.0368		-0.0457	
Obs=8935	(0.018)		(0.028)		(0.056)		(0.062)	
Goiter (wave=2006,2009)								
	-0.0005		-0.0004		-0.0048		-0.0055	
Obs=8344	(0.001)		(0.002)		(0.004)		(0.005)	
Angular Stomatitis Symptom (wave=2006,2009)								
	0.0003		-0.0031	*	-0.0011		-0.0027	
Obs=8344	(0.001)		(0.002)		(0.004)		(0.004)	
Any symptoms (wave=2006,2009)								
	-0.0055	**	0.0032		-0.0070		-0.0089	
Obs=8935	(0.003)		(0.004)		(0.009)		(0.010)	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

The second set of health outcome variables are self-reported. The results for the outcomes are presented in Table 2.6.5. Overall wellbeing is a general self-rating for one's condition, with survey choices in 5 category but grouped into two categories, positive or negative, for simplification. A positive rating represents a self-rating of wellbeing of 3 or above in the 5 scale system. Under the instrumental variable model, URBMI enrollment raised the probability of a positive wellbeing rating by about 13 percentage points. The effect on psychological wellbeing is even more significant. URBMI increases an individual's chance of feeling happy during the past year by more than 20% under IV model. This finding is consistent with other literature on health insurance. The short-term effect of enrolling in medical insurance includes increasing happiness (Finkelstein et al. 2012[16]), although the underlying mechanism of this effect has not been studied

yet.

The other three dependent variables are symptom-related outcomes. Under OLS regression, the effect of URBMI are significant and negative on whether an interviewee feels sick or suffers from obvious symptoms during past 4 weeks. Similarly, the significance disappears in the models addressing self-selection. Notice that these two variables are available for wave 2011 and therefore are under studied in a longer time frame, which should be enough for effect to take place. This finding may be due to the 4-week reporting period of the survey question affects the result. Since variation in health condition is not likely to take place on monthly basis, this short period is more likely to capture random health events instead of the persistent health condition. Therefore, the increase in variation makes it difficult to obtain an estimator with small standard error.

Table 2.6.5: Effect of URBMI on Self-reported Health Outcomes

Model	Pooled OLS		Fixed Effect		FE 2SLS		FE 3-Stage IV	
Overall wellbeing for the past year (wave=2006,2009)								
	0.0046		-0.0235		0.1355	**	0.1233	*
Obs=8935	(0.0158)		(0.0274)		(0.057)		(0.064)	
Happiness for the past year (wave=2006,2009)								
	0.05	***	0.0547	**	0.2088	***	0.2853	***
Obs=8935	(0.015)		(0.027)		(0.057)		(0.064)	
Feeling sick during past 4 week (wave=2006,2009,2011)								
	-0.0171	***	-0.0077		0.0334		0.0345	
Obs=13089	(0.009)		(0.013)		(0.035)		(0.035)	
Have obvious symptoms during past 4 weeks (wave=2006,2009,2011)								
	-0.0372	***	0.00054		0.0159		0.0064	
Obs=13510	(0.010)		(0.015)		(0.040)		(0.039)	
Suffering from chronic disease (wave=2006,2009)								
	0.0159		-0.0232		-0.0429		-0.0532	
Obs=8935	(0.013)		(0.020)		(0.042)		(0.047)	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

2.6.4 CHANGES OF URBMI EFFECTS OVER TIME

In addition to estimate the average effect of URBMI, I am also interested in how the effect varies overtime. The program is first introduced in 2007 and spread out by mid-2009. It is reasonable to suspect that it takes a longer time period for enrollees to learn about the program detail and change their behavior accordingly. In particular, I estimate the modified version of baseline model as following:

$$Y_{ijkt} = \beta_0 + \gamma_1 URBMI_{ijkt} * W09 + \gamma_2 URBMI_{ijkt} * W11 + \beta_2 X_{ijkt} + \beta_3 C_{jkt} + T_t + a_i + \varepsilon_{ijkt} \tag{2.6.1}$$

where W09 and W11 are dummy variables for wave 2009 and wave 2011. The interaction between URBMI status with year dummy allow different effect of on URBMI by year. Similar to the previous specification, individual fixed-effect and instrumental variable method will be added to this baseline model. Table 2.6.6 and 2.6.7 report the estimation result from 2SLS model, for a various outcome variables. The two columns under "time varying effect" report estimated value and standard error for γ_1 , γ_2 from the above equation, i.e. the effect of URBMI enrollment at year 2009 and that at year 2011. The column under "average effect" just reports the estimators from baseline model for the purpose of comparison. Although only 2SLS results are presented, the estimators from other specification yield consistent findings.

In general, allowing the URBMI effect to change across time yields a consistent finding compared to our baseline model. However, the effect of URBMI enrollment is larger in magnitude in year 2011 than in 2009, which is also as expected. For example, the effect of URBMI on seeking formal health care is 4-percentage-points larger in 2011 than in 2009. Also, the effect of URBMI on seeking preventative care is 3-percentage-point bigger in 2011 than in 2009, which means that enrolling in URBMI yields a 3% higher probability of using preventative care than that if enrolled in 2009.Comparing the results with the average effect, the majority of the significance comes from the

significant effect in wave 2011. In wave 2009, URBMI enrollment shows significant impact only on one dependent variable, which is the probability of seeking formal medical service. In contrast, URBMI enrollment significantly affects four dependent variables in wave 2011, including the probability of seeking formal medical service, probability of seeking preventative care, inpatient days and total medical expenditures. Special attention should be paid to outcome variable ln(total medical expenditures+1). In particular, URBMI enrollment is associated with a 36.2% increase in total medical expenditures in 2011, which indicates a substantial increase in the amount of total health care utilization. This effect had not yet taken place in wave 2009.

As for health outcome variables, wave 2011 data are only available for two of them, URBMI has no significant impact on self-reported sickness or symptoms during past 4 weeks. Again, the 4-week reporting limitation may interrupt the accuracy of estimation.

Table 2.6.6: The Change of URBMI Effect Overtime: Full Sample

FE 2SLS	Time Varying Effect				Average Effect	
	URBMI*W09		URBMI*W11		URBMI	
Category A: General Healthcare Choice						
Seek formal medical service in past 4 weeks						
	0.1423	*	0.1842	**	0.1766	**
Obs=13510	0.082		0.094		0.082	
Visit city level hospital in past 4 weeks						
	0.2364		0.1443		0.2911	
Obs=2188	0.196		0.194		0.28	
Visit community level hospital in past 4 weeks						
	-0.2200		0.1651		-0.1220	
Obs=2188	0.235		0.232		0.338	
Seek preventative care in past 4 weeks						
	0.0245		0.0553	**	0.0387	**
Obs=13510	0.027		0.028		0.017	
Category B: Intensity of Utilization						
Inpatient treatment in past 4 week						
	-0.0460		-0.2540		-0.1580	
Obs=13510	0.192		0.191		0.156	
Inpatient days in past 4 week						
	-0.2851		-0.2000	**	-0.2499	**
Obs=13510	0.249		0.102		0.124	
Ln (total medical expenditures+1)						
	-0.002		0.362	**	0.329	**
Obs=13510	0.173		0.016		0.124	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

Table 2.6.7: The Change of URBMI Effect Overtime: Full Sample

FE 2SLS	Time Varying Effect		Average Effect	
	URBMI*W09	URBMI*W11	URBMI	
Category C: Financial Burden of Utilization				
Ln (out-of-pocket expenditures +1)				
	0.078	-0.014	-0.0328	**
Obs=13510	(0.204)	(0.011)	(0.013)	
Health Outcomes				
Feeling sick during past 4 week				
	0.142	0.0358	0.0334	
Obs=13089	(0.04)	(0.04)	(0.04)	
Have obvious symptoms during past 4 weeks				
	0 .008	0.020	0.006	
Obs=13510	(0 .044)	(0 .046)	(0.040)	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

2.7 CONCLUSION

The Chinese Urban Residence Basic Medical Insurance is a large-scale public health insurance program, which affects the insurance status of 200 million urban citizens in China. It also involves a massive investment of fiscal and social resources. This paper examines the four-year impact of having medical insurance through enrollment into the URBMI program. By utilizing city-variation in insurance premium, I identify the exogenous source of URBMI enrollment to provide an unbiased estimation of insurance's effect on health care utilization and health outcomes.

URBMI enrollment is found to increase health care expenditures. The main channel of such change is through increasing the use of basic medical services which involves clinics and preventative care. Nevertheless, contrary to findings of previous studies, having insurance coverage does not lower the financial burden through largely reducing out-of-pocket payments. URBMI is also found to exhibit positive effect on the

usage of medical services. It increases the probability of using medical service by 15-20 percentage points, and the probability of receiving preventative care by 3-5 percentage points. There is also some positive evidence on health outcomes. URBMI enrollment is associated with lower probability of exhibiting high blood pressure symptom and with higher self-reported mental health condition and overall wellbeing. Moreover, URBMI's impact changes overtime, with larger effect in 2011 than in 2009. This result indicates that it requires longer time period for the insured population to learn about the program policy and adjust their behavior accordingly. This may be a plausible explanation of why URBMI enrollment does not induce significant effect on some outcome variables.

The main focus of this chapter is to analyze the impact of health insurance. However, there are some unanswered questions that are beyond the scope of this paper but worth noticing. First, URBMI is a national policy program which covers subpopulations with distinct demographic characteristics and different needs for health care services. For instance, in low income areas, individuals are in need of basic medical care while in more developed regions, individuals with insurance may look for improving the quality of medical care they already receive. The elderly with insurance may benefit primarily from treatments for chronic diseases while children may benefit most from coverage in preventative care. However, in terms of program coverage, URBMI subsidizes different subpopulations in a homogeneous manner, which naturally results in heterogeneous responses from individuals. Therefore, estimating such heterogeneity is crucial in the context of this program.However, the empirical strategy in this chapter only identifies an average of such response, which limits the information for drawing implications on program efficiency for specific subgroups. Second, based on estimation results from this chapter, the impact of URBMI enrollment exhibits several patterns on health care utilization. For example, deduction in out-of-pocket expenditures is less than proportional to the increment of total expenditures. In addition, URBMI does not have significant impact on most of the variables measuring

treatment intensity, such as hospitalization days and total medical cost. The underlying reason behind this could be complicated. It is possible that URBMI's coverage is too minimal that it does not change the cost of treatment and therefore fails to raise the demand for treatment for the majority of program enrollees. To draw insight to this question, it is also important that we turn to estimation of individual heterogeneity to pin down subgroup that's driving the impact.

2.A APPENDIX: TABLES AND FIGURES

Table 2.A.1: Healthcare Utilization Dependent Variables from Survey Question

Healthcare Utilization	***Survey Question***
Seek formal medical service	*Did you seek care from formal medical provider during past 4 week?*
Type of medical provider chosen	*Where did you see a doctor? classified 15 survey categories into 3 types community clinic, community-level hospital, city level hospital*
Receive inpatient treatment	*Was it an inpatient or outpatient visit?*
Days of hospitalization	*How many days during the past 4 weeks were you hospitalized?*
Receive preventative care	*Did you receive any preventative health service during past 4 week?*
Received treatment if suffering from high blood pressure	*Are you currently taking anti-hypertension drugs? (if you have high blood pressure)*
Received medical treatment if suffering from diabetes	*Did you use any of these treatment methods? (if you have diabetes) Note: record only oral medicine and injection of insulin as formal treatment*

Table 2.A.2: Definition of Physical Examination Outcome Variables

Health Outcome	***Physical Examination Result/ Variable Construction***
High Blood Pressure	*Average diastolic >= 90 and average systolic >=140 obtained from three blood pressure tests*
Obesity	*Body mass index (BMI) >= 25*
Underweight	*Body mass index (BMI) <= 18*
Goiter	*Examined by physician*
Angular stomatitis	*Examined by physician*
Any symptoms	*Including severe vision impairment, lost of arm or leg functionality*

Table 2.A.3: Self-reported Health Outcomes from Survey Questions

Health outcomes	***Survey Question***
Wellbeing	*How do you rate your overall wellbeing at present?*
Happiness	*Constructed from 3 happiness related survey questions:* *(1) I am as happy now as I was younger. Do you agree?* *(2) I have as much pep as I had last year. Do you agree?* *(3) As I get older, things are better than I thought they would be.*
Feeling sick during past 4 weeks	*During past 4 weeks, have you been sick or injured?* *Have you suffered from a chronic or acute disease?*
Experiencing any symptoms during past 4 weeks	*Did you have any of these symptoms during the past 4 weeks* *Note: symptoms include fever, sore throat, cough, diarrhea stomachache, headache, dizziness, Joint pain, muscle pain, rash dermatitis, eye/ear disease, other infectious disease*
Suffering from chronic disease	Have a doctor told you that you suffer from high blood pressure / diabetes/ asthma?

Table 2.A.4: Potential Determinants of URBMI Insurance Premium

	(1) URBMIpremium	(2) URBMIpremium	(3) URBMIpremium	(4) URBMIpremium
Urbanicity index	-0.718	0.231	-0.299	-2.699
	(0.880)	(1.676)	(3.343)	(3.278)
Population Density	25.51**	19.38*	19.99*	6.136
	(7.933)	(8.536)	(9.188)	(9.614)
Economic component Score	-1.006	-2.982	-2.469	0.932
	(4.787)	(5.187)	(5.908)	(5.763)
Quality of Health Score		-8.137	-7.549	0.255
		(4.917)	(5.883)	(6.024)
Housing Price Index		-6.268	-5.268	7.670
		(9.600)	(11.06)	(11.18)
Social Service Score		0.838	1.551	4.813
		(3.919)	(5.528)	(5.389)
Transportation Compoenent Score		-0.609	-0.196	4.402
		(5.140)	(5.627)	(5.558)
Community Education Score		11.14	11.81	13.12
		(7.029)	(7.937)	(7.750)
Sanitation Score			1.199	2.597
			(6.536)	(6.583)
Middle China				-79.90***
				(22.47)
Western China				-86.04**
				(29.25)
_cons	6.621	46.45	51.85	134.0
	(53.16)	(79.18)	(84.70)	(85.76)
N	168	168	168	168
R^2	0.0673	0.106	0.106	0.182

Standard errors in parentheses

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

CHAPTER 3

HETEROGENEITY IN THE EFFECT OF URBMI: SEMIPARAMETRIC ANALYSIS

3.1 INTRODUCTION

The second goal of my research on the Chinese public insurance program, URBMI, is to assess the heterogeneity of insurance impact on individuals with different observed and unobserved characteristics. URBMI is a national policy program which covers subpopulations with distinct characteristics and different needs for health care services. Observed and unobserved individual characteristics play an important role in determining the response of an individual to insurance coverage.

3.1.1 MOTIVATION: PARAMETRIC FINDINGS OF HETEROGENEITY

Based on the model used in Chapter 2, I explore the potential heterogeneity in treatment effects by examining the CHNS subsamples. First, I study the subsamples of children and elderly, the main policy target. The regression results on selected outcome variables using fixed-effect 3-stage-IV models are reported in Table3.1.1. Using insurance premium as instrument, F-tests are conducted on the first stage coefficient for different subsamples. For the children sample, the joint significance test

statistics F=9.51, which is just slightly under the threshold number 10 and indicates the possible existence of weak instrument problem. For elderly sample, on the other hand, insurance premium variable passes weak instrument test. In children sample, URBMI enrollment shows significantly larger effect on the majority of outcome variables. In addition to the probability of seeking medical service and preventative care, URBMI enrollment exhibits positive effect on the probability of visiting city level hospital, which indicates an improvement in the quality of health care received.

In comparison, the effect of URBMI among elderly is not as statistically significant as in children sample in most of the outcome variables. There are several things worth discussing in the results. Firstly, unlike in other samples, the probability of seeking health care or preventative care does not significantly increase with URBMI enrollment, which infers that elderly people's health care demand is less elastic to the cost of medical service. Secondly, in elderly sample, URBMI indeed shows a significant effect on increasing usage of high blood pressure treatment. Among all individuals who are suffering from high blood pressure, the ones who enrolls in URBMI are 18-percentage-point more likely to get treated, including using anti-hypertension drugs. Since chronic diseases are more common among the elderly population, the impact of URBMI on chronic disease treatment is a more important criterion in assessing the general effectiveness of the program.

To sum up, the diverse pattern in change of health care utilization under insurance coverage between children and elderly reveals that subgroups of population have different needs in medical services. The average treatment effects of URBMI on total and out-of-pocket expenditure is biased by the utilization pattern of subgroups who respond most significantly to URBMI. For instance, the children sample shifts utilization towards higher-level of health care providers, which has higher cost and lower reimbursement rate. At the same time, this is the sample that benefits significantly from URBMI. When looking at average treatment effect, out-of-pocket payment will

be driven up by this subgroup. Hence, the average treatment effect can be misleading, which requires a more specific estimation on individual heterogeneity in URBMI's effect.

