5-2013

Essays on Health and Medical Care

Yin-Fang Yen
Syracuse University

Abstract

This dissertation consists of two essays that explain health outcomes and medical care in the United States. Health care has been a major concern of economists and policy makers. Policy intervention is one of the key factors that affect health outcomes, especially among low-income families. Welfare programs such as Medicaid and cash assistance are conventionally implemented to assist low-income families. The effectiveness of these efforts to improve health outcomes and medical utilization among low-income families is not entirely clear. As to the supply side of health care, the results of previous studies on how hospitals provide the services are mixed. Additionally, hospitals may compete to attract patients and generate spillover effects. Quality of hospitals may in turn differ by market. My two essays apply econometrics models to investigate the effects of public policies and hospital quality on health and medical care. Specifically, the first essay examines whether welfare programs affect the health outcomes and medical utilization of children in the low-income families, and if so, which policy has the strongest effect on them. The second essay explores how the spillover effects impact the treatment rates of hospitals.

The first essay examines the effect of the Temporary Aid to Needy Families (TANF) program on children's health outcomes using data from the Survey of Income and Program Participation (SIPP) over the period 1994 to 2005. The TANF policies have been credited with increased employment for single mothers and a dramatic drop in welfare caseload. Our results show that these policies also had a significant effect on various measures of children's health and medical utilization especially among low-income families. These health measures include a rating of the child's health status reported by the parents; the number of days an illness or injury

kept the child in bed; the number of times that parents consulted a doctor; and the number of nights that the child stayed in a hospital.

The second essay addresses the effect of hospital ownership on treatment rates allowing for spatial correlation among hospitals. Competition among hospitals and knowledge spillovers generate significant externalities which we try to capture using the spatial Durbin model. Using a panel of 2342 hospitals in the 48 continental states observed over the period 2005 to 2008, we find significant spatial correlation of medical service treatment rates among hospitals. We also get mixed results on the effect of hospital ownership on treatment rates that depends upon the market structure where the hospital is located and which varies by treatment type.

ESSAYS ON HEALTH AND MEDICAL CARE

By

Yin-Fang Yen
B.A. National Chung Cheng University, 2003
M.A. The University of Mississippi, 2008

DISSERTATION

Submitted in partial fulfillment of the requirements for the
degree of Doctor of Philosophy in Economics
in the Graduate School of Syracuse University

May 2013

Acknowledgements

My sincere appreciation goes to all of whom helped me complete this dissertation and contribute my intellectual progress at Syracuse University. I would like to express my special gratitude to my advisor, Professor Badi H. Baltagi, for his support and insightful guidance throughout these essays. I am also indebted to Professors Chihwa Kao and Susan Gensemer, whose encouragement is an essential part of my progress. I also benefit a lot from their wisdom.

I would like to thank Professors Jeffrey Kubik, Perry Singleton, Jeffrey Weinstein, and seminar participants at Syracuse University for their comments and suggestions. I also would like to thank Professors Donald Dutkowsky, William Horrace, Emil Iantchev, Jerry Kelly, Derek Laing, Jan Ondrich, and Stuart Rosenthal for building up my knowledge in economic theory and research technique. I appreciate the contribution of Professor Leonard Burman to my dissertation defense. I am also grateful for comments and advices received from participants at the third Health Econometrics Workshop in December, 2012, and the NY Camp Econometrics VII poster session in April, 2013.

I also benefit a lot from many constructive suggestions, encouragement and help from my classmates and colleagues. They are Ying Deng, Jing Li, Allison Marier, Wael Moussa, Liu Tian, Sanggon Na, Jeonen Shin, Qianqian Cao, Jie Dai, Xiaoxue Li, Jinqi Ye, Ian Wright, Andrew Friedson, Alex Bogin, Shimeng Liu, Chong Li, Shaofang Qi, Chun-Chien Hu, Pallab Ghosh, Tingting Xiong, Melissa Chow, Mallory Vachon, and Bin Peng.

Last but not least, I am sincerely thankful to the help and support from my lovely family, especially my parents, while I was writing up this dissertation. All remaining errors are my own.

Table of Contents

List of Tables

List of Figures

Essay I : Welfare Reform and Children's Health

1. Introduction

It is well-known that poor health for children can lead to deterioration in school performance and lower future earnings (see Case, Lubotsky, and Paxson, 2002; Case, Fertig, and Paxson, 2005; and Currie et al., 2010 to mention a few). The child's health depends among other things on the amount of time and money the parents spend on their children. Children in higher-income families usually have more nutritious diets and better care than children from low-income families. It is well documented that children in poverty have worse health conditions (see Aber et al., 1997; Currie and Lin, 2007 to mention a few). The U.S. government provides welfare programs to improve this situation, for example, medical assistance and cash transfers[1]. However, when the mandates of the programs are restrictive, the recipients are more likely to drop out of welfare. As a result, the child's health will be impacted by the loss of financial support.

Under the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA), Temporary Aid to Needy Families (TANF) program replaced Aid to Families with Dependent Children (AFDC) in 1996. To reduce welfare dependency of low-income families, TANF limits the lifetime welfare use and requires work-attached activities. The restrictive TANF policies lead to a dramatic decrease in welfare caseloads (Moffitt, 2003)[2]. The total amount of children covered by AFDC/TANF dropped from 9.3 million in 1992 to 3 million in 2008. Parents left this program because they either found employment or they failed to meet the restrictive requirements. In the latter case, children lose their cash benefits which in turn could affect their health. Parents that obtain jobs, presumably with higher income, can provide better quality food

[1] In fact, Gertler (2004) finds that cash transfers enhance children's health in Mexico.
[2] However, Ziliak et al. (2000) suggest that economic conditions may have been the major culprit in the caseload decline.

and care for their children[3]. The worker participation rate among AFDC/TANF families increased from 18.8% in 1992 to 29.4% in 2008, even with a recession in the late 2000's (DHHS, 1998, 2009). In fact, Grogger (2004) reports higher employment after the implementation of lifetime limits. As a result, children leaving TANF in either of these two scenarios can have different health outcomes.

Studies investigating the effect of welfare reform policies on children's health are rare. Exceptions are Leonard and Mas (2008) and Dunifon, Hynes, and Peters (2006). Leonard and Mas found that states which imposed shorter time limits on being in welfare had higher infant mortality rates. This was more pronounced for less educated and unmarried women. In contrast, Dunifon, Hynes, and Peters found insignificant effects of welfare reform policies on the child's health status as rated by the parents.