For health outcome variables, Table3.1.2 presents the results. In children sample,

Table 3.1.1: URBMI Effect on Utilization Pattern: Comparison between Children and Elderly

FE 2SLS	Full Sample		Child Sample		Elderly Sample
Weak Instrument Test	F=14.82		F=9.51		F=48.33
Healthcare Utilization					
Seek formal medical service in past 4 week					
	0.1766	**	0.8125	***	-0.0960
Obs=13510	(0.0819)	1699	(0.2356)	4997	(0.0616)
Visit city level hospital in past 4 week					
	0.2911		1.4299	**	0.27119
Obs=2188	(-0.2798)	157	(-0.6317)	1135	(-0.2522)
Seek preventative care in past 4 week					
	0.0387	**	0.3224	*	0.0082
Obs=13510	(0.0172)	1699	(0.2020)	4997	(0.0278)
Inpatient days in past 4 week					
	-0.2499	**	-0.5040	***	-0.8139
Obs=13510	(0.1239)	1699	(0.1453)	4997	(0.4003)
Receive high blood pressure treatment					
	0.0619		/		0.1813*
Obs=302	(0.1829)			158	(0.1079)

Notes: (1) bootstrapped standard errors;*p<0.10, **p<0.05, ***p<0.01.
(2)"/" represents too few observation to produce regression results.

URBMI has no significant effect on reducing high blood pressure symptom or increasing probability of feeling happy. However, in contrast to the results in full sample, URBMI significantly decreases the self-reported sickness or symptom for past 4 weeks. It is estimated that by enrolling in URBMI, a child is about 33 percentage points less likely to suffer from sickness. The interpretation of coefficients here should be dealt with

care. Due to the possibility of weak instrument, the estimators can be inaccurate. Nevertheless, we can still draw some insight from the regression results: children's health care utilization and health conditions are more easily influenced by their insurance status. URBMI program can be very effective among this subpopulation. Moving on to health outcomes, URBMI enrollment imposes effect on only one variable, happiness. For the elderly, URBMI status is associated with a 29 percentage points increase in the probability of feeling happy during the past year, which is an even larger impact in magnitude compared to results for the full sample.

In addition to the subsamples examined above, I also explore the differential

Table 3.1.2: Effect on Health Outcomes: Comparison between Children and Elderly

	Full Sample		Child sample		Elderly Sample	
Health Outcomes						
High blood pressure						
	-0.1638	***	-0.0067		-0.0928	
Obs=8935	(0.0619)	933	(0.1003)		(0.0613)	
Happiness						
	0.2088	***	0.4511		0.2857	***
Obs=8935	(0.0568)	933	(0.3314)	2684	(0.065)	
Feeling sick during past 4 week						
	0.05404		-0.3399	**	0.01258	
Obs=13510	(0.0356)	1688	(0.1607)	4997	(0.0666)	
Have obvious symptoms during past 4 weeks						
	0.0159		-0.3391	**	-0.0254	
Obs=13510	(0.0403)	1699	(0.1602)	4997	(0.0715)	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

effect across geographical regions and household income levels, which is presented in Appendix, Table 3.A.1 3.A.2, Table 3.A.3,3.A.4. Generally speaking, the findings in chapter 2 are robust to different sample specification, with a larger magnitude for subsamples with lower economic status, i.e. lower household subsample and Western China subsample. Moreover, URBMI makes impact through different outcome

variables for different subsample.For example, the effect on preventative usage is more significant for the higher income subsamples and Eastern China subsample, while the effect on total medical expense is more prevalent for lower income subsample and Western China subsample.

3.1.2 SEMIPARAMETRIC MODEL

The estimation results from the parametric model indicate substantial heterogeneity in treatment effect of URBMI. Also, it reveals that commonly used parametric approach that studies heterogeneity, i.e.adding interaction terms or estimating subsamples, has limitations. The marginal effect can only vary by limited number of variables due to restriction in sample size. Moreover, the parametric model must impose certain functional forms to the marginal effect function. However, as discussed in Chapter 2, due to the multidimensional nature of health care consumption, it is difficult to predict how specific individual characteristics affect individuals responses to insurance coverage. Hence, I develop a new semiparametric panel data model with endogenous treatment, which incorporates unobserved individual heterogeneity flexibly into the outcome model as an unknown function of observed time-invariant factors.The nature of panel data allows one to handle sources of endogeneity which are unobserved but persistent over time ("fixed effect"). Departing from usual additive structure of such unobservables, such as the fixed effect specified in linear models, this paper considers a more general class of nonseparable models. The effect of insurance enrollment can therefore be estimated to vary by individual characteristics and individual's unobserved heterogeneity.

The general model studied in this health care can be written as:

$$Y_{it} = F(X_{it}, a_i, T_{it}) + \epsilon_{it}, t = 1, ..., T \tag{3.1.1}$$

where $i = 1, 2, ..., N$, Y_{it} is a continuous outcome of individual i at time t, such as health care expenditure, in-patient treatment days, biomakers or subjective health ratings. X_{it} are observed explanatory variables while T_{it} is the discrete treatment variable, which indicates enrollment in URBMI. (a_i, ϵ_{it}) denotes unobservables, which can both correlated with the enrollment indicator. Specifically, a_i is the time-invariant individual fixed effect, which enters the treatment function nonadditively.

Econometric literatures have intensively explored this issue and have been extending the topic from parametric analysis to nonparametric models, which allows the incremental effect of the discrete treatment to depend on other exogenous covariates flexibly. The main approach for tackling endogeneity in discrete treatment model is IV estimator or nonparametric version of 2SLS. Das (2005)[15] developed a two-step estimator which substitute nonparametric estimation of instrument in the outcome model to identify the local average treatment effect. In a semiparametric context, Klein et.al(2015)[29] propose an IV estimator which is robust to misspecification of the treatment model, and also develop the distributional results for marginal treatment effect.

This chapter builds on the growing literature of discrete treatment model with endogeneity but extends it to panel data setting. Recent literatures have been working on panel data models with fewer parametric restrictions. In most of these literature, individual heterogeneity enter the model in an additive manner. For example, Carroll et.al 2008[24] estimate a nonparametric panel data model with additive fixed-effect using first-differencing. Similarly, Soberon et.al [42] specifically handles a panel data model with discrete treatment and varying coefficient, using first differencing and local linear regression. Meanwhile, there are other paper studied nonseparable panel data models with nonadditive time-invariant unobservables by

imposing various assumptions on such unobservables. Atonji et.al (2005 [3]) impose exchangeability assumption on the distribution of individual fixed-effect conditioned on values of endogenous variable and use control approach to estimate the marginal effect. Hoderlein (2012 [25]), which requires conditional independence of time-varying unobservables and endogenous regressors conditioned on individual fixed-effect and one additional excluded variable, identified local average response on a subpopulation of "stayer", whose explanatory variables stay unchanged over time. However, only continuous endogenous variables are considered in above mentioned non-separable models.

This chapter also deals with nonseparable model but focus specifically on the nonadditivity of the time-invariant unobservables. It differs from existing literature in several ways. First of all, compared to general treatment effect models, we further utilize information from repeated observation within an individual. Hence, marginal treatment effect conditioned on individual's time-invariant characteristics could be estimated, which pins down treatment effect more specifically to an individual. Compared to other panel data model with nonseparable structure, this chapter deals with discrete treatment variable, in which many existing estimation methods do not apply, such as control function approach. Lastly, we do not impose restriction of either exogeneity or stationality of the time-varying unobservables, i.e. ϵ_{it} in Eq (3.1.1). Hence, the endogeneity in this model can arise from either individual fixed-effect, or other time-varying unobservables, which is more applicable in many empirical analysis.

To identify the model, we adopt a flexible version of the modeling device proposed in Mundlak's (1978[36]) and Chamberlain (1984 [11]), which assume that the unobserved individual heterogeneity is related to endogenous regressor only through the time-averages of exogenous variables. Denote $\bar{X}_i \equiv T^{-1}\sum_{t=1}^{T} x_{it}$, the time-average of

all explanatory variable X. Assume:

$$a_i = f(\bar{x}_i) + \eta_i \tag{3.1.2}$$

where $f(.)$ is an unknown function of $\bar{x}_i$, and η_i is an idiosyncratic shock in the fixed-effect, which is independent from the discrete treatment. To be specific, the choice of health insurance purchase can be endogenous because of unobserved underlying health condition of an individual. An individual with better overall" health condition has lower demand on both health insurance and health care service. In the context of our modeling devise, unobserved health condition can be a function of the long run average of observed health measurements, such as blood pressure or physical functionality, or even subjective rating of health, which is represented by $f(\bar{x}_i)$. Meanwhile, there are some unobserved factors in health conditions, such as genetic determinants. However, since such factors are not shown to the individual, it will not directly play a role in his choice of insurance purchase, i.e. the treatment. Hence, such factors will be modeled as idiosyncratic shock, η_i. Note that this shock is time-invariant as well. Similar approach has been used in various literatures studying panel data models, such as Semykina and Wooldridge. (2010[39]), and Maurer et.al 2011.[35]

To reduce dimensionality for feasibility of applications with smaller sample size, semiparametric model with indices specification is estimated. We propose a two-step procedure to recover the marginal treatment effect. Due to the discrete nature of treatment variable, the outcome model can be represented in an additive separable potential outcome framework. This allows the implementation of a semiparametric least square (SLS) with "plug-in" propensity score as instrumental variable. Based on the estimated model parameters, a localized 2SLS procedure is conducted to recover the marginal treatment effect function.

The estimation results suggests substantial heterogeneity in URBMI's impact

which nonlinearly changes with age, gender, income level, geographic region and prior disease history. URBMI is the most effective for children under age of 5, with an increase in expenditure of 158%. Female, individuals with income level ranging from 50th to 75th quantile generally respond more positively to insurance coverage.

The rest of this chapter will be organized as follow to obtain the results: in Section 3.2, I will describe the model in semiparametric context, and discuss condition for identification. Section 3.3 provides estimators for parameters and marginal treatment effect. Lastly, the estimation results on the quantile marginal treatment effect of public health insurance URBMI in China are presented and discussed, followed by concluding remarks.

3.2 ECONOMETRIC MODEL

Consider the following outcome model of discrete treatment, for individual i at time $t = 1, 2, ..., T$, denote Y_{it} as the continuous outcome, X_{it} a vector of exogenous variables, and T_{it} as a binary indicator of treatment [1]. We impose a general structure in the model as follow:

$$Y_{it} = F(X_{it}, a_i, T_{it}) + \epsilon_{it} \tag{3.2.1}$$

where a_i is the time-invariant individual heterogeneity which is not directed observed but can potentially correlate with treatment variable T_{it}. In addition, ϵ_{it} is a time-varying unobserved error term of Y_{it}. Conditional mean independence of ϵ from x is assumed $E(\epsilon|X) = 0$.

To complete the model specification, we assume a threshold crossing model for the binary treatment. For time period $t = 1, 2, ..., T$, individual chooses treatment at time

[1] assume only one treatment choice here but the model could be easily extended to multiple discrete treatment options

t if the perceived gross benefit exceed some threshold:

$$T_{it} = 1\{g(Z_{1it}, b_i) > u_{it}\} \tag{3.2.2}$$

where Z_{it} denotes a vector of exogenous variables. b_i is an unobserved individual fixed effect in the treatment model. There is no additional assumption on the parametric distribution of error term u_{it}. Note that for the model to be identified, Z_{it} contains instrumental variables which are excluded in X_{it}.

Consider the limitation of nonparametric model in applications with smaller sample size, for estimation purposes, semiparametric specification is further imposed on the model. In outcome model, suppose exogenous variables X_{it} enter the model through a linear index $V_{1it} = X_{it}\beta$. Similarly, in the treatment model, Z_{it} take effect through linear index $V_{2it} = Z_{it}\gamma$. Index assumption yields the following model:

$$\begin{aligned} Y_{it} &= F(X_{it}\beta, a_i, T_{it}) + \epsilon_{it} \\ &= F(V_{1it}, a_i, T_{it}) + \epsilon_{it} \end{aligned} \tag{3.2.3}$$

$$\begin{aligned} T_{it} &= 1\{g(Z_{it}\gamma, b_i) > u_{it}\} \\ &= 1\{g(V_{2it}, b_i) > u_{it}\} \end{aligned} \tag{3.2.4}$$

3.2.1 INDIVIDUAL-SPECIFIC HETEROGENEITY

As motivated in Section I, assume that the individual-specific effect, although unobserved, depends on some time-invariant observed factors. Hence, here we model the individual fixed effect as a function of the time average of observed variables. Specifically, the following structure is considered in the outcome model:

$$a_i = f(\bar{X}_i) + \eta_i \tag{3.2.5}$$

where $\bar{X} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$, a vector of time averaging value of each variable X_{it}. And η_i is a time-invariant shock to the individual fixed effect, which is independent of $\bar{X}_i$.

To construct the individual heterogeneity function, it is neither necessary to include time average of all variables in X_{it}, nor required to include excluded variables from the main model. For example, in previous case of health condition as individual heterogeneity, subjective health measures, attitude towards health may serve as better determinant for health condition than education or income. It is also unnecessary to include additional excluded variable. For identification purpose, it is only required for at least 1 variable in X_{it} to be time-varying. For simplification, we assume that $\bar{X}$ and X_{it} contain same set of variable.

The modeling for individual fixed-effect can be easily adopted in a wide range of empirical analysis. For example, in the study of return to college education, decision to attend college is a discrete but endogenous variable which may be correlated with unobserved long run individual ability. Similarly, individual ability can be decomposed into two parts. The first part of ability can be reflected by long run observed cognitive performances, such as average test scores (SAT, GPA etc.), as well as measurable non-cognitive skill sets. However, there can also be a second part of ability which is not reflected by individual's long run characteristics at the moment of college attending decision. For instance, the skill set that predicts academic performance may be different from the skill set that predicts working performance. Nevertheless, by the time of choosing college, abilities for work are not shown to individual and will not directly determine his choice of college attending.

To be consistent with the semiparatric outcome model, linear index assumption is imposed on the fixed-effect structure:

$$a_i = f(\bar{X}_i\alpha) + \eta_i \tag{3.2.6}$$

The original treatment model can be rewritten as a double-index model:

$$\begin{aligned} Y_{it} &= F(X_{it}\beta, a_i, T_{it}) + \epsilon_{it} \\ &= F(V_{1it}, f(Va_i) + \eta_i, T_{it}) + \epsilon_{it} \end{aligned} \tag{3.2.7}$$

Similarly, the treatment model follows the same structure for individual heterogeneity:

$$b_i = h(\bar{Z}_i\kappa) + \mu_i \tag{3.2.8}$$

It can be specified as a double-index model as well:

$$\begin{aligned} T_{it} &= 1\{g(Z_{it}\gamma, b_i) > u_{it}\} \\ &= 1\{g[V_{2it}, h(Vb_i) + \mu_i] > u_{it}\} \end{aligned} \tag{3.2.9}$$

Such specification has an advantage over traditional approach in which the individual-specific effect enters outcome model additively. It allows the unobserved individual heterogeneity to directly enter the treatment function, which enables the marginal effect to be individual specific. Although certain structure is imposed on a_i and b_i, the semiparametric approach still leave room for flexibility in the functional form of fixed effect. Lastly,in contrast to traditional differencing approach for additive specification, this model will preserve the individual fixed-effect during estimation, which will provide additional information specifically on the effect of individual heterogeneity itself.

3.2.2 IDENTIFICATION

The main identification strategy adopted in this paper is instrumental variable approach. Define the conditional probability function for treatment as:

$$\mathrm{E}(T_{it}|Z_{it},\bar{Z_i}) = \mathrm{P}(T_{it}=1|Z_{it},\bar{Z}_i) \equiv p(Z_{it},\bar{Z}_i) \tag{3.2.10}$$

where $p(Z_{it},\bar{Z}_i)$ is an unknown function of instrumental variables z_{it}. Due to the discrete nature of treatment variable, we can write the outcome model can be represented in a separable manner. Based on the estimation of propensity score, a "plug-in" type of method will be conducted by replacing the endogenous treatment with with instrument to perform semiparametric-least-square. For identification, following assumptions on the instrument are specified:

A. 1 (Exclusion Restriction)**.** *Z is an $h \times 1$ vector of instrumental variable which includes X in the outcome model as subvector.*

This means there exists an additional variable z in the treatment model.

A. 2 (Conditional Mean Restriction)**.** $E(\epsilon|z) = 0$.

The conditional mean independence is a weaker assumption than independence of ϵ from z, which is flexible in providing some form of heteroskedasticity from time-varying shocks(Das 2005[15]). Also note that the restriction is conditioned on Z_{it} $\forall\, t = 1,2,...,T$. Under usual index assumption, $p(Z_{it},\bar{Z}_i = E[T|Z_{it},\bar{Z}] = E[T|Z_{it}\gamma,\bar{Z}\kappa] = E[T|V_{2it},V_{bi}] = p(Z_{it},\bar{Z}_i)$, which implies the conditional mean independence of ϵ from the propensity score, i.e. $\mathrm{E}(\epsilon|p) = 0$.