Our study investigates the effect of welfare reform on children's health outcomes using data from the Survey of Income and Program Participation (SIPP) over the period 1994 to 2005. Utilizing the difference-in-differences method, our results show significant changes in various measures of children's health and medical utilization among low-income families. These measures include: (i) a rating of the child's health status as reported by the parents; (ii) the number of days an illness or injury kept the child in bed; (iii) the number of times that parents consulted a doctor; and (iv) the number of nights that the child stayed in a hospital.

In fact, for low-income families, we find an improvement in the child's health as reported by the parents. We also find a decrease in the number of times that parents consulted a doctor. The general health status is impacted by work requirements the most**,** while family caps have the

[3] Empirical studies report mixed results of how a child's health is impacted by maternal employment (see Gennetian et al., 2010; Brooks-Gunn et al., 2002; and Waldfogel, 2004 to mention a few).

largest effect on the number of doctor consultations. One possible explanation is that families are forward-looking as suggested by Grogger (2004) and Swann (2005). Parents tend to reduce welfare use when their children are young, because time limits restrict the total use of welfare. They are more risk-averse and would like to reserve these benefits for possible needs in the future. In addition, recipients worry about non-increment benefits for an additional child. With limited benefits, they may adjust their fertility decision to control the family size and pay more attention to health, nutrition, and care for their children.

2. Welfare Reform in the 1990's

Before the PRWORA, families receiving AFDC benefits were typically low-income single-parent families with at least one child under 18 years of age. Cash-aid continued until they earned higher income or all the children in the family became 18 years or older. AFDC generated work disincentive for low-income female headed families (Moffitt, 1992). In addition, Currie and Cole (1993) argued that it also generated undesired maternal behavior, such as inappropriate prenatal care. To reduce the dependency on welfare programs, TANF mandated several restrictive requirements. The requirements include: (i) lifetime limits, (ii) work-attached activities, (iii) initial sanctions, and (iv) family caps.

The *lifetime limits* restrict the total cumulative use of TANF to only 60 months in the recipients' lifetime. Families leave TANF when their income is higher than the threshold, and enroll again when their income drops lower than the threshold. If families reach the lifetime limits, they are not able to enroll in TANF again. Similarly, the federal program requires recipients to participate in the labor force within 24 months. If the parents fail to meet this *work-activity requirement*, their benefits may be partly or fully sanctioned. It is even more challenging for low-income families if the state mandates full-benefit *initial sanctions* when parents cannot fulfill the first time requirements.

Besides welfare dependency, economists and policy makers also worry about the fertility decision of low-income families. Most welfare programs increase benefits if the family has one additional child. Families may intentionally have additional children due to these benefits. In fact, Robins and Fronstin (1996) find that AFDC benefits increase the birth rate among black and Hispanic unmarried women. To reduce these incentives, families are given zero or partial incremental benefits for an additional child under *family caps*.

The federal policy is a general guideline of TANF. State governments decide which policy to implement, and how, and when to implement these policies. Each state can modify the restrictions according to their economic situations or concerns. Some states have shorter lifetime limits, but no family caps. Two states may both implement immediate work activity requirements, but only one may have full sanction policy. As a result in 2005, 11 states have lifetime limits shorter than 60 months, while four states do not have this mandate. In addition, 43 states require immediate work activities in 2005. The implementation dates also vary by states. Some states enforced state-wide welfare reforms and implemented restrictive waivers before TANF. The waivers resemble the TANF policies, however, with a less comprehensive design. One state may implement part of the four policies along with some other requirements as its waivers. Table I-1a presents the number of states[4] implementing waivers and TANF from 1994 to 1999, and Table I-1b presents the number of states implementing policies after 1994. States are counted in both categories at the year that waivers were replaced with TANF. About half of the states implemented waivers prior to TANF. In fact, waivers are not replaced immediately after

[4] This includes 50 U.S. states and Washington D.C.

the PRWORA in 1996. For example, Hawaii adopted waivers in 1997 and replaced it with TANF in the same year. All states implemented TANF between 1996 and 1997. Table I-1b shows that almost all states adopt time limits and work requirements, regardless of the duration limits. 22 states adopted family caps and 18 states adopted full initial sanctions in 2005, respectively. The amount of benefits also varies by state and depends on the arrangement of its TANF block grant from the federal government[5]. For example, both Mississippi and Alaska have 60-month lifetime limits in 2005. However, Mississippi has the lowest benefits and Alaska has the highest benefits in the US.

3. Previous Literature

Many papers studying the effect of TANF focus on employment, caseload, and welfare use among low-income families. Grogger (2003, 2004) and Moffitt (2002) report an increase in employment among low-income families after the implementation of lifetime limits. The restrictive policies are an important barrier to entry and a primary factor for why families leave the TANF program. Recipients may run out of time limits or are not able to find a job. Around 25 to 40 percent of women who leave welfare do not work. The non-working situation makes it even more economically disadvantageous to them and their children (Moffitt, 2002, 2003; Stuber and Kronebusch, 2004). Parents also tend to be forward-looking. They reduce welfare use when their children are young because time limits restrict the total use of welfare (Grogger, 2004; Swann, 2005). The increase in employment and the decrease in welfare enrollment have marked implications for the health of children in these families.

[5] The lowest maximum benefit for a family of three is $170 per month in 2005, and the median amount is $379.

For parents that obtain jobs, and leave welfare, one presumes a higher family income[6]. London et al. (2004) interviewed families that enrolled in welfare programs regarding the changes in their life due to work. These parents reported that work increases self-esteem and instills better self-sufficiency values within children. They also reported that they can afford better medical services and quality of life with higher income. However, these parents stated that they are usually exhausted after work and agreed that going to work decreases the time and energy devoted to their children. Bianchi (2000) also argues that the time that working mothers spent on their children is less than that of unemployed mothers, even though the difference of time spent on direct childcare is relatively small. Studies report that there is a greater chance for single working mothers to neglect their children. This includes medical neglect. In fact, the substantiated cases of children maltreatment significantly increased in states with short lifetime limits and tough initial sanctions (Paxson and Waldfogel, 2002, 2003).

Bitler, Gelbach, and Hoynes (2006) find that after welfare reform, more black and Hispanic children live with married parents, or neither parent (likely to be a relative with higher income). In other words, the percentage of children living with an unmarried parent decreases. The results are mixed for white children. They argue that, compared to living with a single parent, children could have better outcomes when they live with a grandparent and no parent. Paxson and Waldfogel (2003) also suggest that it is more likely for children to be sent to out-of-home care (primarily foster care) in states with short lifetime limits, tough initial sanctions, family caps, and immediate work requirements. Conversely, states with more generous benefits are associated with a lower out-of-home care rate. Children may or may not receive proper care depending on

[6] Grogger (2003) indicates that family income increased over the study period. However, this increase is mainly because of the Earned Income Tax Credit (EITC). Moffitt (2002) finds moderate increments in earnings for women who leave welfare. The gains in earnings exceed the losses of benefits in one or two years after they leave the program. The income is slightly higher with EITC. The main source is from the income change of other family members.

the parent’s living arrangements. According to Bitler, Gelbach, and Hoynes, children who are sent to out-of-home care may be better off than staying home alone. On the other hand, Gordon et al. (2007) argue that center-based childcare provides less quality than maternal care. Young children in center-based care tend to have more injuries and infectious diseases.