A. 3 (Exogeneity of time-varying error)**.** *$Z \perp \eta$, which implies $p \perp \eta$.*

The outcome model can be rewritten as:

$$\begin{aligned}
Y_{it} &= F(X_{it}\beta, a_i, T_{it}) + \epsilon_{it} \\
&= F(V_{1it}, f(V_{ai}) + \eta_i, T_{it}) + \epsilon_{it} \\
&= \int_\Omega F(V_{1it}, f(V_{ai}) + \eta_i, T_{it}) dF(\eta_i | V_{1it}, V_{ai}, T_{it}) + [F(V_{1it}, f(V_{ai}) + \eta_i, T_{it}) \\
&- \int_\Omega F(V_{1it}, f(V_{ai}) + \eta_i, T_{it}) dF(\eta_i) | V_{1it}, V_{ai}, T_{it}] + \epsilon_{it} \\
&= E(F(V_{1it}, f(Va_i) + \eta_i, T_{it}) | V_{1it}, V_{ai}, T_{it}) + F(V_{1it}, f(V_{ai}) + \eta_i, T_{it}) \\
&- E(F(V_{1it}, f(Va_i) + \eta_i, T_{it}) | V_{1it}, V_{ai}, T_{it}) + \epsilon_{it} \\
&= G(V_{1it}, V_{ai}, T_{it}) + \delta_{it}
\end{aligned} \tag{3.2.11}$$

where the new error term $\delta_{it} = [F(V_{1it}, f(V_{ai}) + \eta_i, T_{it}) - E(F(V_{1it}, f(Va_i) + \eta_i, T_{it}) | V_{1it}, V_{ai}, T_{it}) + \epsilon_{it}$. Based on **Assumption A.1-A.3**, conditional mean independence applies to the new error term: $E(\delta_{it}|p) = 0$. Substituting (2.10) into the condition yields:

$$E(Y|p) = E[G(T)|p] \tag{3.2.12}$$

Therefore, in semiparametric setting, the above argument suggests minimizing an objective function, an SLS estimation approach proposed in Ichimura (1993 [26]), exploiting the discrete nature of treatment variable.

$$S(\beta, \alpha) = E\{[(Y - E(Y|V_1, V_a, P_{it})]^2\} = 0 \tag{3.2.13}$$

This model is hence specified as a triple-index semiparametric model, where (V_{1it}, V_{ai}, P) are the three indexes. An estimated treatment probability $\hat{P}$ will be used to replace P. Since P is an index with stand-along variable, in practice, only two sets of parameters (β, α) will be estimated. Additional index assumption is presented for identification.

A. 4 (Existence of time-varying variable)**.** $\exists X_{1it}$*, such that for some* $t = j, k$*,* $X_{1ij} \neq X_{1ik}$.

At least one variable in X is varying across time periods.

In usual semiparametric model with more than one indices, the standard assumption is the existence of one distinct variable in each index. Nevertheless, due to the nature of indices in our model specification, X_{it} in index V_{1it} and $\bar{X}_i$ in index V_a will contain a distinct variable as long as there exist one variable X_{1it} in the dataset, which indeed changed through time. With time-varying variable, $X_{1it} \neq \bar{X}_i$, which will serve as the excluded variable for each index. In the empirical application, this requires to include at least one variable which is changing over time, such as income or age, in the individual heterogeneity specification.

3.3 ESTIMATION

The key parameter in estimation is the marginal treatment effect. To begin with, rewrite the outcome model using a potential outcome framework. Suppose Y_1, Y_0 are the outcomes when treatment T_{it} is 1 or 0 respectively.

$$\begin{aligned} Y_{it} &= Y_{1it}T_{it} + Y_{0it}(1 - T_{it}) \\ &= (Y_{1it} - Y_{0it})T_{it} + Y_{0it} \end{aligned} \tag{3.3.1}$$

where $Y_{1it} = F(V_{1it}, a_i, T_{it} = 1) + \epsilon_{it}$ and $Y_{0it} = F(V_{1it}, a_i, T_{it} = 0) + \epsilon_{it}$. Hence, the outcome equation reduces down to:

$$\begin{aligned} Y_{it} &= [F(V_{1it}, a_i, T_{it} = 1) - F(V_{1it}, a_i, T_{it} = 0)]T_{it} + F(V_{1it}, a_i, T_{it} = 0) + \epsilon_{it} \\ &= [F(V_{1it}, f(V_{ai}) + \eta_i, T_{it} = 1) - F(V_{1it}, f(V_{ai}) + \eta_i, T_{it} = 0)]T_{it} \\ &+ F(V_{1it}, f(Va_i) + \eta_i, T_{it} = 0) + \epsilon_{it} \\ &= M(V_{1it}, f(V_{ai}) + \eta_i) * T_{it} + B(V_{1it}, f(V_{ai}) + \eta_i) + \epsilon_{it} \end{aligned} \tag{3.3.2}$$

The individual marginal effect for individual i at time t is $M(V_{1it}, f(V_{ai}) + \eta_i)$. Since η_i cannot be separately identified from the main model, the object of interest for estimating marginal treatment effect will be:

$$\begin{aligned} MTE &= \int_{\Omega} M(V_{1it}, V_{ai} + \eta_i) dF(\eta_i) \\ &= \int_{\Omega} M(V_{1it}, V_{ai} + \eta_i) dF(\eta_i | V_{1it}, V_{ai}) \\ &= E[M(V_{1it}, V_{ai})] \\ &\equiv \bar{M}(V_{1it}, V_{ai}) \end{aligned} \tag{3.3.3}$$

A two-step method to estimate the average marginal effect: (1) The index parameters in V_{1it} and V_{ai} will first be estimated consistently from the main outcome model using 2- stage semiparametric least square method (SLS). (2) Based on the estimated indexes, the average marginal effect can be derived using a localized 2SLS approach. Detailed estimation strategy is provided in sections below.

Index parameters will be obtain by minimizing an objective function:

$$S(\beta, \alpha) = E\{[(Y - E(Y|V_{1it}, V_{ai}, P_{it})]^2\} = 0 \tag{3.3.4}$$

In sample analog of $S(\beta, \alpha)$, we minimize:

$$S(\beta, \alpha) = \frac{1}{T \times N} \sum_{i=1}^{N \times T} \{[(Y - \hat{E}(Y|V_{1it}, V_{ai}, P_{it})]^2\} \tag{3.3.5}$$

where $\hat{E}(Y|V_{1it}, V_{ai}, P_{it})$ is the kernel estimator of true expectation $E(Y|V_{1it}, V_{ai}, P_{it})$, which is given by:

$$\hat{E}(Y|V_{1it}, V_{ai}, P_{it}) = \frac{\sum_{i \neq j} \sum_t y_{it} \left\{ \frac{1}{h_1} k\left(\frac{v_{1it} - V_{1jt}}{h_1}\right) * \frac{1}{h_2} k\left(\frac{v_{ai} - V_{aj}}{h_2}\right) * \frac{1}{h_3} k\left(\frac{P_{it} - P_{jt}}{h_3}\right) \right\}}{\sum_{i \neq j} \sum_t \frac{1}{h_1} k\left(\frac{v_{1it} - V_{1jt}}{h_1}\right) * \frac{1}{h_2} k\left(\frac{v_{ai} - V_{aj}}{h_2}\right) * \frac{1}{h_3} k\left(\frac{P_{it} - P_{jt}}{h_3}\right)} \tag{3.3.6}$$

Note that the propensity score P is unobserved and needs to be estimated.Recall from Section 3.2.1, $P_{it} \equiv E(T_{it}|Z_{it}, \bar{Z}_i) = E(T_{it}|V_{2it}, V_{bi})$, under index assumption. A semiparametric binary response model with double-index is estimated here using maximum likelihood method to recover the propensity score (Klein 1993,2002 [31],[30]). The estimated propensity $\hat{P_{it}}$ will replace P_{it} in actual estimation process, which constitute a semiparametric version of 2SLS.

The above method is conducted by pooling observations from all time period $t = 1, ..., T$. Alternatively, we can obtain the parameter by jointly minimizing the objective function in each period. For a particular period,

$$S_t(\beta, \alpha) = \frac{1}{N} \sum_{i=1}^{N} \{[(Y_{it} - \hat{E}(Y_{it}|V_{1it}, V_{ai}, P_{it})]^2\} \tag{3.3.7}$$

where $(\hat{E}|V_{1it}, V_{ai}, P_{it})$ is estimated data only in period t, whereas in pooling method all data are used in kernel estimation. Weighting matrix can be imposed on each period's condition, which is beneficial under heteroskedasticity of error term across time periods.

Replacing the marginal effect function with its mean, the outcome model is equivalent to:

$$\begin{aligned} Y_{it} &= E[M(V_{1it}, V_{ai})] * T_{it} + E[B(V_{1it}, V_{ai})] + [M(V_{1it}, f(Va_i) + \eta_i) - E[M(V_{1it}, V_{ai})] * T_{it} \\ &\quad + [B(V_{1it}, f(Va_i) + \eta_i) - E[B(V_{1it}, V_{ai})]] + \epsilon_{it} \\ &= E[M(V_{1it}, V_{ai})] * T_{it} + E[B(\hat{V}_{1it}, V_{ai})] + \xi_{it} \\ &= \bar{M}(V_{1it}, V_{ai}) * T_{it} + \bar{B}(V_{1it}, V_{ai}) + \xi_{it} \end{aligned} \tag{3.3.8}$$

where ξ_{it} is the sum of ϵ_{it} and the residuals from demeaning.

The estimation strategy is using localized two-stage-least-square. Using only observations (V_{1it}, V_{ai}) in a neighborhood of (V_{1jt}, V_{aj}), we can develop a local 2SLS

estimator for $\bar{M}(V_{1jt}, V_{aj})$ and $\bar{B}(V_{1jt}, V_{aj})$ by replacing regressor T_{it} by its conditional expectation P_{it}, which is estimated from above sections. Denote $R_{it} = [P_{it}\ 1]$ and $ME_{jt} = [\bar{M}(V_{1jt}, V_{aj})\ \bar{B}(V_{1it}, V_{ai})]$. Denote $\Delta_{ij} = R_i tME_{it} - R_{it}ME_{jt}$. The localized model can be written as:

$$Y_{jt} = R_{it}ME_{jt} + \Delta_{ij} + \xi_{it} \tag{3.3.9}$$

The local 2SLS estimator can be calculated as:

$$\hat{ME}_{jt} = [R' D_N(V_{1jt}, V_{aj}) R]^{-1} R' D_N(V_{1jt}, V_{aj}) Y \tag{3.3.10}$$

where the diagonal matrix $D_N(V_{1jt}, V_{aj})$ represents the weights for localization. To be specific:

$$D_N(V_{1jt}, V_{aj}) = diag\left\{ \frac{1}{h} k\Big(\frac{v_{1jt} - V_{1it}}{h} \Big) * \frac{1}{h} k\Big(\frac{v_{aj} - V_{ai}}{h} \Big) \right\} \tag{3.3.11}$$

The kernel function imposes heavy weight on observations close to (V_{1jt}, V_{aj}), which serves as the localization device in estimation. Through this process, the estimated marginal effect will be unbiased because the conditional mean of error component is zero.

$$\begin{aligned} E[\Delta_{it} + \xi_{it} | P_{it}] &= E(\Delta_{ij} | P_{it}) + E\Big[\big\{ M(V_{1it}, V_{ai}, \eta_i) - E[M(V_{it}, V_{ai})] \big\} * T_{it} \Big| P_{it} \Big] \\ &\quad + E\Big[B(V_{2it}, V_{ai}, \eta_i) - E[B(V_{1it}, V_{ai})] \Big| P_{it} \Big] + E[\epsilon_{it} | P_{it}] \\ &= 0 \end{aligned} \tag{3.3.12}$$

Using the estimated index $\hat{V}_{1it}$,$\hat{V}_{ai}$, and estimated conditional propensity score $\hat{P}$ obtained from first-stage estimation, we can obtain the recover the marginal effect function from the localized procedure.

After obtaining the marginal effect at every observation point of $(\hat{V}_{1it}, \hat{V}_{ai})$, following Klein and Shen [2015 [29]], I summarize this information by quantile marginal effect. Let t_{qj} as an indicator for a particular variable of interest X_{jk} being in quantile q.

Define population quantile marginal effect as:

$$\bar{M}_{qj} = \frac{E[t_{qj}\bar{M}(V_{1jt}, V_{aj})]}{E(t_{qj})} \tag{3.3.13}$$

The sample analog of quantile marginal effect can be presented by:

$$\hat{M}_{qj} = \frac{\sum_{j=1}^{N} \hat{t}_{qj}\hat{M}(\hat{V}_{jt}, \hat{V}_{aj})}{\sum_{j=1}^{N} \hat{t}_{qj}} \tag{3.3.14}$$

A Monte-Carlo study is provided in Appendix, which estimate simulated data in a size similar to the application. The estimation results under different functional forms and the length of panel are explored.

3.3.1 LARGE SAMPLE THEORY

3.3.1.1 DEFINITIONS

Next we begin by giving some standard definitions before stating the main theorem. All technical proofs are left in the Appendix. Definitions and notations are used in developing asymptotic theories are provided here.

D. 1. Treatment Probability.

Denote $P_{it} \equiv E(T_{it}|Z_{it}, \bar{Z}_i) = E(T_{it}|Z_{it}\gamma, \bar{Z}_i\kappa) = E[T_{it}|V_{2it}(\gamma), V_{bi}(\kappa)]$ under index assumption. The estimated conditional treatment probability is denoted as $\hat{P_{it}} = \hat{P_{it}}((V_{2it}(\gamma), V_{bi}(\kappa))) = \hat{E}[T_{it}|V_{2it}(\gamma), V_{bi}(\kappa)]$, which is given by:

$$\hat{E}(P|V_{2it}, V_{bi}) = \frac{\sum_{i\neq j}\sum_t T_{it}\left\{\frac{1}{h}k\left(\frac{v_{2it}-V_{2jt}}{h}\right) * \frac{1}{h}k\left(\frac{v_{bi}-V_{bj}}{h}\right) * \right\}}{\sum_{i\neq j}\sum_t \left\{\frac{1}{h}k\left(\frac{v_{2it}-V_{2jt}}{h}\right) * \frac{1}{h}k\left(\frac{v_{bi}-V_{bj}}{h}\right) * \right\}} \tag{3.3.15}$$

D. 2. Kernel.

Assume the total number of indices is m, denoted as $v_1, v_2, ..., v_m$. Define kernel $K \equiv$

$\prod_1^m \frac{1}{h} k\left(\frac{v_{im}-V_{jm}}{h}\right)$, where $k(\cdot)$ is a symmetric density with bounded $\int z^2 k(z)dz$ and $h = O(N^{-r})$.

D. 3. Trimming

Denote λ as quantile fraction and W as a vector of variables and $q(\lambda)$ is the population quantile vector for λ^{th} quantile. Define sample trimming function as an indicator function representing whether W_i is contained in the specified quantile:

$$\hat{t}_i(\hat{q}) \equiv 1\{\hat{q}(\lambda_1) < W_i < \hat{q}(\lambda_1)\}$$

This trimming function can be used to represent trimming on index as well when W_i denotes estimated indices.

In what follows, Theorem 1 and 2 gives results on the consistency and asymptotic normality of the finite-dimensional index parameter estimators.

Theorem 1. Consistency.

Denote $\theta = (\beta, \alpha)$, all parameters in outcome model, with $\hat{\theta}$ as the estimator which minimizes (3.5).

Under Assumption (A.1)-(A.5) and definition (D.1)-(D.3):

$$\hat{\theta} \xrightarrow{p} \theta_0$$

Theorem 2. Normality Under Assumption (A.1)-(A.5) and definition (D.1)-(D.3):

$$\sqrt{N}(\hat{\theta} - \theta_0) \xrightarrow{d} W \sim N(0, \Sigma)$$

where

$$\Sigma \equiv H_0^{-1} E[\sqrt{N} G_0 G_0' \sqrt{N}] H_0^{-1}$$

$$\text{Gradient } G_0 \equiv E[\nabla_\theta S(\theta_{0_0})]$$

$$\text{Hessian } H_0 \equiv E[\nabla_\theta G(\theta_{0_0})]$$

Theorem 3. Properties of Quantile Marginal Treatment Effect Under Assumption (A.1)-(A.5) and definition (D.1)-(D.3): quantile marginal effect is consistent and asymptotically normal.

$$\hat{M}_q \xrightarrow{p} M_q$$

$$\sqrt{N}(\hat{M}_q - M_q) \xrightarrow{d} W \sim N(0, \Omega)$$

3.4 ESTIMATION RESULTS

3.4.1 INDEX PARAMETERS

Using the parametric results as baseline comparison, I estimate the data using semiparametric model described above. In Table 3.A.5 in Appendix, I list the estimation results for selected index parameters. There are two indexes estimated in the model, one used to summarize information on time-varying characteristics ("characteristic index") and the other summarize individual time invariant heterogeneity ("fixed-effect index"). Note that each index is only identified up to location and scale. The coefficient for age and the average of age are set to be one. We can,nevertheless, compare the relative contribution of variables in each index to evaluate whether the estimation results is reasonable. First of all, the signs of parameters are relative consistent between the characteristic and fix-effect index, indicating that the same feature affects the treatment effect in the same direction, regardless of whether it is a short-term or a long-term factor. On the other hand, the relative size of parameters are different between the two index, meaning that for a single factor, it may play a different role when it appears as long-term or short-term impact. For example, marital status and household income have a much larger relative parameter in the fix-effect index than the characteristic index, indicating that these factors plays a more important role in affecting individuals' long-term consumption habit in health care.