Second, if parents do not obtain a job in time or families run out of time limits, they lose their benefits temporarily or permanently. Their income is likely to be lower than that when they were under welfare. Even with income from other family members and welfare programs, a fraction of these families will still be worse off after they leave TANF (Moffitt, 2002). As a result, these families facing a tougher situation without benefits and sufficient income may not be able to provide the same nutritious food or proper care for their children. Studies have shown that children in poverty are more likely to have poor health (Aber et al, 1997; Currie and Lin, 2007).

Combining these two effects, it is ambiguous if the waivers and TANF policies will result in a negative or positive effect on children’s health and medical utilization. Few studies investigate the welfare reform policy effects on children’s health and medical utilization. Dunifon, Hynes, and Peters (2006) studied how changes in welfare reform policies influenced children’s well-being via their influence on income, employment, or welfare participation of the parents. They used data from the 1992, 1993 and 1996 panels of SIPP. One of the measures of child well-being was the child’s health (but only for children with ages 0–5). This was reported by the child's primary caregiver and is one of the health variables that we will use in our study. They argued that if changes in welfare policies increase family income, one may see improvements in child’s health. However if changes in welfare policies increase employment without changing income, one may see reductions in child health due to less parental supervision and/or stressful family situation. They argue that their results are inconclusive and do not suggest that welfare reform policies have a uniform, strong effect on the aspects of parenting behavior and child well-being.

Leonard and Mas (2008), on the other hand, showed that infant mortality rates increased in states with shorter lifetime limits. Using the Centers for Disease Control and Prevention (CDC) data covering 1995-2002 and a linear probability model, they found that this effect was larger for blacks than for whites. However, they do warn that time limits did not account for the whole increase in mortality rates. The bad economy in the early 2000's and state differences could also be part of the reasons.

4. Data and Methodology

We apply the difference-in-differences methodology to estimate the effects of welfare reform on children's health and medical utilization. We use the SIPP data which consists of several panels. The duration of each panel is between 2.5 to 4 years. We combine these panels into a larger dataset spanning the period 1994 to 2005. A longer duration dataset allows us to investigate long-term health effects, which were not feasible in previous studies that were based upon shorter periods. SIPP collects general individual information with different topical modules every four months. The health module reports the following four measures of children's health and medical utilization: (i) a health status rating by parents, varying from excellent, very good, good, fair, to poor; (ii) days of an illness or injury that kept the child in bed for more than half a day in the past 12 months[7]; (iii) the number of times that parents consulted a doctor or an assistant regarding child health in the past 12 months; and (iv) the number of nights that the child spent in a hospital in the past 12 months. Even though our four measures are related to the child's health, the latter three may also be considered as measures of medical utilization. All of these

[7] This measure is limited to young adults between the ages of 15 and 17.

measures were reported by the primary caregiver. We modified our health status variable to a dummy variable which takes the value one if the child's health is rated as fair or poor and zero otherwise. The child health data was not available prior to 1994[8].

To utilize a quasi-experimental method, it is important to know who are most likely to be impacted by TANF. We target three *treatment groups*: (i) unmarried parents that have at most a high school degree, (ii) families with income under 100% of the federal poverty level (FPL), and (iii) families with income under 200% of the FPL. These families are the most likely to enroll in welfare programs. The control group for the first treatment group includes married parents who have more than a high school degree. For the latter two treatment groups, the control group includes married parents with income higher than 200% of the FPL. One possible problem with using income as the treatment is possible sample selection bias (Evans and Garthwaite, 2010). Families may adjust their behavior due to the income threshold. However, the income threshold of the TANF program is usually much less than 200% of the FPL. It is true that families with income between 100% and 200% of the FPLs are very likely to be affected by the policies. These families may leave welfare due to the more stringent requirements or higher income after obtaining a job. Including families up to 200% of the FPL reduces the possible bias. Moreover, the restrictive policies are more likely to be the factors for the decision to enroll or not to enroll in TANF. See Moffitt (2003) who reports that many families leave or avoid the program because of these restrictive policies.

Table I-2 presents our summary statistics. The mean of poor health status for all groups is 0.02, which implies that on the average parents rate their children in good health. Similarly,

---

[8] The health modules are usually surveyed in the latter half of the year and the first two months of the next year. If the survey is taken in the latter half of the year, our measures are mostly impacted by the policies in the same year. However, if the interviews are completed in January and February of the next year, they are combined with the previous year.

while some children are ill for the whole year, the low means of the other three measures indicate that on the average there were few days in bed, few doctor consultations and few nights of hospital stays. There are substantial differences in the health measures considered between the treatment and control groups. Children in low-income, and low-educated unmarried parents groups, are more likely to be reported in poor health, with fewer doctor consultations, and more hospital stays. In addition, there are large percentages of black and younger mothers in these treatment groups.

Figure I-1 shows the proportion of children reported in poor health over the period 1994-2005. The treatment group in Figure 1a is unmarried parents that have at most a high school degree; while that in Figure 1b is families with income under 100% of the FPL; and that in Figure 1c is families with income under 200% of the FPL. In all Figures, the proportion of children in poor health in the treatment group declines over time, while that of the control group has relatively smaller fluctuations. The largest difference between the treatment and control groups occurs before 1998, the year in which all states implemented TANF. This difference between the treatment and control groups declines after the reform. This is contrary to most of the previous literature that suggest a deleterious influence of welfare reform on children.

In addition, these treatment groups are only affected when the state implements these policies. As we discussed earlier, states vary in their adoption of these policies**.** Not all states implement all four policies we are focusing upon. For example, Michigan and Vermont did not adopt any termination time limits. Similarly, 27 states never had family caps, and 32 states never set the initial sanctions to be full benefits. Since these policies have never been implemented, we are not able to observe their effects in these states. Likewise, the effects are unobservable in those few states that implemented the policies before 1994. Hence, we dropped states that never implemented the policies or had previously implemented them. In addition, SIPP grouped nine states into larger regions before 1996[9]. For these larger regions, we could not determine which interviewee belonged to which state. Therefore, we are left with 41 states with lifetime limits, 42 states with work requirements, 18 states with family caps, and 17 states with initial sanctions being full benefits, respectively.