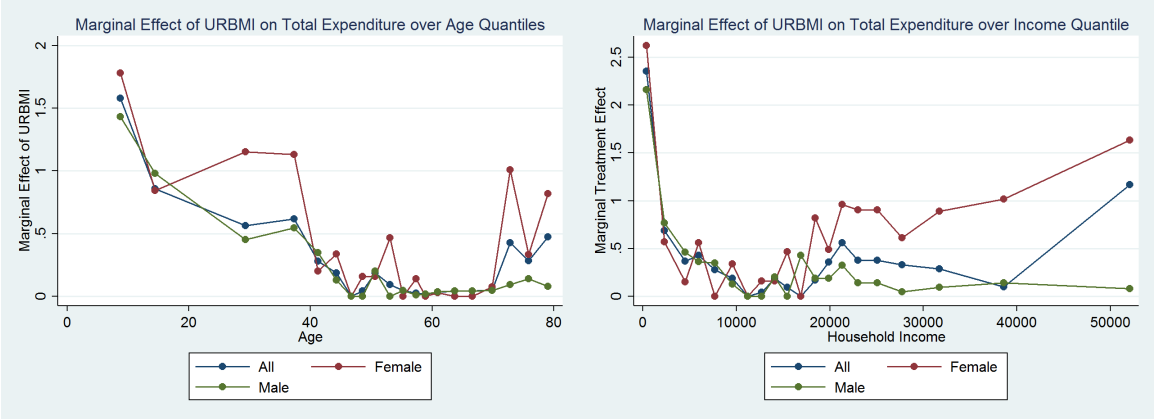
3.4.2 MARGINAL TREATMENT EFFECT

To compare the semiparametric results with the parametric baseline, marginal treatment effect function is calculated on the observation points and summarized into quantile marginal effect. The marginal effect function of URBMI are plot over age

and income quantiles,which is presented in Figure3.4.1 to Figure3.4.3. (Detail results are summarized in Appendix) With each group, marginal effect of different gender are also presented for comparison purpose. In general, the pattern of marginal treatment function follows similar pattern across different expenditure measures. For age, the treatment effect is the largest for children under 18. For the smallest quantile with an average age of 4, the effect of URBMI is as high as 170%, 48% and 152% for the magnitude of increase in total, preventative and inpatient expenditure accordingly. As age increases, the effect of URBMI dropped drastically. For the age group between 55 to 65, the effect is low and not statistically significant. Not until after the age of 70, marginal effect starts to increase.

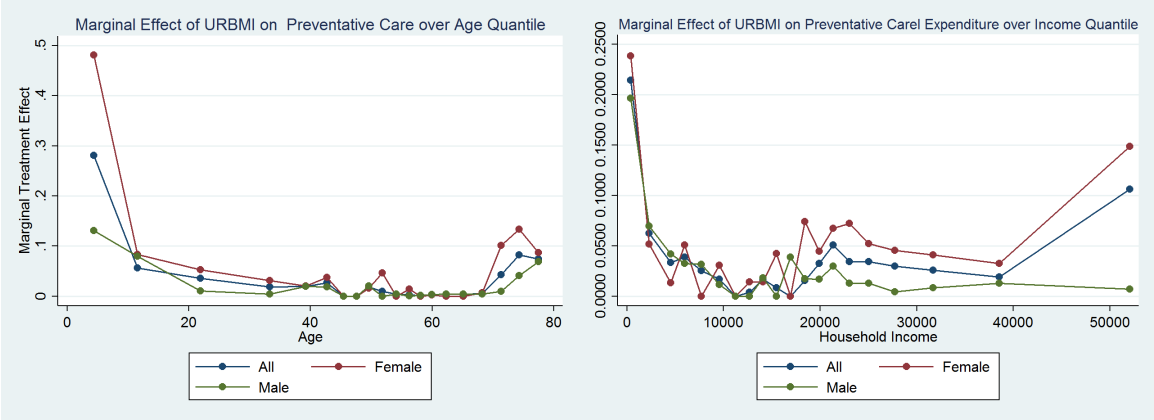
For income, there is also significant variation in treatment effect. Individuals in the lowest income decile are benefited the most from URBMI, with an increase in total expenditure of 231%. However, except for the lowest income group, individuals from low-to-median income level do not respond positively to insurance coverage. In contrast, when income moves up to higher quantiles, URBMI's effect becomes larger and significant. One possible explanation is possibly related to the insurance coverage, which is less than full coverage. For the lowest income group, since health care utilization can be non-existed, being partially covered will induce utilization significantly compared to original level. However, for low-to-median income group, since they are originally having health care consumption to necessary level, the partial coverage will not elicit more usage of service.

One last point worth discussing is the gender discrepancy in treatment effect between female and male. In general, URBMI has larger impact on female than male across age groups and income groups, which is consistent with existing literatures (e.g. Kowalski 2006, Antwi 2013). In addition, the discrepancy between genders are the largest at the age of 20-40, which indicates that women at the age of childbearing are likely to benefit from the program.



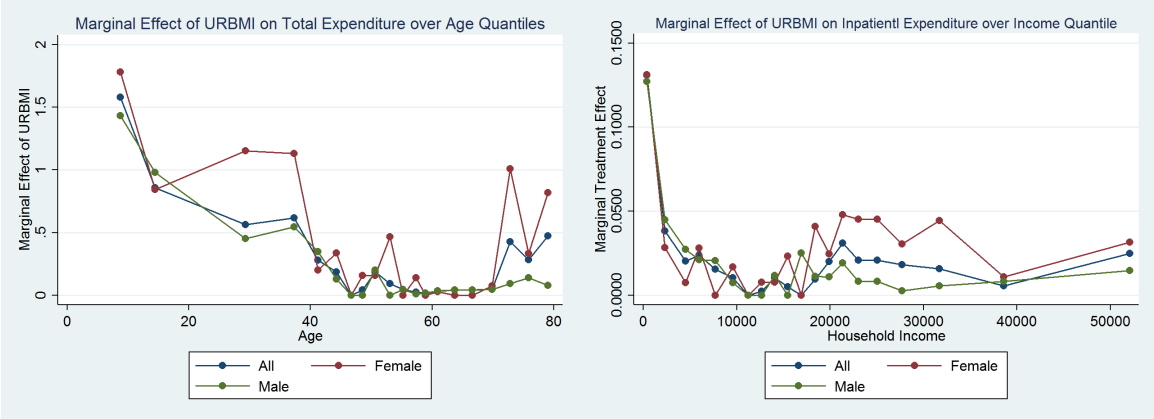
(a) MTE over Age Quantiles (b) MTE over Income Quantiles

Figure 3.4.1: Marginal Treatment Effect of URBMI on Total Expenditure



(a) MTE over Age Quantiles (b) MTE over Income Quantiles

Figure 3.4.2: Marginal Treatment Effect of URBMI on Preventative Expenditure



(a) MTE over Age Quantiles (b) MTE over Income Quantiles

Figure 3.4.3: Marginal Treatment Effect of URBMI on Inpatient Care Expenditure

3.5 CONCLUDING REMARKS

Extending from Chapter 2, the goal of this paper is to assess the heterogeneity in the impact of health insurance. This paper builds a panel data model with endogenous treatment, which incorporates unobserved individual heterogeneity non-additively into the outcome. The model is estimated in the context of a semiparametric setting. I first propose a two-stage semiparametric least square (SLS) method to consistently estimate the model parameters and then conduct a localized 2SLS procedure to recover the quantile treatment effect. Identification, consistency and root-N asymptotic normality of estimators for parameters and marginal effects are proved.

URBMI enrollment is found to increase health care expenditures on average. The main channel of such change is through increasing the use of basic medical services which involves community clinics and preventative care. Nevertheless, contrary to findings of previous studies, having insurance coverage does not lower the financial burden through largely reducing out-of-pocket payments. The semiparametric estimation results provides a possible answer to this contradictory outcomes. Due to less-than-full reimbursement rate, individuals who make use of URBMI are those with above average family income, who mainly substitute into higher quality of services instead of acquiring basic medical services. Moreover, children and female enrollees who lean towards preventative care and routine services respond more positively to URBMI coverage. In contrast, individuals from lower income family benefit less from URBMI.

Whether URBMI has met the policy goals is unclear under the analysis of this chapter. The primary goal of URBMI is to provide universal coverage to urban residents without employment. However, based on CHNS data, only 30-50% eligible population has signed up for the program. There exists geographic and demographic variation in enrollment rate. Since the insurance premium is minimal compared

to median household income in China, the variation of insurance take-up may lie in the administrative process for program enrollment. Different cities may have devoted different levels of efforts in promoting the program and reaching out to eligible population. In addition, notice the enrollment rate for children is much higher than other adults. This can be explained by the fact that parents obtain information on URBMI through schools and the networks with other parents, indicating that network effect plays an important role in the enrollment of this program. To further explore this, detailed information on city level investment in URBMI as well as the pattern of enrollment within a community must be studied, which is one of the possible extension from this paper.

In terms of URBMI's effect, if the primary policy target is to ensure accessibility of basic medical services and provide financial protection, URBMI is still short on meeting the objective. If the policy goal is simply to encourage medical care utilization, this insurance program has had some success. An important policy implication can be drawn from the results in this paper: based on the individual heterogeneity estimated, the efficiency in this public insurance program can be improved by redesigning differentiated policy packages for different subgroups of the population.

Lastly, I would like to address some caveats to this research. The main concern is the limitation on data. This study is based on CHNS data from 2006 to 2011. The time frame is still short for the impact to take place especially for health outcomes. Secondly, although CHNS samples from nationally representative locations, it is only conducted in nine provinces in China, which is less than one-third of the provinces. Due to the large heterogeneity in the impact of URBMI, it is important to examine the rest of the provinces for specific policy implications. Lastly, due to the nature of survey data, the accuracy of reporting in many of the health related variables such as treatment choices and disease history is under suspicion. This study is limited by data to pin down the effect of URBMI on a more detailed level regarding to health care utilization.

Administrative data on hospital admission should be explored in order to further study this.

3.A TABLES AND FIGURES

Table 3.A.1: Effect of URBMI on Selected Outcomes across Geographic Regions

	Eastern China		Mid-China		Western China	
FE 2SLS	F=14.73		F=8.63		F=27.02	
Seek formal medical service in past 4 week						
	0.11045		0.08286		0.27871	***
Obs=6580	(0.1039)	4072	(0.1647)	2858	(0.1009)	
Visit city level hospital?						
	0.60474		0.48912		0.04806	
Obs=1161	(0.8255)	636	(0.5307)	391	(0.3836)	
Visit community level hospital?						
	-0.11077		-0.53868		1.22969	
Obs=1161	-0.96621	636	-0.60798	391	-0.75543	
Seek preventative care in past 4 weeks						
	0.10156	***	-0.0213		0.01159	
Obs=6580	(0.0381)	4072	(0.0439)	2858	(0.0533)	
Impatient treatment in past 4 week?						
	-0.01523		-0.55005		-0.00187	
Obs=6580	(0.4742)	4072	(0.4553)	2858	(0.8718)	
Impatient days in past 4 week						
	-0.16148		-0.35052		-0.29323	
Obs=6580	(0.2280)	4072	(0.3420)	2858	(0.5354)	
ln(total medical expenditure+1)						
	-0.08475		-0.36741		1.21811	**
Obs=6580	(0.2715)	4072	(0.3641)	2858	(0.5340)	
ln(out-of-pocket+1)						
	-0.0327		-0.29349		0.64512	
Obs=6580	(0.2574)	4072	(0.3501)	2858	(0.5091)	
Receive high BP treatment						
	0.30083		-0.09549			/
Obs=610	(0.2175)	417	(0.3596)			

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

Table 3.A.2: Effect of URBMI on Selected Outcomes across Geographic Regions (continued)

	Eastern China			Mid-China			Western China	
FE 2SLS	F=14.73			F=8.63			F=27.02	
High blood pressure								
	-0.0928			-0.2601	**		-0.2757	*
Obs=3572	-0.0813		1727	-0.1167		1636	-0.145	
Happiness								
	0.16875	**		0.12696	**		0.04173	
Obs=6580	-0.0797		3727	-0.06		2858	-0.1642	
Feeling sick during past 4 week								
	-0.0404			0.06163			0.20024	*
Obs=6580	-0.0574		4072	-0.0635		2858	-0.1059	
Have obvious symptoms during past 4 weeks								
	0.01103			-0.0494			0.13359	
Obs=6580	-0.0569		4072	-0.0728		2858	-0.1181	

Notes: bootstrapped standard errors are reported in parenthesis;
*p<0.10, **p<0.05, ***p<0.01

Table 3.A.3: Effect of URBMI on Selected Outcomes across Household Income Groups

Household Income Level		Lowest Quarter			Quarter 2-4	
FE 2SLS		F=4.67			F=7.72	
Seek formal medical service in past 4 week						
		0.2855	*		0.15166	*
	Obs=3377	(0.1472)		10132	(0.0902)	
Visit city level hospital?						
		0.6790			0.1955	
	Obs=547	(1.0932)		1641	(0.3198)	
Visit community level hospital?						
		0.1293			-0.1122	
	Obs=547	(1.4200)		1641	(0.3490)	
Seek preventative care in past 4 week						
		0.0551			0.0349	*
	Obs=3377	(0.0847)		10132	(0.0198)	
Impatient treatment in past 4 week						
		0.3858			0.0516	
	Obs=3377	(0.8575)		10132	(0.3519)	
Impatient days in past 4 week						
		0.2814			-0.0332	
	Obs=3377	(0.7791)		10132	(0.2007)	

Notes: bootstrapped standard errors are reported in parenthesis; *p<0.10, **p<0.05, ***p<0.01

Table 3.A.4: Effect of URBMI on Selected Outcomes across Household Income Groups

Household Income Level		Lowest Quarter			Quarter 2-4	
FE 2SLS		F=4.67			F=7.72	
ln(total medical expense+1)						
		1.0648			0.2537	
	Obs=3377	(0.8518)		10132	(0.2204)	
ln(out-of-pocket expenses+1)						
		-0.9536			0.0257	
	Obs=3377	(0.8259)		10132	(0.2085)	
High blood pressure						
		0.0879			-0.1450	**
	Obs=2233	(0.2565)		6701	(0.0730)	
Happiness						
		0.5473	**		0.1401	**
	Obs=2233	(0.2438)		6701	(0.0651)	
Feeling sick during past 4 week						
		0.1715			0.0021	
	Obs=3377	(0.1533)		10132	(0.0393)	
Have obvious symptoms during past 4 weeks						
		-0.1691			0.0372	
	Obs=3377	(0.1708)		10132	(0.0452)	

Notes: bootstrapped standard errors are reported in parenthesis; *p<0.10, **p<0.05, ***p<0.01
*p<0.10, **p<0.05, ***p<0.01

Table 3.A.5: Estimation Results of Selected Index Parameters

Selected Index Parameters												
Characteristics Index												
Outcome	lmed_cost		lmed_costp		lmed_inpatient		lmed_cost_op		lmed_costp_op		lmed_inpatient_op	
	$\hat{\beta}$Time-Varying Index Parameter Estimates (with respect to age)											
Male	-3.9135	***	-2.0707	*	-9.3255		-9.3798	***	7.6702	**	9.1586	
	1.1221		1.2890		6.5681		1.0147		3.2015		8.4334	
Married	-8.8302	**	36.3834		1.0989	***	-10.7857		-10.1501	*	-6.7360	***
	4.3287		42.1323		0.0536		0.4438		6.2434		2.3425	
Educ_col	-5.2855	***	9.5248	*	28.2759		20.8506	*	0.6548	***	0.2750	
	1.1254		5.1264		26.1213		12.1341		0.0949		1.2318	
lfamily_inc	-2.8286	***	-0.3304	***	7.4643		-1.5454	***	-3.9781	***	-0.9572	
	0.1590		0.0113		6.8651		0.3141		0.2413		1.1321	
Fixed-Effect Index												
	$\hat{\eta}$ Individual Heterogeity Index Parameter Estimates (with respect to age)											
Male	-4.5576426	***	-0.46162	*	-8.799816	***	-0.06812		29.12204		28.219376	
	0.2376		0.2701		2.4336		0.1320		24.3412		13.1251	
Married	-21.715598		28.35992	*	26.53586		-8.160221	***	-17.316	***	-17.069495	
	37.4571		17.1312		20.8831		1.2531		4.1315		32.1101	
Educ_col	-3.1669843		0.97829	*	3.0562416		14.14331	*	2.78783		2.497681	
	2.3482		0.5115		2.1101		8.3134		2.4142		4.1333	
lfamily_inc	-46.3387	***	-8.4067	***	11.3813	***	9.4258	*	-1.9244		-1.2556	***
	6.5281		1.0213		2.3158		5.3838		1.1214		0.3156	

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

3.B APPENDIX: ASYMPTOTIC RESULTS AND PROOF

Theorem 1. ***Consistency.***

Denote $\theta = (\beta, \alpha)$, all parameters in outcome model, with $\hat{\theta}$ as the estimator which minimizes (3.5).

Under Assumption (A.1)-(A.5) and definition (D.1)-(D.3):

$$\hat{\theta} \xrightarrow{p} \theta_0$$

Proof. (Here the outline of proof will be provided. For intermediate results and lemma, one can refer to appendix for detail)

The main proof strategy is as follows. Recall from estimation, $\hat{\theta}$ minimizes the objective function $\hat{S}(\theta)$ given as:

$$\hat{\theta} = (\hat{\beta}, \hat{\alpha}) = \underset{\theta}{\operatorname{argmin}}\, \hat{S}(\theta, \hat{P}) = \underset{\theta}{\operatorname{argmin}}\, \frac{1}{T \times N} \sum_{i=1}^{N \times T} \{[Y - \hat{E}(Y|V_{1it}, V_{ai}, \hat{P}_{it})]^2\} \tag{3.B.1}$$

We can further establish a uniform convergence results:

$$\sup_{\theta} |\hat{S}(\theta, \hat{P}) - E[S(\theta)]| \xrightarrow{p} 0 \tag{3.B.2}$$

If the uniform limit of the moment condition is uniquely minimized at θ_0, it follows straightly that: $\hat{\theta} \xrightarrow{p} \theta_0$.