Our reduced form model is as follows:

$$\begin{aligned} \text{Health}_{ist} = {} & \alpha + \beta_1 \text{ Treatment}_{ist} + \beta_2 P_{st} + \beta_3 P_{st}{*}\text{Treatment}_{ist} + \beta_4 \text{ Maxben}_{st} \\ & + \beta_5 X_{ist} + \beta_6 \text{ unemployment}_{st} + \beta_7 \text{ Medicaid coverage}_{st} + u_s + v_t + \varepsilon_{ist} \end{aligned}$$

where Health_{ist} is the health measure of child i in state s at year t. We employ the logistic regression when our dependent variable is the child's binary health status variable. We also apply the negative binomial regression when our health variable is days in bed, number of doctor consultations, or nights of hospital stays[10]**.** Treatment_{ist} is an indicator variable which takes the value one if child i belongs to that treatment group in state s at time t. P_{st} denotes the welfare reform policies for state s at time t. This is measured as a proportional dummy which is the share of the year that the policy is implemented. This is done for lifetime limits, work requirements, family caps, and initial sanctions being the full benefits. With the initial implementation dates, we can match the proportion of families with the month they are interviewed, and calculate the exact proportion of families that are impacted that year. If the policy is implemented after the interview, the proportional dummy is set equal to zero. Max Benefit_{st} is the maximum AFDC/TANF benefit for a family of three in state s at time t. Unemployment_{st} is the

[9] The nine states include: Alaska, Idaho, Iowa, Maine, Montana, North Dakota, South Dakota, Vermont, and Wyoming.
[10] We also tried the Poisson model for days in bed and doctor consultations. This was rejected statistically in favor of the less restrictive negative binomial model. Also, the probit model was also applied for the child's health status variable and this produced similar results which are not reported here to save space.

unemployment rate in state s at time t, and Medicaid coverage$_{st}$ is the Medicaid child coverage rate in state s at year t[11]. X_{ist} controls for individual characteristics, including child's age, race, and gender, mother's age, mother's education which consists of indicators of whether the mother is a high school dropout, or has a post high school degree, and a dummy variable for whether the family lives in a metro area. u_s and v_t are the state and year dummies.

One concern with the difference-in-differences method is that the standard errors are likely to be understated because of autocorrelation. To correct for this problem, our standard errors are clustered by states (see Bertrand et al., 2004; and Donald and Lang, 2007). For the nonlinear models we calculate the average marginal effects following the method suggested by Ai and Norton (2003) and Karaca-Mandic, Norton, and Dowd (2010).

As explained above, there are two possible outcomes from the restrictive policies on the health of children. If the parents participate in labor force, they leave the program with possibly higher income. Children are more likely to be sent to out-of-home care. They may have more nutritious food and sufficient attention. On the other hand, if parents are not able to seek out-of-home care, children receive less time and care from their parents. Also, if parents run out of time limits or face a sanction, they lose their benefits and the children in turn suffer from the loss of these benefits. Encountering family caps will generate a similar situation as well. The marginal effects will determine which effect is stronger and whether the child's health is improved due to the policy when comparing the treatment and non-treatment group.

We also include maximum benefits and Medicaid child coverage in our model. According to Gertler (2004), a more generous benefit is expected to generate a better child health outcome. Medicaid is a public health insurance program for low-income individuals, including children.

[11] The Medicaid child coverage rate is equal to the total number of children covered by Medicaid divided by the total number of children under age 21.

The threshold for Medicaid is lower than that for the TANF program. Most of the children under AFDC/TANF are covered by Medicaid (Medicare and Medicaid Statistical Supplement, 2009). The TANF income thresholds are mostly lower than or equal to 100% of the federal poverty level, but the state Medicaid thresholds for children under age 6 are between 133% and 275% of the FPLs in 1997. This direct medical assistance benefits many low-income families, especially those with sick children. As noted by Currie and Gruber (1996), medical utilization would increase with the expansion of Medicaid. The restrictive requirements of the TANF program may push them out of TANF causing a switch to Medicaid. Parents may not meet the requirements of this program or run out of the lifetime limits, but are still eligible for Medicaid. Many families may choose to opt out of TANF. Children in low-income families may have better health due to Medicaid. Interestingly, Medicaid is rarely discussed in previous studies on TANF.

We also include the state unemployment rate to controls for the effects of the economy[12]. However, the state economy is likely to correlate also with Medicaid child coverage. More children enroll in Medicaid in a bad economy. Currie and Grogger (2002) argue that if the unemployment rate can perfectly control for state economic conditions, we expect children to have better health with the expansion of Medicaid, holding everything else equal. However, if the unemployment rate cannot perfectly control for state economic conditions, the high Medicaid coverage rate reflects the hardship of low-income families.

5. Results

Table I-3 presents the logistic estimates with state and time dummies where the dependent variable is a dummy variable indicating whether the *child is in poor health* or not. The first three columns in each table pertain to the first policy (*lifetime limits*) and this is done for the three

[12] Ruhm (2000) argues that individuals have healthier habits and weight during recessions, and that the effect of a recession on preventive health care is insignificant.

different treatment groups considered. The next three columns repeat this regression for the second policy (*work-attached activities*), and so on for *family caps*, and *initial sanctions*, respectively. For the work requirements policy in Table I-3, we observe a negative and significant effect on the *probability that a child is in poor health* for all treatment groups considered. The time limits, family caps and initial sanctions welfare reform policies had insignificant effects on the *probability that a child is in poor health* for all treatment groups.

The average marginal effects for the work requirements policy in Table I-3 are negative and significant for all treatment groups. Implementation of the work requirements policy decreases the *probability that a child is in poor health* by about 1 to 1.6 percentage points. The largest effect is for families with income *under 100% of the FPL*. One possible explanation is an increase in confidence through work suggested by London et al. (2004). The marginal effects are insignificant for the other welfare policy reforms.

Our results in Table I-3 indicate that the unemployment rate is insignificant. The only exceptions are for low-educated families under time limits, and for low-income families (under *100% or 200% of the FPL*) under initial sanctions. Medicaid coverage is only significant for the family caps policy for families with income under *200% of the FPL*.

Table I-4 presents the estimates using a negative binomial regression with state and time dummies where the dependent variable is the *number of days an illness or injury kept the child in bed for more than half a day*. None of the welfare policy requirements is significant. This holds for all treatment groups. The average marginal effects are also insignificant. Note that only children between the ages of 15 and 17 are examined in this measure due to data availability.