For uniform convergence of $\hat{S}(\theta)$, the above upper bound can be written as three pieces: A+B+C

$$\sup_{\theta} |\hat{S}(\theta, \hat{P}) - \hat{S}(\theta, P)| + \sup_{\theta} |\hat{S}(\theta, P) - S(\theta, P)| + \sup_{\theta} |S(\theta) - E[S(\theta, P)]| \tag{3.B.3}$$

The last piece C goes through straight forwardly because i.i.d. sample mean converges uniformly to its expectation.(Amemiya 1984 [4], Klein 1993[31]). Therefore, piece C is

$O_p(1)$. For second piece B, there is no generated regressor $\hat{P}$. The difference of $S(\theta, P)$ from $\hat{S}(\theta, P)$ is that it uses the true expectation instead of estimated $\hat{E}$. Note that $|\hat{E} - E| = O(N^{-1/2}h^{-3})$ with three indices. It will converge faster than root-N if $r < 1/6$. With $S(\theta, P)$ a function of E, the uniform convergence results follows directly if $r < 1/6$.

The only piece left unproved is piece A with generated regressor $\hat{P}$. With $\sup_{\gamma,\kappa} |\hat{P} - P| = O_p(N^{-1/2}h^{-2})$ when estimated under specification of two indices. Perform a taylor series expansion on $\hat{S}(\theta, \hat{P})$ on P yields:

$$\hat{S}(\hat{P}) = \hat{S}(P) + \hat{S}'(P^+)(\hat{P} - P) \tag{3.B.4}$$

Therefore, $\hat{S}(\hat{P}) - \hat{S}(P) = \hat{S}'(P^+)(\hat{P} - P)$. Since $\sup_{\gamma,\kappa} |P^+ - P| \xrightarrow{p} 0$, and $\hat{S}'(P) = \hat{G}(P) = \frac{1}{N*T}\sum(Y - \hat{E})\frac{\partial \hat{E}}{\partial P}$, which converges to the true gradient. Following argument similar to Klein (2010)[28], we can show that $\sup_\theta |\hat{S}(\theta, \hat{P}) - \hat{S}(\theta, P)| \xrightarrow{p} P$. Next step is to show that θ_0 is a unique minimizer of $E(S(\theta, P))$. First the expectation can be written as:

$$\begin{aligned}
E[S(\theta)] &= E\{\sum_{i=1}^{NT}[Y_{it} - E_{it}(\theta_0) + E_{it}(\theta_0) - E_{it}(\theta]^2\} \\
&= E\{\sum_{i=1}^{NT}[[Y_{it} - E_{it}(\theta_0)]^2 + [E_{it}(\theta_0) - E_{it}(\theta)]^2] + 2[Y_{it} - E_{it}(\theta_0)] * [E_{it}(\theta_0) - E_{it}(\theta)]]\} \\
&= E\Big\{E\{\sum_{i=1}^{NT}[[Y_{it} - E_{it}(\theta_0)]^2 + [E_{it}(\theta_0) - E_{it}(\theta)]^2 + \\
&\quad 2[Y_{it} - E_{it}(\theta_0)] * [E_{it}(\theta_0) - E_{it}(\theta)]]\}|X_{it}\beta, \bar{X}\gamma, P\Big\} \\
&= E\Big\{E\{\sum_{i=1}^{NT}[[\delta_{it}]^2 + [E_{it}(\theta_0) - E_{it}(\theta)]^2 + 2[\delta_{it}] * [E_{it}(\theta_0) - E_{it}(\theta)]]\}|X_{it}\beta, \bar{X}\gamma, P\Big\} \\
&= E\Big\{E\{\sum_{i=1}^{NT}[E_{it}(\theta_0) - E_{it}(\theta)]^2\}|X_{it}\beta, \bar{X}\gamma, P\Big\}
\end{aligned} \tag{3.B.5}$$

The last step goes through due to conditional mean independence assumption of the instrumental variable P. Hence, for each observation it, θ_0 makes $E_{it}(\theta_0) - E_{it}(\theta) = 0$, which shows that θ_0 is an minimizer of $E[S(\theta)]$. Uniqueness of solution relies on index

assumption can shown by similar argument from Ichimura et.al (1991[27]). □

Theorem 2. ***Normality*** *Under Assumption (A.1)-(A.5) and definition (D.1)-(D.3):*

$$\sqrt{N}(\hat{\theta}-\theta_0) \xrightarrow{d} W \sim N(0,\Sigma)$$

where

$$\Sigma \equiv H_0^{-1} E[\sqrt{N} G_0 G_0' \sqrt{N}] H_0^{-1}$$

$$\textit{Gradient } G_0 \equiv E[\nabla_\theta S(\theta_{0_0})]$$

$$\textit{Hessian } H_0 \equiv E[\nabla_\theta G(\theta_{0_0})]$$

Proof. Starting with the first-order condition (F.O.C) for objective function $\hat{S}(\theta, P)$,denote:

$$\hat{G}(\hat{\theta}) = \frac{1}{NT}\sum_{i=1}^{NT}(Y_{it}-\hat{E}_{it})\frac{\partial \hat{E_{it}}}{\partial \theta}. \tag{3.B.6}$$

Using Taylor Expansion on true parameter θ_0, and $\theta^+ \in (\hat{\theta},\theta_0)$,as an intermediate point, the above gradient can be written as:

$$\hat{G}(\hat{\theta}) = \hat{G}(\theta_0) + \hat{H}(\theta^+)(\hat{\theta}-\theta_0) \tag{3.B.7}$$

where $\hat{H(\theta)} \equiv \nabla_\theta \hat{G}(\theta)$, and it follows that:

$$\sqrt{N}(\hat{\theta}-\theta_0) = -H^{-1}(\theta^+)\sqrt{N}\hat{G}(\theta_0) \tag{3.B.8}$$

As outline of a proof strategy, it will be conducted in the following step:

- $\sup_\theta |\hat{H}(\theta) - E(H(\theta))| \xrightarrow{p} 0$
- $\theta^+ \xrightarrow{p} \theta_0$, which follows that $H^{-1}(\theta^+) \xrightarrow{p} E(H(\theta_0)) \equiv H_0$

- For $\sqrt{N}\hat{G}(\theta_0) = \sqrt{N}\frac{1}{NT}\sum_{i=1}^{NT}(Y_{it} - \hat{E}_{it})\frac{\partial \hat{E_{it}}}{\partial \theta}$, the proof strategy is by showing the convergence of the gradient function to the true function without estimated components. With the establishment of such argument and bias reduction mechanism from Klein and Shen[2015[29]], asymptotic normality will follow from standard central limit theorem.

□

3.B.1 INTERMEDIATE LEMMAS

Notational convention. Let $\widehat{f}(v,\theta) \equiv N^{-1}\sum_{i=1}^{N} K_h(V_i(\theta) - v)Y_i$ and $\widehat{g}(v,\theta) \equiv N^{-1}\sum_{i=1}^{N} K_h(V_i(\theta) - v)$.

Lemma 4 (Convergence rates)**.** For V a d-dimensional vector of continuous random variables with density g_V. Let $\bigtriangledown_\theta^l g_V$ be the l^{th} partial derivatives of g_V with respect to θ, and $\bigtriangledown_\theta^0 g_V = g_V$. Let $\widehat{g}_V$ represents the estimator of g_V. Then, for θ in a compact set and v in a compact subset of the support of V, the following rates hold for $l = 0,1,2$,

$$i). \quad \sup_{v,\theta} E\left\{\left[\bigtriangledown_\theta^d \widehat{g}_V(v,\theta) - E\left(\bigtriangledown_\theta^d \widehat{g}_V(v,\theta)\right)\right]^2\right\} = O(\frac{1}{Nh^{2d+2l+1}})$$

$$ii). \quad \sup_{v,\theta}\left|E\left(\bigtriangledown_\theta^d \widehat{g}_V(v,\theta) - \bigtriangledown_\theta^d g_V(v,\theta)\right)\right| = O(h^2)$$

The proof follows from Lemma 3 in Klein 2010[28] where they consider the univariate case for $d = 1$.

Lemma 5 (Double convergence)**.** Suppose θ in a compact set and v in a compact subset of the support of a $d-$dimensional vector of continuous variables V, if $1/8 < r < 2/d$, then

$$\sqrt{N}\left|\widehat{E}(Y|v,\theta) - E(Y|v,\theta)\right| = \sqrt{N}\left|\widehat{f}(v,\theta) - E(Y|v,\theta)\widehat{g}(v,\theta)\right|/g(v,\theta) + o_p(1)$$

Lemma 6 (Bahadur Representation from Bahadur 1966. Suppose that $\widehat{q}_V(\lambda)$ and $q_V(\lambda)$ are estimated and true quantile functions of a $d-$dimensional continuous vector of random variable V evaluated at a vector of $\lambda \in [0,1)$. ^{d}.

$$\sqrt{N}(\widehat{q}_V(\lambda) - q_V(\lambda)) = N^{-1}\sum_{i=1}^{N} B_i + o_p(1)$$

where $B_i = (B_{1i}, B_{2i}, \cdots, B_{di})'$ and for each $j = 1, 2, \cdots, d$,

$$B_{ji} = \frac{\mathbf{1}[V_{ji} \leq q_{V_j}(\lambda_j)] - \lambda_j}{g_{V_j}(v)} \tag{3.B.9}$$

3.C Appendix: Monte Carlo Result

3.C.1 Exploration of Functional Forms of Outcome Model

In the first Monte Carlo study, I use different specification of outcome function to explore the estimation method for indexes. The general structure of model is as follow:

$$\begin{aligned} T &= 1\{g(V_{2it}, b_i) > u_{it}\} \\ &= 1\{V_{2it} + b_i > u_{it}\} \\ &= 1\{Z_{it}\gamma + \bar{Z}_i\theta + \mu_i > u_{it}\} \end{aligned} \tag{3.C.1}$$

$$\begin{aligned} Y_{it} &= F(V_{1it}, a_i, T_{it}) + \epsilon_{it} \\ &= F(X_{it}\beta, f(\bar{X}_i\alpha) + \eta_i, T_{it}) + \epsilon_{it} \end{aligned} \tag{3.C.2}$$

In this subsection, data is generated to satisfy the following:

1. Error terms in both treatment and outcome models are homoskedastic and standard normally distributed. u_{it} and ϵ_{it} are correlated.

2. X_{1i},X_{2i} and X_{3i} are all normally distributed with expectation 0 and standard

deviation 1. X_{1i} is correlated with X_{2i}. X_{3i} is generated to be independent of X_{1i} and X_{2i}.

3. Serial correlation: X_{1it} is correlated with X_{1is}. Same for X_2 and X_3.

4. $Z_{it} = [X_{1it}X_{2it}X_{3it}]$. $X_{it} = [X_{1it}X_{2it}]$

Four variation in specification of outcome model can be explored:

1. Linear Marginal Effect in V_{1it} and a_i:

   $F(V_{1it}, a_i, T_{it}) = 2 * V_{1it} * T_{it} + b_i * T_{it}$

2. Non-linear Marginal Effect in V_{2it} and V_b:

   $F(V_{1it}, a_i, T_{it}) = exp\{2V_{1it} + a_i\} * T_{it} + (V_{1it} + 0.26 * a_i)$

3. Quadratic in index V_{1it} V_{ai}:

   $F(V_{1it}, V_{ai}, T_{it}) = V_{1it}^2 * T_{it} + a_i^2 * T_{it}$

Using bias correction, Sample size $N = 2000$ and repetition of $i = 100$. Window size $r = 1/11$. For each functional specification, I reported the estimates after bias correction.[2]

Specification	Parameter	True Value	Mean	Standard Deviation	Median
(1.1)	β	2	2.26	0.12	2.25
(1.1)	α	1	0.95	0.114	0.95
(1.2)	β	2	2.16	0.15	2.16
(1.2)	α	1	0.91	0.37	0.87
(1.3)	β	2	2.12	0.13	2.12
(1.3)	α	1	0.96	0.27	0.96

[2]Note: Here I set individual fixed effect $b_i = V_{bi}^2 + \eta_i$; Result is similar if $b_i = V_{bi} + \eta_i$.

3.C.2 EXPLORATION ON TIME PERIOD

Due to the fact that X_{it} and $\bar{X}_i$ can be highly correlated in practice if the variation in time dimension is limited, here we use a Monte-carlo study to compare estimation method of pooling data with separating estimation, which is given by (3.7). The following study uses design (1) above with bias correction. The results confirms the linear issue in index variable specification. As the number of period increases, the estimation gets closer to the true value with lower standard devidation.

Period	Parameter	True Value	Mean	Standard Deviation	Median
2	β	2	2.22	0.12	2.25
2	α	2	1.20	0.24	1.15
3	β	1	2.17	0.14	2.17
3	α	2	1.15	0.13	1.15
4	β	2	2.06	0.07	2.06
4	α	1	1.22	0.10	1.22
5	β	2	2.02	0.09	2.02
5	α	2	1.14	0.16	1.34
6	β	2	1.97	0.09	1.97
6	α	2	1.41	0.18	1.41

3.D APPENDIX: INDEX ASSUMPTION

To obtain the treatment effect, it would be useful to estimate the conditional mean of outcome Y_{it}:

$$E[Y|X_{it}, T_{it}, b_i] \tag{3.D.1}$$

To estimate the conditional mean, it can be proceeded to estimate the outcome and treatment model simultaneously by conditioning on all the indexes in the two models and recover the index parameters, i.e. to estimate

$$E[Y|X_{it}, T_{it}, b_i] = E[Y|V_{1it}, V_{2it}, V_{ai}, V_{bi}] \tag{3.D.2}$$

To further simplify, it would be desirable to conduct a two-stage procedure to estimate the treatment model first and replace true treatment variable by the treatment probability (propensity score). If the following condition holds, the outcome estimation could be represented by a triple-index model instead of four indexes.

$$E[Y|V_{1it}, V_{2it}, V_{ai}, V_{bi}] = E[Y|V_{2it}, V_{bi}, T_{it}] = E[Y|V_{2it}, V_{bi}, P(T|V_{1it}, V_{ai})] \tag{3.D.3}$$

where $P(T|V_{1it}, V_{ai}$ is the conditional probability of treatment conditioned on the two indexes assumed in the treatment model.

To verify the validity of the above conditions, it could be proceeded in several steps:

1. Treatment model:
   (a) Check $E[T|Z_{it}, Z_{is}] = E[T|Z_{it}, \bar{Z}]$
   (b) Check $E[T|Z_{it}, \bar{Z}] = E[T|V_{1it}, V_{ai}] = P[T = 1|V_{1it}, V_{ai}]$
2. Outcome model:
   (a) Check $E[Y|X_{it}, T_{it}, b_i] = E[Y|X_{it}, X_{is}, T_{it}, T_{is}]$

(b) Check $E[Y|X_{it}, X_{is}, T_{it}] = E[Y|X_{it}, \bar{X}, T_{it}]$

(c) Check $E[Y|X_{it}, \bar{X}, T_{it}] = E[Y|V_{1it}, V_{2it}, V_{ai}, V_{bi}]$

(d) Check $E[Y|V_{1it}, V_{2it}, V_{ai}, V_{bi}] = E[Y|V_{2it}, V_{bi}, P(T|V_{1it}, V_{ai})]$

3.D.1 TREATMENT MODEL INDEX ASSUMPTION

For treatment model, the conditional mean can be rewritten as follow:

$$\begin{aligned} E[T|Z_{it}, Z_{is}] &= Pr[T = 1|Z_{it}, Z_{is}] \\ &= Pr[u_{it} < g(Z_{it}\beta, a_i)|Z_{it}, Z_{is}] \\ &= Pr[u_{it} < g(Z_{it}\beta, f(\bar{Z}\alpha) + \epsilon_i)|Z_{it}, Z_{is}] \\ &= f_{u_{it}|Z_{it},Z_{is}}(g(Z_{it}\beta, f(\bar{Z}\alpha))) \end{aligned} \tag{3.D.4}$$

Where $f_{u_{it}|Z_{it},Z_{is}}$ is the conditional probability distribution function for error term u_{it}. We can make additional assumptions on the distribution of error term to make the index assumption go through. Assume that all variables in Z_{it} are exogenous to error u_{it}, which is not an unreasonable assumptions to make because endogeneity in the treatment model is not the focus of this chapter. Under this assumption, the distribution of u_{it} is independent of Z_{it}, Z_{is} and $\bar{Z}$ as well.

$$\begin{aligned} E[T|Z_{it}, Z_{is}] &= Pr[T = 1|Z_{it}, Z_{is}] \\ &= f_{u_{it}|Z_{it},Z_{is}}(g(Z_{it}\beta, f(\bar{Z}\alpha))) \\ &= f_{u_{it}}(g(Z_{it}\beta, f(\bar{Z}\alpha))) \\ &= f_{u_{it}|Z_{it},\bar{Z}}(g(Z_{it}\beta, f(\bar{Z}\alpha))) \\ &= E[T|Z_{it}, \bar{Z}] \end{aligned} \tag{3.D.5}$$