Our results in Table I-4 indicate that the effect of unemployment rate is insignificant for all treatment groups. Medicaid coverage rate has a positive and significant effect for all treatment groups under the family caps policy. It is also significant for low-income families (under *100% or 200% of the FPL*) under the initial sanctions policy.

Table I-5 presents the negative binomial estimates with state and time dummies where the dependent variable is the *number of times that parents consulted a doctor*. For low-income families (*under 100% or 200% of the FPL*), the time limits, work requirements, and family caps policies all have a negative and significant effect on the *number of doctor consultations.* For the low-educated unmarried parent treatment group, none of the policies have a significant effect on the *number of doctor consultations.* The initial sanctions remain insignificant for all the treatment groups except for the low-income families (*under 100% of the FPL*).

Focusing on the first three columns of Table I-5, the average marginal effect estimates of the time limits policy indicate a decrease in the *number of doctor consultations* by 0.4 for the 100% low-income treatment group, and by 0.28 for the 200% low-income treatment group, respectively. The work requirements and family caps also lower the *number of doctor consultations* by around 0.55 for families with income under 100% of the FPL, and by around 0.37 for families with income under 200% of the FPL, respectively. The initial sanctions are associated with a decline by 0.4 for the 100% low-income treatment group.

This is in line with the Bitler, Gelbach, and Hoynes (2005) results which suggest that single mothers reduce their usage in preventive health care after the implementations of waivers and/or TANF. Our results indicate that this reduction in medical utilization may also carry over to their children.

Table I-5 also shows that Medicaid coverage has no significant effect for all policies considered. On the other hand, unemployment has a positive and significant effect on the *number of doctor consultations* for the regressions with the family caps policy and all treatment groups. It is also significant for families with income under *100% of the FPL* under the time limits and work requirements policies.

Table I-6 presents the negative binomial estimates with state and time dummies where the dependent variable is the *number of nights that a child stayed in a hospital*. Time limits have a significant and negative effect for all treatment groups. However, work requirements, family caps, and initial sanctions are not significant for all treatment groups.

The average marginal effects in Table I-6 are negative and significant for the time limits policy for low-educated families and low-income families (under *200% of the FPL*). The implementation of time limits decreases the *number of nights that a child stayed in a hospital* by around 0.1 for these two treatment groups.

Table I-6 indicates that the unemployment rate is not significant for all policies and treatment groups. The only exception is the *100% low-income* families under the family caps policy. On the other hand, Medicaid coverage has a significantly negative effect on the *number of nights that child stayed in a hospital* for both low-income treatment groups under work requirements and family caps. It is also associated with a decline for the 100% low-income treatment group under time limits and initial sanctions. This is in line with the results of Aizer (2007) who reports a reduction in hospitalization after Medicaid expansion.

6. TANF, Waivers and Treatment Groups

One might argue that focusing on specific welfare reform policies may overestimate their effects. Estimating the effects of one policy may be contaminated with the effects of other policies implemented at the same time in some states. In addition, one could argue that the effects of welfare reform should not be limited to one particular policy since it is a combination of various policies. To study the robustness of our results, we estimate an alternative model described as follows:

$$\begin{aligned} \text{Health}_{ist} = {} & \alpha + \beta_1 \text{ Treatment}_{ist} + \beta_2 \text{ Waiver}_{st} + \beta_3 \text{ Waiver}_{st}{*}\text{Treatment}_{ist} \\ & + \beta_4 \text{ TANF}_{st} + \beta_5 \text{ TANF}_{st}{*}\text{Treatment}_{ist} + \beta_6 \text{ Maxben}_{st} \\ & + \beta_7 \text{ X}_{ist} + \beta_8 \text{ unemployment}_{st} + \beta_9 \text{ Medicaid coverage}_{st} + u_s + v_t + \varepsilon_{ist} \end{aligned}$$

Waiver_{st} and TANF_{st} denote the welfare reform implementations for state s at time t. They are measured as a proportional dummy which is the share of the year that the policy is implemented in the first year, and equal to one afterwards. Following the argument of Bitler, Gelbach, and Hoynes (2005), we cannot assume that waivers and TANF have the same effect across states and over time. The policy variables only measure the average effects of waivers and TANF. However, by not turning off Waiver_{st} to zero after the implementation of TANF, we can identify states having waivers before TANF. If waivers or TANF are implemented after the interview, the proportional dummy is set equal to zero. The other variables are identical to those in the policy model.

Table I-7 presents the nonlinear regression estimates with state and time dummies. The first three columns in the table pertain to the first health measure (the *probability that the child is in poor health*), for the three different treatment groups considered. This uses the logistic specification. The next three columns repeat this regression for the second measure (the *number of days that the child was in bed*), and so on for the *number of doctor consultations*, and the *number of hospital stays*, respectively. These use the negative binomial specification. For low-income families (under *100% or 200% of the FPL*), TANF has a negative and significant effect on the *probability that the child is in poor health* and the *number of doctor consultations*. TANF is also associated with a negative relationship with the *number of hospital stays* for unmarried low-educated families and low-income families (under *100% of the FPL*). On the other hand, waivers are not significant for any of the treatment groups, no matter what dependent variable we focus on.

The average marginal effects in the bottom of Table I-7 present the overall effects of waivers and TANF. Waivers are not significant for all treatment groups. The only exception is that waivers lower the *probability that the child is in poor health* by 0.6 percentage points on average for families with income under *200% of the FPL*. TANF is also associated with a decline of 0.8 percentage points on the *probability that the child is in poor health* and a decline of 0.5 to 0.34 for the *number of doctor consultations* for low-income families (under *100% and 200% of the FPL*). TANF is not significant for days in bed and hospital stays.

Comparing the results in Table I-7 and Table I-3, we see that waivers and TANF result in a small but significant decline in the *probability that a child is in poor health* for families with income under *200% of the FPL*. In contrast, this is only significant for the work requirements policy in Table I-3, but for all treatment groups. Comparing the results in Table I-7 and Table I-4, we see that neither waivers nor TANF have any significant effects on the *number of days that the child was in bed*. This is also the case for all policies considered in Table I-4. Comparing the results in Table I-7 and Table I-5, we see that TANF results in a small but significant decline in the *number of doctor consultations* for low-income families. This is also true for both low-income treatment groups for all policies considered, except the 200% low-income families under initial sanctions, in Table I-5. Comparing the results in Table I-7 and Table I-6, we see that neither waivers nor TANF have any significant effects on the *number of hospital stays*. This is by and large true for all policies considered in Table I-6 except for time limits which find a small but significant decline in the *number of hospital stays*.

7. Conclusion

Our results indicate that for low-income families the implementations of restrictive policies reduced the probability of being in poor health and the utilization of doctor consultations. The comprehensive welfare reform model agrees with these results. Among the restrictive policies, work requirements dominate the effect on probability of being in poor health. All four welfare policies reduce the number of doctor consultations, but family caps have the greatest effect. Interestingly, we found that Medicaid has a negative and significant effect on the *number of hospital stays* in Table I-7, and this is also true for families with income under *100% of the FPL* for all policies considered in Table I-6[13].

In conclusion, our results have to be tempered by the fact that the health measures used in this study are reported measures by the caregiver and are subject to the usual criticism of such subjective measures. Also, one may argue that there may be other policies that we have not accounted for and not spanned by the state and time dummies included.

[13] We did include unemployment but we found it insignificant in most regressions.

References

Ai, Chungrong, and Edward C. Norton. 2003. "Interaction Terms in Logit and Probit Models." *Economics Letters* 80: 123-129.

Aizer, Anna. 2007. "Public Health Insurance, Program Take-Up, and Child Health." *The Review of Economics and Statistics* 89 (3): 400-415.

Aber, J. Lawrence, Neil G. Bennett, Dalton C. Conely, and Jiali Li. 1997. "The Effects of Poverty on Child Health and Development." *Annual Review of Public Health* 18: 463-483.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. 2004. "How Much Should We Trust Differences-In-Differences Estimates?" *The Quarterly Journal of Economics* 119 (1): 249-275.

Bianchi, Suzanne M. 2000. "Maternal Employment and Time with Children: Dramatic Change or Surprising Continuity?" *Demography* 37(4): 401-414.

Bitler, Marianne P., Jonah B. Gelbach, and Hilary W. Hoynes. 2005. "Welfare Reform and Health." *The Journal of Human Resources* 40 (2): 309-330.

Bitler, Marianne P., Jonah B. Gelbach, and Hilary W. Hoynes. 2006. "Welfare Reform and Children's Living Arrangements." *The Journal of Human Resources* 41 (1): 1-27.

Brooks-Gunn, Jeanne, Wen-Jui Han, and Jane Waldfogel. 2002. "Maternal Employment and Child Cognitive Outcomes in the First Three Years of Life: The NICHD Study of Early Child Care." *Child Development* 73 (4): 1052-1072.

Case, Anne, Angela Fertig, and Christina Paxson. 2005. "The Lasting Impact of Childhood Health and Circumstance." *Journal of Health Economics* 24: 365-389.

Case, Anne, Darren Lubotsky, and Christina Paxson. 2002. "Economic Status and Health in Childhood: The Origins of the Gradient." *The American Economic Review* 92 (5): 1308-1334.

Currie, Janet, and Jeffrey Grogger. 2002. "Medicaid Expansions and Welfare Contractions: Offsetting Effects on Prenatal Care and Infant Health?" *Journal of Health Economics* 21: 313-335.

Currie, Janet, and Jonathan Gruber. 1996. "Health Insurance Eligibility, Utilization on Medical Care, and Child Health." *The Quarterly Journal of Economics* 111 (2): 431-466.

Currie, Janet, Mark Stabile, Phongsack Manivong, and Leslie L. Ross, 2010. "Child Health and Young Adult Outcomes." *The Journal of Human Resources* 45 (3): 517-548.

Currie, Janet, and Nancy Cole. 1993. "Welfare and Child Health: The Link between AFDC Participation and Birth Weight." *The American Economic Review* 83 (4): 971-985.

Currie, Janet, and Wanchuan Lin. 2007. “Chipping Away at Health: More on the Relationship between Income and Child Health.” *Health Affairs* 26 (2): 331-344.

Donald, Stephen G., and Kevin Lang. 2007. “Inference with Difference-In-Differences and Other Panel Data.” *The Review of Economics and Statistics* 89 (2): 221-233.

Dunifon, Rachel, Kathryn Hynes and H. Elizabeth Peters. 2006. “Welfare reform and child well-being.” *Children and Youth Services Review* 28 (11): 1273-1292.

Evans, William N., and Craig L. Garthwaite. 2010. “Giving Mom a Break: The Impact of Higher EITC Payments on Maternal Health.” National Bureau of Economic Research (NBER) Working Paper No. 16296.

Gennetian, Lisa A., Heather D. Hill, Andrew S. London, and Leonard M. Lopoo. 2010. “Mothers Employment and the Health of Low Income Children.” *Journal of Health Economics* 29 (3): 353□36.

Gertler, Paul. 2004. “Do Conditional Cash Transfers Improve Child Health? Evidence from PROGRESA’s Control Randomized Experiment.” *The American Economic Review* 94 (2): 336-341.

Gordon, Rachel A., Robert Kaestner, and Sanders Korenman. 2007. “The Effects of Maternal Employment on Child Injuries and Infectious Disease.” *Demography* 44 (2): 307-333.

Grogger, Jeffrey. 2003. “The Effects of Time Limits, The EITC, and Other Policy Changes on Welfare Use, Work, and Income Among Female-Headed Families.” *The Review of Economics and Statistics* 85 (2): 394-408.

Grogger, Jeffrey. 2004. “Time Limits and Welfare Use.” *The Journal of Human Resources* 39 (2): 405-424.

Karaca-Mandic, Pinar, Edward C. Norton, and Bryan Dowd. 2011. “Interaction Terms in Nonlinear Models.” Health Services Research. Health Research and Educational Trust.

Leonard, Jonathan, and Alexandre Mas. 2008. “Welfare Reform, Times Limits, and Infant Health.” *Journal of Health Economics* 27 (6): 1551-66.

London, Andrew S., Ellen K. Scott, Kathryn Edin, and Vicki Hunter. 2004. “Welfare Reform, Work-Family Tradeoffs, and Children Well-Being.” *Family Relations* 53 (2): 148-158.

Moffitt, Robert. 1992. “Incentive Effects of the U.S. Welfare System: A Review.” *Journal of Economic Literature* 30 (1): 1-61.

Moffitt, Robert. 2002. "From Welfare to Work: What the Evidence Shows." Policy Brief No. 13. Washington, DC: Brookings Institution.

Moffitt, Robert. 2003. “The Role of Nonfinancial Factors in Exit and Entry in the TANF program.” *The Journal of Human Resources* 38 (supplement): 1221-1554.

Paxson, Christina, and Jane Waldfogel. 2002. “Work, Welfare, and Child Maltreatment.” *Journal of Labor Economics* 20 (3): 435-474.

Paxson, Christina, and Jane Waldfogel. 2003. “Welfare Reforms, Family Resources, and Child Maltreatment.” *Journal of Policy Analysis and Management* 22 (1): 85-113.

Robins, Philip K., and Paul Fronstin. 1996. “Welfare Benefits and Birth Decisions of Never-Married Women.” *Population Research and Policy Review* 15 (1): 21-43.