Next step is to verify the index assumption is valid here to summarize the information given by Z_{it} and $\bar{Z}$, i.e. to check $E[T|Z_{it},\bar{Z}] = E[T|Z_{it}\beta,\bar{Z}\alpha] = E[T|V_{1it},V_{ai}]$, which follows by regular semiparametric index assumption. As results, the conditional probability of treatment can be represented by $E[T|V_{1it},V_{ai}] = P[T=1|V_{1it},V_{ai}]$

3.D.2 OUTCOME MODEL INDEX ASSUMPTION

For the outcome model, the assumptions to validate steps (a)-(c) listed above will be similar to those given in the treatment model. Here the key step is to check that the two-stage method by plugging in the conditional probability of treatment is valid. The conditional expectation of Y_{it} on all variable Z_{it} will be:

$$\begin{aligned}
E(Y_{it}|Z_{it},Z_{is}) &= E(Y_{it}|Z_{it},,Z_{is},T_{it}=1)Pr(T=1|Z_{it},Z_{is}) \\
&\quad + E(Y_{it}|Z_{it},Z_{is},T_{it}=0)Pr(T=0|Z_{it},Z_{is}) \\
&= E(Y_{it}|Z_{it},Z_{is},T_{it}=1)Pr(T=1|Z_{it},Z_{is}) \\
&\quad + E(Y_{it}|Z_{it},Z_{is},T_{it}=0)[1-Pr(T=1|Z_{it},Z_{is})] \\
&= Pr(T=1|Z_{it},Z_{is})[E(Y_{it}|Z_{it},Z_{is},T_{it}=1) - E(Y_{it}|Z_{it},Z_{is},T_{it}=0)] \\
&\quad + E(Y_{it}|Z_{it},Z_{is},T_{it}=0)
\end{aligned} \tag{3.D.6}$$

where T_{it} follows the same model above. The key is whether the conditional means $E(Y_{it}|Z_{it},Z_{is},T_{it}=1)$ and $E(Y_{it}|Z_{it},Z_{is},T_{it}=0)$ are functions of $Pr(T|Z_{it},Z_{is})$. Take

$E(Y_{it}|Z_{it}, Z_{is}, T_{it} = 1)$ as example,

$$\begin{aligned} E(Y_{it}|Z_{it}, Z_{is}, T_{it} = 1) & \\ &= \int_{\eta} F(X_{it}, f(\bar{X}) + \eta_i, T_{it} = 1) dF(\eta|Z_{it}, Z_{is}, T = 1) + \\ &\quad \int_{\epsilon} \epsilon_{it} f(\epsilon|Z_{it}, Z_{is}, T_{it} = 1) d\epsilon \\ &= \int_{\eta} F(X_{it}, f(\bar{X}) + \eta_i, T_{it} = 1) dF(\eta) + \\ &\quad \int_{\epsilon} \epsilon_{it} f(\epsilon|Z_{it}, Z_{is}, T_{it} = 1) d\epsilon \end{aligned} \tag{3.D.7}$$

The first term is a function of $Pr(T|Z_{it}, Z_{is})$ since T_{it} can be presented as P_{it}+residual. As for, $f(\epsilon|Z_{it}, Z_{is}, T_{it} = 1)$, the conditional pdf for error term ϵ.

$$\begin{aligned} f(\epsilon|Z_{it}, Z_{is}, T_{it} = 1) &= f\epsilon|Z_{it}, \bar{Z}, T_{it} = 1 \text{[By imposing assumption2 on error } \epsilon\text{]} \\ &= f\epsilon|Z_{it}, \bar{Z}, g(Z_{1it}\beta, a_i) > u_{it} \\ &= \frac{\int_{-\infty}^{g(Z_{it}\beta, a_i)} f(\epsilon, u|Z_{it}, \bar{Z}) du}{\iint_{-\infty}^{g(Z_{it}\beta, a_i)} f(\epsilon, u|Z_{it}, \bar{Z}) d\epsilon du} \\ &= \frac{\int_{-\infty}^{g(Z_{it}\beta, a_i)} f(\epsilon, u|Z_{it}, \bar{Z}) du}{Pr[u_{it} < g(Z_{it}\beta, a_i)|Z_{it}, \bar{Z}]} \\ &= \frac{\int_{-\infty}^{g(Z_{it}\beta, a_i)} f(\epsilon, u|Z_{it}, \bar{Z}) du}{Pr[T = 1|Z_{it}, \bar{Z}]} \end{aligned} \tag{3.D.8}$$

Where $f(\epsilon, u|Z_{it})$ is the joint distribution of ϵ and u. Therefore, $E(Y_{it}|Z_{it}, Z_{is}, T_{it} = 1)$ is also a function of $Pr[T = 1|Z_{it}, \bar{Z}]$. Similar argument holds for $E(Y_{it}|Z_{it}, Z_{is}, T_{it} = 0)$. As results, the conditional mean of Y can be written as a function of $Pr[T = 1|Z_{it}, \bar{Z}]$.

$$E(Y_{it}|Z_{it}, Z_{is}) = H(P_{it}) = E(Y_{it}|P_{it}) \tag{3.D.9}$$

Therefore, the two-stage method for index estimation should go through.

CHAPTER 4

THE ROLE OF TAX SUBSIDIES AND COMMUNITY BENEFIT REPORTING REQUIREMENTS ON HOSPITALS

4.1 INTRODUCTION

The hospital industry is one of the few sectors (for example, nursing home, day care, vocational education and publishing) in United States where different ownership types, including public, private nonprofit and private for-profit, coexist. Private nonprofit hospitals have dominated the market since 1940s. A nonprofit status is traditionally seen as a signal of good quality in the health care market with severe asymmetric information problem, (Hansman 1981[21],Weisbrod 1975[**?**],Arrow 1963[6]).

However, recent trend has moved away from this traditional form of ownership. Since mid-1980s, the number of for-profit hospitals has been steadily increasing due to both new entries and conversions from other ownership forms (Shen 2001[40], Chakravarty 2006 [10]). Not only is there an increase in number, in terms of the size and quality, for-profit hospitals are also catching up with its nonprofit counterpart. For example, the number of average beds in nonprofit hospitals compared to for-profit ones, dropped from three times larger in 1985 to only one-third more in 2008. Apart from time trend, regional disparities in hospital ownership pattern are also noticeable.Figure4.A.1 and 4.A.2 compare the percentage of for-profit hospitals by states from year 1999 to 2013,

which implies that such trend is a national phenomenon. Southern states have had the highest proportion of for-profit hospitals since as early as 1960s and the number is still growing fast. The north-eastern states only start seeing an increase in for-profit ownership form in the late 1990s but the rate of change has accelerated since 2000s.

The underlying factors driving the ownership type change in hospital industry have not been widely studied in the economic literature, especially from the perspective of tax policy. Due to their tax exempt status, nonprofit hospitals are in practice heavily subsidized by federal, state and local governments. The variation in tax rates and policies which limit the behavior of nonprofit hospitals cause the net benefit of choosing a nonprofit ownership status to differ across state and over time.

This chapter focuses specifically on the interaction between tax rates and the recently established community benefit reporting requirements. These two policy dimensions capture the benefit and cost of being a nonprofit hospital. On the benefit side, I consider both state and federal level corporate income tax rates. Using panel data, variation in tax rates across state and over time can be exploited to capture the differences in benefits. As for cost, nonprofit hospitals are required implicitly by tax regulations to provide community benefit which is comparable in size to the tax subsidy. Nevertheless,this condition has not be enforced until recent state and federal policies regulate the amount of "community benefit" a nonprofit hospital provides and link it to hospital's tax exemption status. Since 1990, 34 states have imposed requirements for nonprofit hospitals to report community benefit (as summarized in Appendix Table 4.A.1). In general, four types of expenditures by hospitals are considered as community benefit: education and teaching; uncompensated care; under-compensated care for patients with government subsidized insurance coverage; and lastly community services. Adequate amount of community benefit is considered to be comparable to the amount of tax exempted. However, some state regulations do not explicitly specify such term. Although varying by state, failure of meeting such

requirement will result in civic penalties and the risk of revocation of nonprofit status. On Federal level, the Internal Revenue Service (IRS) revised tax filing forms in 2007 to promote uniform and comprehensive reporting system of hospital community benefit provisions, while the Affordable Care Act further requires a detailed evaluation plan of community service produced by hospital itself.

In practice, community benefit requirements raise the operating cost of nonprofit hospitals and weaken the benefit of tax subsidy. Therefore, it is expected that this policy may potentially cause conversion in ownership status and changes in hospital behavior, such as the amount of uncompensated care provided and quality of care. Moreover, since the cost of community benefit policy is built on existing intensity of tax benefit, a higher tax rate represents a higher benefit for complying the reporting requirement, which may lead to fewer ownership conversion and different patterns in behavior. Hence, I evaluate tax rate and community benefit requirement together.

There is an ongoing policy debate on whether nonprofit hospitals should be taxed. The answer is determined by whether nonprofits are similar to their for-profit counterparts in terms of treatment choices, especially choices for less profitable patients. The empirical literatures have not reached consensus on this question. For example, Sloan (2001 [41]) found no significant difference in cost and quality of care by hospital ownership, while Picone (2002 [37]) estimated a lower quality of care in terms of patient mortality in for-profit hospitals. In most of these studies,hoIver, hospital ownership is not treated as an endogenous choice

This chapter tries to fill the hole in literature by identifying the determinant of hospital ownership from public policy perspectives. This analysis uses a panel dataset of hospitals and focuses on questions: (1) How does variation in federal and state tax rate interact with community benefit reporting requirement to affect hospital's ownership choice; (2) How do hopsitals respond to community benefit reporting requirements in terms of the amount of community benefit provided.

The chapter is organized as follows: Section 4.2 provides detailed back ground of tax policies for nonprofit hospitals. Section 4.3 presents a state-level estimation which establishes the causal link between tax policies and hospital ownership share, while in Section IV, hospital-level analysis explores the impact of tax policies on ownership choice decision and provision of community benefit of hospitals.

4.2 BACKGROUND

4.2.1 TAX EXEMPTION OF NOT-FOR-PROFIT HOSPITALS

Not-for-profit (NFP) hospitals receive various tax advantages relative to for-profit (FP) hospitals in the US. The main forms of tax subsidy include exemption from federal and state corporate income tax, exemption from state and local property tax, as Ill as the granted financing channel of tax-exempt bonds. Gentry(2001)[17] developed a frame work to estimate the amount tax benefit gained by hospitals. He estimated that in 1995 the annual aggregate value of federal and state income tax exemption to nonprofit hospitals is around $4.6 billion, while the aggregate property tax exemption is $1.7 billion. It is reasonable to believe that due to the expansion of health care sector during the past decade, the aggregate number now can only be larger. Moreover, Gentry estimated that for a median hospital, the combine value of annual tax subsidy worths approximately 2.5% of total asset value. The estimation of aggregate benefit from access to tax-exempt bond market was $354 million per year.

In addition,Gentry(2001)[17] found wide variation of tax benefits across hospitals. The sources of income tax benefit are not only the variation in state and local tax rules, but also the profitability of hospitals, which differs greatly by region. In contrast, the variation of property tax benefit comes almost only from difference in state and local tax rates. Therefore, in order to correctly identify the tax subsidy a hospital received,

it is important not only to understand the difference in tax rates across states, but also the detail specifications. For example, the state corporate income tax could be as high as 9.99 percent in Pennsylvania and as low as 0 in Washington. Some states allow tax deduction from federal income tax payment, and some states impose property tax on NFP hospitals under certain conditions.

4.2.2 COMMUNITY-BENEFIT REPORTING REQUIREMENT

Recently, public attention has focused on the justification of the tax advantages NFP hospitals receive. There has been a long lasting policy debate on whether the community benefit providing to the society is enough to justify their tax subsidy. At a hearing in 2005, Commissioner Everson from IRS said:

> *"What I have seen since 1969 has been a convergence of practices between the for-profit and nonprofit hospital sectors, rendering it increasingly difficult to differentiate for-profit from non-profit health care providers. In our review of tax-exempt hospitals, some of the issues I are finding include complex joint ventures with profit making companies, excessive executive compensation, operating for the benefit of private interest rather than the public good, unrelated business income and employment taxes."* [23, Hellinger 2009]

The growing interest in this issue has led to legislative responses from local, state government as well as federal government. The focus of this legislation has been on assessing the actual amount of community benefit by mandating detailed reporting from hospitals. As a first step, these reporting requirements serve not only to gather information, but are also expected to elicit positive response from hospital industry.

By 2015, 34 states had enacted laws requiring the community-benefit reporting by NFP hospitals.The states involved are not geographically concentrated, showing the

wide spread of concern about this issue over the country. The general format of state laws includes requiring hospitals to identify community needs and submit detail lists of service expenditures targeted at meeting those needs. However, it should be noticed that there is wide variation in defining the meaning of community needs. In general, community benefits mainly consist of unreimbursed costs to hospital from public insurance programs, charity care to disadvantaged population, research and education, as well as community clinic service such as free screening and Illness promotion. Some states require separate reporting on charity benefit and unreimbursed cost in order to encourage such services, while others do not emphasize on it. Moreover, some state impose penalties for hospitals failing to report. For instance, Texas and Indiana impose a $1000/day civic penalty for missing reporting deadline. Some states further uses the reported services to evaluate and reassess the tax-exempt status of a NFP hospital. There is a famous case in Illinois where the tax exempt status granted to a Catholic-affiliated hospital, Provena Covenant Medical Center in Urbana was revoked by the Department of Revenue, in 2004. The heterogeneous specification of the requirement may complicate the analysis in this study because the impact of such laws clearly depend on how the enforcement is carried out.

The state effort has moved to federal level in 2007. Each not-for-profit organization in the US, is required to submit Form 990 every tax year to IRS, revealing information on their expense, revenue and compensation to officers and directors. HoIver, prior to 2007, it did not require any information about uncompensated care or charity contribution to be included. In addition, according to Hellinger 2009 [23, Hellinger 2009], less than 1 percent of 990 forms are audited for a hospital in a given year. Therefore, in 12/2007, IRS revised the form to require hospitals to input community-benefit related items, which is the first federal action to put forward a uniform reporting system in the country. Later, the Affordable Care Act (ACA) further requires tax-exempt hospitals to conduct an assessment of community needs every 3 years and develop an implementation strategy

to address identified needs, starting from 2012.

4.2.3 RESEARCH QUESTION AND LITERATURE REVIEW

In this paper, I explore the following research question: What is the impact of tax rate and community-benefit reporting requirement on (1)ownership choice of a private hospital; (2)the amount of community benefits a NFP hospital is providing relative to a FP hospital

A few past studies have examined the effect of tax rate or community-benefit reporting law separately. For taxes, most attention has been placed on exploring the effect on market share. The motivation is that a higher tax rate, which is equivalent to higher subsidy to NFPs, should lead to greater advantage in competition for NFP institutions. Therefore, the market share should be larger. Hannsman (1987)[22] studied nonprofit versus for-profit organizations in general, including hospitals, nursing homes and schools, using state level cross-sectional data to estimate the effect of differential tax rate across state on market share of NFP hospitals. It is found that only higher corporate income tax is significantly correlated to higher market share, while property and sales effect demonstrate no impact. Later, Gully(1993)[20] reexamined this topic focusing only on hospitals. He utilized a panel data set to better address the issue of potential endogeneity, which leads to positive and significant result on market share. It is estimated that if state corporate income tax and property tax are decreased by 5 percentage point at the same time, the average market share of NFP hospitals will decrease by around 4.5% on state level.

There are a few limitations to these studies of the effect of tax rate. First, they only examine state level effect rather than effect at the hospital level. Many health literature suggests the market for medical provider is geographically small and very sensitive to the structure of local market. Using state level date will fail to control for

many market specific characters that may alter the hospital decision. Second, they only look at market share instead of looking at more behavior-related factors that reveal the underlying competitive advantage of NFP hospitals, such as pricing, quality, etc. By using hospital-level information to examine a broader set of dependent variable, my research will extend the previous studies and provide more insight into the issue.

On the other side, some research has been conducted on community-benefit reporting requirements. The Congressional Budget Office (CBO) used Medicare Cost Report Data to study the determinants of the volume of uncompensated care by hospitals in 5 states[1], where community-requirement laws are enacted. The study shows that NFP status is a not a significant factor determinning the level of uncompensated treatment, indicating that community-benefit requirements have not increased the charity service provided by NFPs relative to FPs. Other similar studies have been conducted by Sutton and Stenslend (2004), Cryan (2005) using similar methods, but examining data from different states. Generally, their stud find that in a state where the reporting law specify more detail about standards, the effect on community benefit is larger. Nevertheless, these studies have not a use more econometric model that allow them to identify the causal effect of reporting requirements on community benefit outcomes. Hence, my research project adds value to the existing literature in two ways. First of all, I proposed to identify the causal effect of reporting requirements using difference-in-difference method, by including states without these laws as control group. Moreover, I will include the federal action in 2007 into consideration, which will provide an opportunity for “reverse" DD, where the states that already enacted the law will now be in control group.

In addition, there are no previous study that explore the effect of tax rates and reporting laws together. The actually tax benefit from exemption not only depends on the tax rate, but also on the condition to obtain the exemption. If the community-benefit

[1] California, Florida, Georgia, Indiana, Taxes

reporting law is so strict that it requires every penny of tax subsidy to be contributed into community service, there is essentially no tax benefit at all. Similarly, the cost of reporting really depends on the tax rate. The loIr the tax rate, the smaller the subsidy and the easier for hospital to meet the benefit requirement. As result, tax rate and reporting requirement together represent the “net-benefit" of NFP status and should be worth studying.

To sum up, I perceive that my research could add value to the existing literature in two aspects. First, I link tax rate and reporting law together which better represent the true value of NFP granted by public policy. Second, I extend from previous study to examine a larger set of dependent variables that indicate the underlying behavioral difference between for-profit and not-for-profit hospitals.

4.3 State-level Analysis

4.3.1 Empirical Methodology

As start, I exploit variations in tax rates and CRR across state and over time to conduct a state-level analysis, which compares the ownership choice and market share of hospitals between states with and without community-benefit reporting requirements. On the state level, the following reduced form model is considered:

$$Y_{st} = \beta_0 + \beta_1 CRR_{st} + \beta_2 Tax_{st} + \beta_3 CRR_{st} * Tax_{st} + X_{st} + S_s + Yr_t + \varepsilon_{st} \tag{4.3.1}$$

where Y_{st} one measure of for-profit hospital share in state s at year t. CRR_{st} is an indicator for reporting requirement; Tax_{st} is state income tax rate and X_{st} is a set of state characteristics including characteristics. State fix-effect S_s and year trend Yr_t are also included to control for state specific heterogeneity and potential time trend.

4.3.2 STATE-LEVEL DATA

Data is obtained and merged from multiple sources. For dependent variables, state-level aggregate data is from American Hospital Association (AHA) Annual Survey[2], year 1999 to 2013. There measures of for-profit market shares are evaluated: (1) Percentage of FP hospital in number; (2) FP shre of hospital beds; (3)FP share of hospital service utilization, which is constructed by weighted averaging the market share for various service type: FP share of hospital service utilization= $\sum_{i=1}^{n} \alpha_i Share_i$, i for each service type, including inpatient services, outpatient services, emergency room and general hospital admission.

For tax policy variables, state community-benefit reporting requirement indicator and state and federal tax rates are collected manually. Starting from the initial panel year 1999, there are only 12 states which have relevant CRR legislations, while in 2013, the number has increased to 31. For tax rate variables, state statutory corporate income tax rates are used as the main variable. We also include indicator for whether the state exempts NFP hospitals from sales tax and property tax. On the federal level, CRR is adopted in year 2007, which is captured by a dummy indicator for after 2007. Effective federal income tax rate for hospital industry on the specific year is collected from Corporation Tax Statistics provided by Internal Revenue Service (IRS) to capture the effective tax cost for FP hospitals.

State characteristics are included in the model as additional controls. Variables considered include real GDP per capita in state population, percentage of population as Medicare enrollee, number of public hospitals in state s at a given year t. To further address for the state heterogeneity, state fixed-effect and year trend are included in the model.

[2]provided by Kaiser Family Foundation: http://kff.org

4.3.3 RESULTS

Table C.1-C.4 summarize the result of regression, which compares results from various model specifications. State CRR increases share of for-profit hospitals in the market by 4-6 percentage points all with statistical significance. This result is consistent across different specifications of market share measurement. In a state with CRR, FP hospital number increases by 5.88 percentage-point while hospital beds and service utilization increases by 4.1 and 4.8 percentage-points respectively. Among all type of services, emergence room service utilization is the most sensitive to the presence of CRR, with a increase rate of 9.878 ppt. Emergency room service is usually considered to be impartial for patients with different insurance types, regardless of hospital ownership. Therefore, it is the service that is least endogenous to individual patient choice. A more than proportional increase in ER services further confirms the expansion of FP hospitals.

Higher state tax rate is associated with loIr share of FP hospitals, i.e. 1 percentage point increase in statutory state corporate income tax rate leads to 0.4-0.8 percentage point decrease in FP share, which is comparable to past literature (Gully 1993 [20],Hannsman 1987[22]).The key parameter of interest is β_3 in the above equation, which identifies the difference of CRR's effect as tax rate changes. Estimation result shows that as state tax rate increases, the effect of CRR on for-profit share tends to diminish. As tax rate increase by 1 ppt, the effect of CCR decreases by 0.4-0.9 ppt. This confirms our hypothesis that as tax rate increases, the oppurtunity cost of forgoing nonprofit tax exemption status increases, which makes CRR a relative small cost and a minimal factor in ownership conversion. Hence, hospitals will be more reluctant to choose for-profit ownership form.

On the federal level, Federal effective tax rate has no impact on FP share in any specification. Federal CRR has significant impact only on FP percentage in terms of number. With Federal CRR, FP market share in number is increased by 2.957

percentage-point, which is in a smaller magnitude than state CRR. One possible reason is that by the time federal government uses CRR, there are 26 states which has already been using CRR in tax reporting. Hence, if state CRR and federal CRR are substitutes for hospitals, it is reasonable that the federal effect is diluted by the states with existing CRR.

4.4 HOSPITAL-LEVEL ANALYSIS

4.4.1 EMPIRICAL METHODOLOGY

The state-level estimation confirms the linkage between tax policies and hospital ownership pattern. HoIver, it is limited in providing further information about the source of change in for-profit share. It remains unclear that whether the change results from new entry of FP hospital, conversion from nonprofits or closure of nonprofit hospitals. A multinomial logit model is underestimation to evaluate the probability of a specific type of change for either For-profit or NFP hospitals. For each hospital at a given year, outcome events on ownership change can take on the following values: 0 = no change (baseline); 1 = conversion; 2 =closure. For k^{th} type of event of hopital i in state s at time t, the probability of change can be specified as a multinomial logit model:

$$Pr_{kt}(change = k|X_{ijst}) = \frac{\exp\{Z'_{ijst}\beta_k\}}{1+\sum_t \exp\{Z'_{ijst}\beta_k\}} \tag{4.4.1}$$

where $Z'_{ijst}\beta_k = \beta_{k0} + \beta_{k1}CRR_{st} + \beta_{k2}Tax_{st} + \beta_{k3}CRR_{st} * Tax_{st} + X_{ijst} + M_{jst} + S_s$

CRR_{st} is an indicator for reporting requirement; Tax_{st} is state income tax rate and X_{ijst} is a set of hospital characteristics including facility characteristics, financial health which will be discussed in detail in data session. M_{jts} is a set of market characteristics by hospital referral region (HRR).

To study the effect of CRR and tax rate on the provision of community benefit by for-

profit versus not-for-profit hospitals, the following equation is estimated:

$$Y_{ijst} = \beta_0 + \beta_1 FP_{ijst} + \beta_2 CRR_{st} + \beta_3 FP_{ijst} * CRR_{st} + \beta_4 Tax_{st} + \beta_5 CRR_{st} * Tax_{st} + X_{ijst} + M_{jst} + S_s + \varepsilon_{ijst} \tag{4.4.2}$$

where Y_{ijst} is one measure of community benefit provided by hospitals, including percentage of cost on teaching-related activity, percentage of cost for uncompensated care, percentage of cost for patients with Medicare and those with Medicaid eligibility. FP_{ijst} is an indicator for for-profit ownership type for a hospital. CRR_{st} is an indicator for reporting requirement; Tax_{st} , X_{ijst}, M_{jts} are defined the same as in previous specification.

4.4.2 DATA

Multiple data sources are used and merged for estiamtion. For hospital-level characters, Medicare Cost Report from Center of Medicare and Medicaid Services which contains provider information is used. Dartmouth Atlas of Health Care data on local market (hospital referral region) characteristics are used to market characteristics accordingly. CMS cost report data is restricted to the reporting period from 1996-2015. Only private hospitals are selected in the sample. The full sample of analysis contains 4,721 nonprofit hospitals (62.55%), 2,821 for-profit hospitals (37.45%). There are total 1,524 conversion incidence over the 20 year periods.

I select control variables to capture hospital's financial health and size. For financial health, profitability is measure by net patient revenue-operating cost, debt-to-asset ratio and occupation rate including ratio of hospital bed utilization. For hospital size, I consider number of workers, teaching hospital indicator and equipment

owned. As for market characteristics, demand side factor is captured by percentage of population over 65 and percentage of Medicare enrollee. Supply side factor is controlled by Herfindahl-Hirschman Index (HHI) in hospital beds. Hospitals are mapped to market characteristics by their geographic location. Summary statistics on control and dependent variables is provided in Appendix Table C.4.

4.4.3 RESULT

Table 4.B.5 summarizes the regression result for multinomial logistic regression. Conversion events of hospitals with FP and NFP origins are estimated separately. Column (1)-(2) provides the result for NFP hospitals with or without state fix-effect and year trend accordingly. For outcome 1, conversion to FP ownership, the community benefit reporting requirement significantly increases the probability of this event to occur, which is consistent with the state-level findings. Meanwhile, tax rate, both state and federal level, has negative impact on conversion to FP. The effect of CRR decreases as tax rate increases. Looking at Outcome 2, closure of NFP hospitals, is also significantly affective the new community benefit reporting requirement, indicating that the profitability of NFP tends to decrease when the amount of community benefit required to provide increases. The CRR decreases the competitiveness of NFP hospitals relative to their FP counter part.

For comparison, Column (3)-(4) presents the result for conversion behavior of FP hospitals. A higher tax rate, on both state and federal level increases the probability of conversion to NFP and to closure for a FP hospital because it loIrs the profitability of FP hospital compared to NFP in local market. HoIver, community benefit reporting requirement is not significantly associated with both conversion and closure outcome.

Lastly, Table 4.B.6 summarizes the estimation result for provision of community benefit by NFP and FP hospital. Four categories of community benefit are studied, log

cost on education and teaching related activities, uncompensated care, percentage of Medicare patient (in discharge cases) and Medicaid patient (in discharge cases). FP hospitals are spending significantly less on all of the outcome measures, which is not surprising. HoIver, looking at the interaction term, FP*CRR which captures the change in gap of community benefit provision, there are mixed evidence over the four measures of outcomes. A negative coefficient here indicates a larger gap in community benefit provision after CRR while a positive coefficient indicates that the discrepancy decreases. For provision of education, after CRR, NFP hospitals increases significantly in spending in this area compared to FP counter parts. HoIver, for uncompensated care, CRR actually leads to a smaller gap between NFP and FP hospitals, which indicates that after CRR, NFP has smaller lead in allocating cost to treatment for uninsured population compared to FP hospitals. Similar results can be found in treatment for Medicare population. The mixed result indicates a change in pattern on community benefit provided by NFP hospitals. Being required to provide community benefit to the society, NFP hospitals are selective in terms of the type fo benefit they increases. Teaching and education related activities receive the largest increase in funding by NFP hospitals.

4.5 CONCLUDING REMARKS

This chapter explores the effect of variation in state and federal level tax policy on the ownership choice and performance of hospitals. Given the preferential tax treatment on nonprofit hospitals, tax rate, in conjunction with the recently established community benefit reporting requirement (CRR), determine the net subsidy provided to nonprofit hospital compared to its for-profit counterpart. Using panel data, this chapter exploits the variation in tax policy across states and over time to identify the effect of tax subsidy on ownership choice of hospitals, and further the different behavior between nonprofit versus for-profit hospitals, including cost as well as provision of undercompensated

care. A state-level analysis estimates 4-6 percentage-point increase in for-profit market share due to CRR. Moreover, the effect of CRR diminishes as tax rate increases. Using hospital-level data, I examine the choice of conversion and closure by NFP and FP hospitals after CRR using multinomial logit regression. CRR significantly increases the probability of conversion and closure of NFP hospitals. Lastly, the effect of CRR and tax rates on provision of community benefit is studied. It is found that NFP hospitals allocate fundings disproportionally to different types of community benefits.

To draw implications on the whether community benefit requirement laws have met its goal in mandating provision of community benefit, we can discuss it from the following aspects. Firstly, CRR imposes higher operating cost for NFP hospitals, making them less competitive in the market. The NFPs that are previously behaving more similar to FP hospitals will be more likely to be at the margin of conversion. Therefore, CRR is effective in the sense that it reduces the inefficiency of tax subsidy. Secondly, examining the detailed change in community benefit contribution, we can see that NFP hospitals increase their contribution in a selective manner. The underlying reason why NFPs increase expenditures in education and teaching more than in other categories is uncertain. However, one possible reason is due to the easiness of documentation and changes. For NFP hospitals, to meet the CRR requirement, it is easier to purchase equipments for teaching purposes than to organize free clinics. In addition, the lump-sum expenditures from such spending are also easier to document than case-by-case entries of admission of Medicaid and Medicare patients. Further studies must be conducted on a more specific level of NFP contributions to address the issue. However, this primary result indicates that CRR laws may lack the necessary detailed requirements to reach their intended goals.

Lastly, based on the reduced form analysis, we can only obtain insight on partial effect of CRR and tax policies. Nevertheless, it is difficult to draw conclusion on the welfare implication for the hospital industry and consumers in general. Whether it is

a good thing for the market if NFP hospitals convert to FP, can not be analyzed unless a general equilibrium model of hospital industry is examined, which will be my future focus of research on this topic.

4.A Appendix: Hospital Ownership Pattern over Time and across Regions

Figure 4.A.1: Percentage of For-profit Hospital by State in year 1999

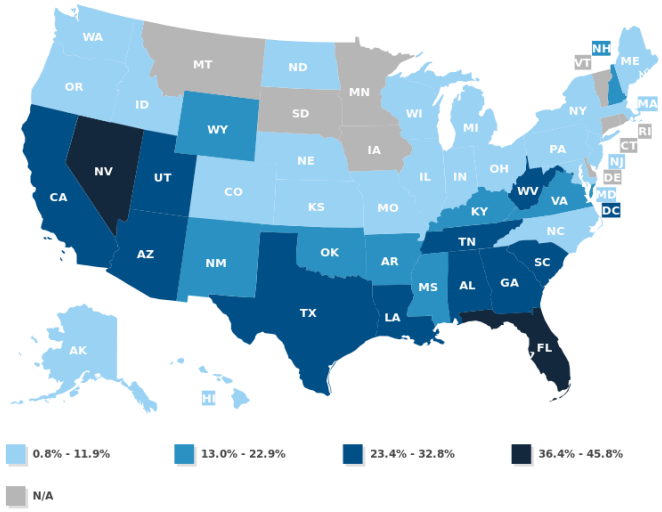
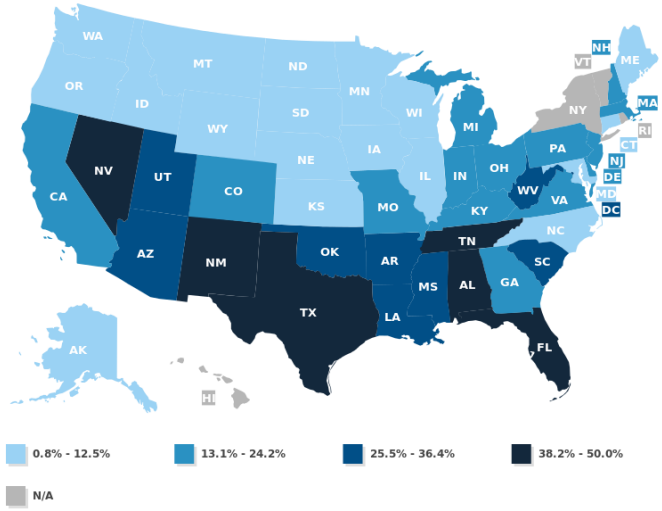