Ruhm, Christopher J. 2000. “Are Recessions Good For Your Health?” *The Quarterly Journal of Economics* 115 (2): 617-650.

Stuber, Jennifer, and Karl Kronebusch. 2004. “Stigma and Other Determinants of Participation in TANF and Medicaid.” *Journal of Policy Analysis and Management* 23 (3): 509-530.

Swann, Christopher A. 2005. “Welfare Reform When Recipients Are Forward-Looking.” *The Journal of Human Resources* 40 (1): 31-56.

U.S. Department of Health and Human Services, Administration for Children and Families, Office of Planning, Research and Evaluation. 1998. “Temporary Assistance for Needy Families (TANF) Program: First Annual Report to Congress.” Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Health and Human Services, Administration for Children and Families, Office of Planning, Research and Evaluation. 2009. “Temporary Assistance for Needy Families (TANF) Program: Eighth Annual Report to Congress.” Washington, D.C.: U.S. Government Printing Office.

U.S. Department of Health and Human Services, Health Care Financing Administration. 2009. “Medicare and Medicaid Statistical Supplement.” Baltimore, MD.

Waldfogel, Jane. 2004. “Welfare Reform and the Child Welfare System.” *Children and Youth Services Review* 26: 919-939.

Ziliak, James P., David N. Figlio, Elizabeth E. Davis, and Laura S. Connolly. 2000. “Accounting for the Decline in AFDC Caseloads: Welfare Reform or the Economy?” *The Journal of Human Resources* 35 (3): 570-586.

Table I-1. Number of states implementing policies by year

Table 1a. Number of states implementing waivers and TANF by year

	1994	1995	1996	1997	1998	1999
Waivers	11	19	24	12	0	0
TANF	0	0	16	51	51	51

Table 1b. Number of states implementing specific policies by year

	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005
Time limits	1	5	28	48	49	47	47	47	47	47	47	47
Work requirements	3	8	29	51	51	51	51	51	51	51	51	51
Family caps	3	9	17	21	21	21	22	22	22	23	22	22
Initial sanctions	0	0	6	11	13	12	12	12	13	13	17	18

Table I-2. Descriptive Statistics

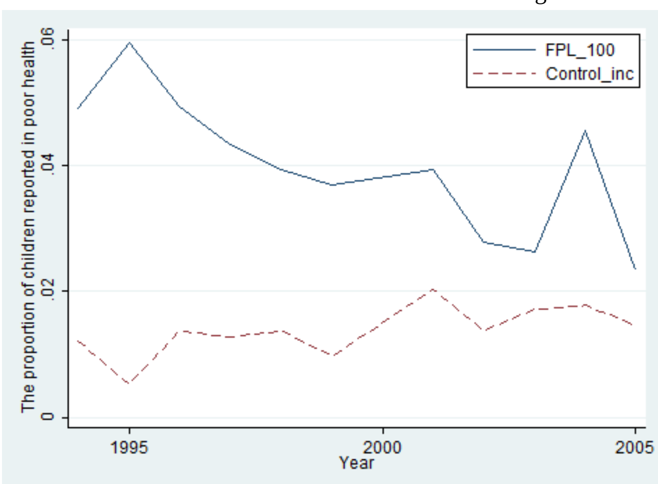
		Treatment groups			Control groups	
	All Groups	Under 100% FPL	Under 200% FPL	Unmarried parents (at most HS degree)	Married parents (above 200% FPL)	Married parents (above HS degree)
Dependent variables:						
Poor health status	0.023	0.043	0.036	0.043	0.015	0.013
	(0.150)	(0.202)	(0.187)	(0.204)	(0.121)	(0.115)
Number of days in bed	1.856	1.790	1.872	1.822	1.714	1.816
	(8.278)	(6.427)	(7.548)	(6.173)	(8.066)	(8.521)
Number of doctor consultations	2.875	2.562	2.638	2.672	2.942	3.116
	(6.720)	(6.128)	(6.628)	(6.629)	(6.652)	(7.103)
Nights of hospital stays	0.215	0.306	0.306	0.308	0.176	0.188
	(2.753)	(3.358)	(3.631)	(3.584)	(2.182)	(2.306)
Independent variables:						
Child's age	8.450	7.598	7.861	8.052	8.556	8.305
	(0.165)	(4.966)	(5.001)	(5.200)	(5.135)	(5.119)
Number of siblings	1.443	1.976	1.813	1.619	1.345	1.351
	(1.24)	(1.516)	(1.415)	(1.428)	(1.124)	(1.079)
Male	0.509	0.507	0.508	0.504	0.508	0.508
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
White	0.785	0.653	0.708	0.590	0.862	0.859
	(0.411)	(0.476)	(0.455)	(0.492)	(0.345)	(0.348)
Black	0.154	0.288	0.238	0.355	0.076	0.078
	(0.361)	(0.453)	(0.426)	(0.478)	(0.266)	(0.268)
Living in a metro area	0.796	0.787	0.782	0.787	0.800	0.814
	(0.403)	(0.409)	(0.413)	(0.409)	(0.400)	(0.389)
Mother's age	35.847	32.785	33.483	32.557	37.093	37.299
	(7.392)	(7.354)	(7.320)	(8.079)	(6.827)	(6.666)
Max benefits (in thousands)	0.408					
	(0.165)					
Unemployment	5.284					
	(1.113)					
Medicaid coverage	24.883					
	(7.120)					

The first number is the mean and the second number in parentheses is the standard deviation.

Figure I-1. The Proportion of Children Reported in Poor Health

a. Low-educated unmarried parents vs. Higher-educated married parents

b. Parents with income lower than 100% of the FPL vs. Higher-income married parents



c. Parents with income lower than 200% of the FPL vs. Higher-income married parents

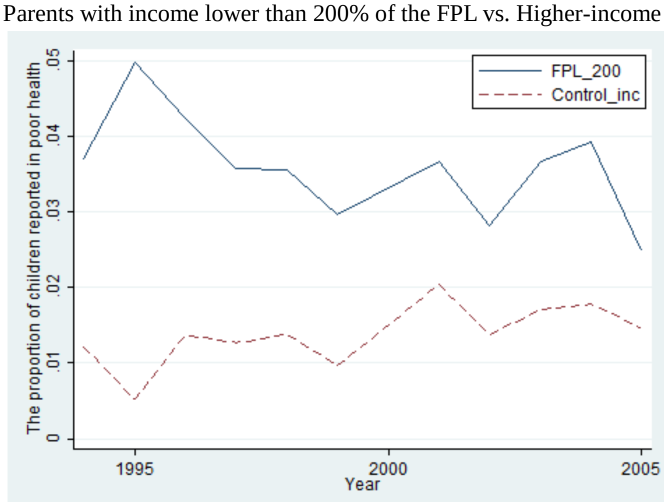


Table I-3. Logistic Estimates of the Effect of Welfare Reform Policies on the Child's Health Status