Figure 4.A.2: Percentage of For-profit Hospital by State in year 2013



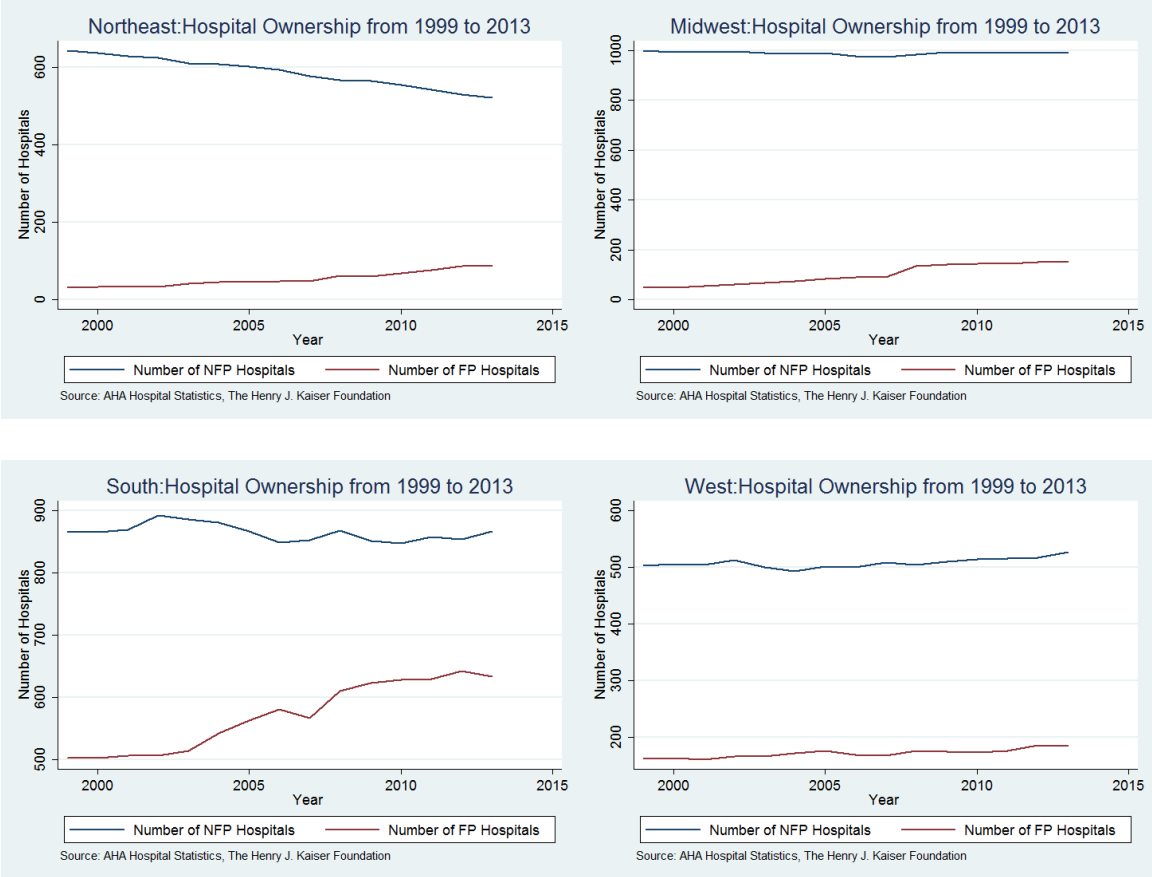


Figure 4.A.3: Hospital Number by Ownership and Census Region

Table 4.A.1: Effective Year of State Community-benefit Requirement Law

State	Year
Utah	1990
West Virginia	1990
Indiana	1994
Minnesota	1994
Texas	1995
California	1996
New York	1996
Georgia	1997
Pennsylvania	1997
Rhode Island	1997
Missouri	1999
Idaho	2000
New Hampshire	2000
Maryland	2001
North Carolina	2001
Florida	2002
New Mexico	2003
Ohio	2003
West Virginia	2003
Illinois	2004
Virgin	2004
Washington	2004
Connecticut	2005
Nevada	2005
New Jersey	2006
Delaware	2009
Montana	2009
Tennessee	2010
Vermont	2011
South Carolina	2012
Maine	2013
Arizona	2014
Mississippi	2014
Oregon	2015

4.B APPENDIX: TABLES

Table 4.B.1: Effect of CCR and Tax Rates on FP Share of Hospital Number

	(1) FPshare	(2) FPshare	(3) FPshare	(4) FPshare
CRR	2.680**	6.555**	2.635*	5.881**
	(0.048)	(0.002)	(0.056)	(0.002)
State tax	-0.841***	0.404	-0.840***	0.424
	(0.000)	(0.276)	(0.000)	(0.205)
CRR*State tax	-0.751*	-0.549*	-0.753*	-0.519*
	(0.020)	(0.093)	(0.020)	(0.092)
Real GDP/Capita	0.00568***	-0.00211	0.00577***	-0.00691
	(0.000)	(0.772)	(0.000)	(0.348)
% Medicare	-11.63***	-7.919***	-10.13**	-5.105***
	(0.000)	(0.000)	(0.001)	(0.000)
Federal CRR			1.816**	2.957**
			(0.026)	(0.004)
Federal Tax Rate (Effective)			-0.0277	-0.0154
			(0.715)	(0.189)
Federal CRR*Federal Tax Rate			-3.366	-3.667
			(0.789)	(0.091)
_cons	23.04***	13.91***	23.06***	14.18***
	(0.000)	(0.000)	(0.000)	(0.000)
FE	No	Yes	No	Yes
N	765	765	765	765
F	21.20	9.262	13.36	6.793

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.B.2: Effect of CCR and Tax Rates on FP Share of Hospital Beds

	(1) FP Bed share	(2) FP Bed share	(3) FP Bed share	(4) FP Bed share
CRR	6.365**	4.420**	6.403**	4.114**
	(0.003)	(0.006)	(0.003)	(0.008)
State tax	-0.544*	-0.565*	-0.538*	-0.564*
	(0.010)	(0.050)	(0.011)	(0.046)
CRR*State tax	-1.143***	-0.352	-1.145***	-0.332
	(0.000)	(0.221)	(0.000)	(0.237)
Real GDP/Capita	0.00122	-0.00232	0.00105	-0.00398
	(0.381)	(0.714)	(0.454)	(0.536)
% Medicare	-7.867***	-4.515**	-10.60***	-3.344**
	(0.001)	(0.003)	(0.000)	(0.007)
Federal CRR			-1.598	1.457
			(0.651)	(0.101)
Federal Tax Rate (Effective)			-0.0201	-0.00645
			(0.785)	(0.625)
Federal CRR*Federal Tax Rate			-0.213	-2.463
			(0.986)	(0.246)
_cons	19.91***	11.83***	21.87***	11.95***
	(0.000)	(0.000)	(0.000)	(0.000)
State FE	No	Yes	No	Yes
Year FE	No	Yes	No	No
N	676	676	676	676
F	15.79	5.155	10.12	4.036

p-values in parentheses

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

Table 4.B.3: Effect of CCR and Tax Rates on FP Share of Hospital Care Utilization

	(1) FP Utilizaton %	(2) FP Utilizaton %	(3) FP Utilizaton %	(4) FP Utilizaton %
CRR	5.024**	4.833*	5.057**	4.830*
	(0.010)	(0.013)	(0.009)	(0.014)
State tax	-0.482*	-0.711*	-0.479*	-0.711*
	(0.012)	(0.049)	(0.012)	(0.050)
CRR*State tax	-0.986***	-0.468	-0.985***	-0.467
	(0.000)	(0.106)	(0.000)	(0.108)
Real GDP/Capita	-0.000256	-0.00100	-0.000428	-0.00114
	(0.837)	(0.812)	(0.733)	(0.791)
% Medicare	-6.420**	-2.831*	-9.263***	-2.743*
	(0.002)	(0.030)	(0.001)	(0.017)
Federal CRR			-1.381	-0.117
			(0.667)	(0.892)
Federal Tax Rate (Effective)			-0.00323	0.00324
			(0.961)	(0.786)
FCRR*FTR			-1.180	0.643
			(0.912)	(0.764)
_cons	18.10***	8.639**	19.63***	8.539**
	(0.000)	(0.005)	(0.000)	(0.008)
State FE	No	Yes	No	Yes
Year FE	No	Yes	No	No
N	676	676	676	676
F	14.57	4.829	9.449	4.102

p-values in parentheses

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

Table 4.B.4: Effect of CCR and Tax Rates on FP Share in Specific Hospital Care

	(1) FP Admission %	(2) FP ER %	(3) FP Inpatient Day %	(4) FP Outpatient %
CRR	2.588*	9.878***	3.465***	3.117***
	(0.011)	(0.000)	(0.000)	(0.000)
State Tax Rate	-0.525***	-1.297***	-0.515***	-0.654***
	(0.000)	(0.000)	(0.000)	(0.000)
CRR*State Tax Rate	-0.122	-0.998***	-0.250	-0.457***
	(0.402)	(0.000)	(0.065)	(0.000)
Fedral CRR	1.448	-2.996*	1.376	-0.479
	(0.074)	(0.038)	(0.068)	(0.477)
	(0.613)	(0.403)	(0.557)	(0.016)
Federal Tax Rate Effective	-0.358	3.460	-1.693	0.0487
	(0.831)	(0.246)	(0.279)	(0.972)
FCRR	FTR	-2.568	8.248	-1.955
-0.598				
	(0.344)	(0.088)	(0.439)	(0.791)
% Medicare	-2.036**	-5.992***	-2.593***	-0.346
	(0.007)	(0.000)	(0.000)	(0.577)
GDP per Capita	-0.00154	0.00448	-0.00166	-0.00607*
_cons	10.29***	4.381	10.42***	7.720***
	(0.000)	(0.085)	(0.000)	(0.000)
State FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
N	676	676	676	672
F	12.74	12.74	18.48	6.933

p-values in parentheses

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

Table 4.B.5: Effect of CCR and Tax Rates on FP Share in Specific Hospital Care

	(1)	(2)	(3)	(4)
	NFP Origin	NPF Origin	FP Origin	FP Origin
1	Convert FP	Convert FP	Convert NFP	Convert NFP
CRR	0.321 *	0.685 *	-0.394	0.177
	(0.086)	(0.088)	(0.309)	(0.795)
State Tax	-0.0484 *	-0.0188 *	0.000721 *	0.0833 *
	(0.084)	(0.091)	(0.088)	(0.073)
CRR*State Tax	-0.00633 *	-0.0499 ***	0.0203	-0.0966
	(0.053)	(0.002)	(0.724)	(0.354)
federal CCC	0.578**	0.360	-0.579*	-0.0515
	(0.008)	(0.185)	(0.044)	(0.892)
Effective Federal Rate	-1.034 *	-1.049 **	2.223**	1.820 *
	(0.071)	(0.070)	(0.036)	(0.091)
2	Closure	Closure	Closure	Closure
CRR	0.0733 *	0.307 **	0.0960	-0.939
	(0.082)	(0.013)	(0.741)	(0.128)
State Tax	0.0182	0.0164	0.0419 *	0.194 *
	(0.238)	(0.731)	(0.070)	(0.054)
CRR*State Tax	0.0238	0.0859	-0.00173	0.0928
	(0.306)	(0.092)	(0.967)	(0.345)
Federal CRR	1.209**	1.134**	-0.765*	0.0690
	(0.002)	(0.009)	(0.020)	(0.845)
Effective Federal Rate	0.485	0.377	1.744**	2.250***
	(0.319)	(0.444)	(0.008)	(0.001)
N	42399	42399	17309	17309
State FE	No	Yes	No	Yes
Year Trend	No	Yes	No	Yes

p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Control variables include debt-to-capital ratio, operating margin, occupancy rate, indicator of teaching hospital percentage of medicare population, bed-to-population ratio

Table 4.B.6: Effect of CCR and Tax Rates on Provision of Community Benefit

	(1) Education	(2) Uncompensated Care	(3) Medicare	(4) Medicaid
FP	-0.406**	-0.243***	-0.0261***	-0.0199***
	(0.002)	(0.000)	(0.000)	(0.000)
FP*CRR	-0.0437 **	0.149***	0.00722*	-0.00827***
	(0.008)	(0.000)	(0.023)	(0.000)
CRR	0.0305	0.0143	-0.0367***	-0.00612*
	(0.869)	(0.679)	(0.000)	(0.022)
State Tax	0.0537**	0.0192***	0.000455	0.000180
	(0.003)	(0.000)	(0.274)	(0.524)
State Tax*CRR	-0.0267	-0.00480	-0.000233	0.000768*
	(0.248)	(0.307)	(0.652)	(0.029)
Federal CRR*FP	0.196 *	-0.456***	-0.0429***	-0.00289 *
	(0.008)	(0.000)	(0.000)	(0.007)
Effective Federal Tax Rate	-0.734	-0.386***	0.0425***	-0.0274***
	(0.459)	(0.000)	(0.000)	(0.000)
Debt_to_Cap Ratio	-1.34e-08	1.92e-08	-1.72e-09	7.73e-10
	(0.550)	(0.196)	(0.482)	(0.633)
Operating Margin	-1.296***	1.940***	-0.0399***	-0.00459
	(0.000)	(0.000)	(0.000)	(0.089)
Occupancy Rate	4.571***	0.188***	-0.00293***	0.000270
	(0.000)	(0.000)	(0.000)	(0.491)
Teaching Hospital	1.041***	0.528***	-0.0783***	0.0152***
	(0.001)	(0.000)	(0.000)	(0.000)
Size of Bed	0.00344***	0.00475***	-0.000244***	0.0000112**
	(0.000)	(0.000)	(0.000)	(0.003)
% Medicare Population	-0.429*	-1.053***	0.0693***	-0.0435***
	(0.025)	(0.000)	(0.000)	(0.000)
Bed-to-Population Ratio	13.32	25.06***	-3.124***	1.322***
	(0.081)	(0.000)	(0.000)	(0.000)
HHI	-1.465	-0.718**	-0.571***	0.0969***
	(0.295)	(0.006)	(0.000)	(0.000)
_cons	-49.41**	29.90***	0.207	3.779***
	(0.009)	(0.000)	(0.676)	(0.000)
N	31846	49599	59500	56325
F	100.9	2337.5	643.4	40.62
State FE	Yes	Yes	Yes	Yes
Year Trend	Yes	Yes	Yes	Yes

p-values in parentheses

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

4.C APPENDIX: DYNAMIC STRUCTURAL MODEL FOR HOSPITAL INDUSTRY

Based on Gowrisankaran (1997)[19], I construct a dynamic model of hospital market. On the demand side, patients differ by insurance type and income level, who chooses particular hospital to maximize their utility. On supply side, hospitals differs in ownership status and maximize different objective functions which incorporate investment options, tax rate and community benefit reporting requirement. Each period, hospitals chooses investment, entry, exit and conversion decision. The model is estimated by calibration and GMM method based on hospital and market level data. The main advantage of this structural model is that it provides a behavioral frame work which specifically targets hospital's ownership choice. Moreover, based on estimated model paremeters, it would be easy to construct counter-factuals under alternative tax policy.

4.C.1 DEMAND SIDE

For demand side, I model patient's decision by a discrete choice model. Suppose there are three different types of patient by their insurance status: private insurance, medicare and uninsured. Patient's choice of hospital is modeled as a differentiated-product discrete choice problem. For patient i with insurance type T will derive utility from choosing hospital j, which depends on the price paid out-of-pocket p_{ij} and the quality of care k_j, and patient's income level Y_i. Adopting the representation from Gowrisankaran (1997)[19], the utility for patient i of type T for visiting hospital j is written as:

$$U_{ij}^T = k_j + \beta_1 \ln(Y_i^T - \beta_2 p_{ij}^T) + \epsilon_{ij}^T \tag{4.C.1}$$

where ϵ_{ij}^T is an idiosycradic shock which is assume to has the same exponential distribution across patient type. Suppose each patient has some outside alternative treatment option, e.g. home remedy, drug etc. The utility obtained from this alternative can be written as:

$$U_{i0}^T = k_0 + \beta_1 \ln(Y_i^T - \beta_2 p_{i0}^T) + \epsilon_{i0}^T \tag{4.C.2}$$

where k_0 can be normalized to zero in usual representations.

To calculate the market share for each hospital , it can be obtained by evaluating the probability of patient i of type T to choose hospital j. Patient chooses to visit hospital j if the utility derive from that choice dominates other options. Subtracting utility from based line model, the probability of choosing hospital j is the probability that utility from j is larger than any other alternative k. Based on the exponential distribution of shocks, the market share can be represented by a standard logit model.

$$\begin{aligned} S_{ij}^T(p_{ij}^T) &= \int_{U_{ij}^T > U_{ik}^T \forall k \neq j} S_{ij}^T(\epsilon | p_{ij}^T) dF(\epsilon) \\ &= \frac{\exp[k_j + \beta_1 \ln(\frac{Y_i^T - \beta_2 p_{ij}^T}{Y_i^T - \beta_2 p_{i0}})]}{1 + \sum_{k=1}^J \exp[k_k + \beta_1 \ln(\frac{Y_i^T - \beta_2 p_{ij}^T}{Y_i^T - \beta_2 p_{i0}})]} \end{aligned} \tag{4.C.3}$$

4.C.2 Supply Side Static Decision

In this model, I assume that there are two types of hospitals, nonprofit and for-profits. The number of FPs and NFPs are determined by entry, exit and conversion. NFPs and FPs differ in their objective functions. FP hospitals operate to maximize expected profit while NFPs incorporate quality in its objective function. Moreover, FP hospitals face tax cost from fedral and local level while NFP hospitals are exempted. HoIver, it is specified that it costs NFPs a share of their revenue as community benefits.

Assume that hosptal j operates under fixed cost F and have properties S subject to property tax rate γ_p. Also, positive profits are subject to corporate income tax rate

γ_I. I is the chosen level of investment while $r^F P$ represents the cost of capital for FP hospitals. Write out the hospital objective function as follows:

$$O_j^{FP}(p) = [\pi_j(p) - F - \gamma_p S - r^{FP} I] - \gamma_1 \max\{0, \pi_j(p) - F - \gamma_I S - r^{FP} I\} \tag{4.C.4}$$

For nonprofit hospitals, the objective is a weighted average of profits and quality k_j. Also, NFP hospitals are paying ρ_1 share in their profit as community benefit. I is the chosen level of investment by NFP while $r^N FP$ represents the cost of capital for NFP hospitals. Note that the cost of capital can be difference for FPs and NFPs because NFPs are alloId to issue tax-exempt bonds.

$$O_j^{NFP}(p) = \alpha_P[\pi_j(p) - F - r^{NFP} I - \rho_1 \max\{0, \pi_j(p) - F - r^{NFP} I\}] + (1 - \alpha_P) k_j \tag{4.C.5}$$

4.C.3 SUPPLY SIDE DYNAMIC DECISION

Based on the static objective function of hospitals, I now turn to the dynamic choice of entry, exit and conversion. Hospitals choose strategies to maximize their expected present value of all future payoffs.

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