Welfare Reform Policies	**Time Limits**			**Work Requirements**			**Family Caps**			**Initial Sanctions**		
Treatment Group	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL
Treatment	1.205***	1.004***	0.898***	1.368***	1.134***	0.962***	1.007***	0.792***	0.772***	1.138***	0.906***	0.778***
	(0.148)	(0.142)	(0.107)	(0.116)	(0.133)	(0.103)	(0.175)	(0.141)	(0.112)	(0.096)	(0.070)	(0.062)
Policy	0.093	0.248	0.205	-0.077	-0.150	-0.040	-0.037	0.095	0.050	-0.045	0.119	0.048
	(0.157)	(0.152)	(0.134)	(0.151)	(0.154)	(0.130)	(0.182)	(0.161)	(0.134)	(0.145)	(0.146)	(0.137)
Treatment*policy	-0.099	-0.232*	-0.213**	-0.287***	-0.411***	-0.296***	0.083	-0.035	-0.085	-0.052	-0.103	-0.114
	(0.140)	(0.122)	(0.101)	(0.108)	(0.123)	(0.099)	(0.167)	(0.104)	(0.101)	(0.145)	(0.131)	(0.149)
Max benefit[a]	-2.071**	-0.151	-0.592	-2.392***	-0.824	-1.035	-2.834**	-1.003	-1.164	-4.754**	-5.847***	-5.774**
	(0.811)	(1.063)	(1.048)	(0.824)	(0.864)	(0.868)	(1.284)	(1.038)	(1.151)	(2.290)	(2.182)	(2.461)
Child's age	-0.000	0.002	-0.002	0.000	0.003	-0.001	-0.008	-0.010	-0.011	-0.004	0.007	-0.000
	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)	(0.009)	(0.007)	(0.008)
Number of siblings	0.005	0.003	-0.009	-0.001	-0.002	-0.011	0.024	0.034	0.019	-0.025	-0.084**	-0.062**
	(0.022)	(0.022)	(0.019)	(0.022)	(0.022)	(0.019)	(0.029)	(0.028)	(0.026)	(0.036)	(0.034)	(0.031)
Male	0.232***	0.163***	0.203***	0.236***	0.161***	0.206***	0.183***	0.090*	0.141***	0.178**	0.130**	0.175***
	(0.066)	(0.062)	(0.054)	(0.064)	(0.060)	(0.052)	(0.065)	(0.052)	(0.047)	(0.087)	(0.056)	(0.049)
White	-0.266**	-0.148	-0.176	-0.268**	-0.164	-0.185	-0.317***	-0.076	-0.151	-0.278*	-0.156	-0.191
	(0.114)	(0.126)	(0.123)	(0.110)	(0.124)	(0.121)	(0.116)	(0.145)	(0.156)	(0.167)	(0.208)	(0.199)
Black	0.019	0.094	0.176	0.025	0.081	0.163	-0.075	0.247	0.282	-0.133	-0.040	0.062
	(0.138)	(0.149)	(0.134)	(0.132)	(0.142)	(0.130)	(0.133)	(0.195)	(0.178)	(0.201)	(0.230)	(0.202)
Living in a metro area	-0.118	-0.166*	-0.181**	-0.121	-0.156	-0.168**	0.003	0.006	-0.043	-0.181*	-0.347***	-0.315***
	(0.079)	(0.096)	(0.077)	(0.076)	(0.095)	(0.076)	(0.088)	(0.125)	(0.101)	(0.101)	(0.108)	(0.084)
Mother 's age	0.006*	0.010***	0.012***	0.006**	0.009**	0.012***	0.005	0.016***	0.017***	0.009***	0.013**	0.015***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.006)	(0.006)
Mother being a high school dropout		0.439***	0.413***		0.454***	0.427***		0.456***	0.437***		0.493***	0.425***
		(0.085)	(0.084)		(0.084)	(0.083)		(0.141)	(0.130)		(0.134)	(0.148)
Mother has post high school degree		-0.356***	-0.379***		-0.339***	-0.359***		-0.324***	-0.336***		-0.352***	-0.363***
		(0.075)	(0.067)		(0.075)	(0.068)		(0.111)	(0.098)		(0.114)	(0.100)
Unemployment	-0.113*	-0.046	-0.056	-0.097	-0.060	-0.062	-0.065	-0.088	-0.092	-0.098	-0.152***	-0.130**
	(0.065)	(0.057)	(0.055)	(0.062)	(0.052)	(0.050)	(0.099)	(0.057)	(0.058)	(0.099)	(0.046)	(0.053)

Medicaid coverage	0.002	-0.001	0.006	0.001	-0.002	0.004	0.014	0.017	0.022*	-0.001	-0.000	0.007
	(0.008)	(0.011)	(0.010)	(0.008)	(0.012)	(0.010)	(0.014)	(0.015)	(0.013)	(0.010)	(0.012)	(0.011)
Marginal effect of the policy-treatment interaction at the mean (wrt treatment):												
	-0.0004	-0.001	-0.002	-0.008***	-0.010***	-0.007***	0.001	0.0005	-0.001	-0.002	-0.0003	-0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Marginal effect of the policy-treatment interaction at the mean (wrt policy):												
	-0.001	-0.003	-0.003	-0.013***	-0.015***	-0.009***	0.002	0.0004	-0.002	-0.003	-0.001	-0.003
	(0.005)	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)
Average marginal effect (wrt treatment):												
	-0.001	-0.002	-0.003	-0.012***	-0.013***	-0.009***	0.002	0.0005	-0.001	-0.003	-0.001	-0.003
	(0.005)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)
Average marginal effect (wrt policy):												
	-0.001	-0.003	-0.003	-0.013***	-0.016***	-0.010***	0.002	0.0004	-0.002	-0.003	-0.001	-0.003
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.002)	(0.005)	(0.003)	(0.002)	(0.005)	(0.004)	(0.004)
Observations	120826	126190	147462	125468	130810	152806	62921	65951	76676	48222	50090	58901
P-value of Wald test on joint significance of…												
State dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: All models include state and year dummies. Standard errors are adjusted for clustering at the state level.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

a. Max benefit is measured in thousands.

Table I-4. Negative Binomial Estimates of the Effect of Welfare Reform Policies on the Number of Days the Child spent in Bed due to Illness or Injury

Welfare Reform Policies	Time Limits			Work Requirements			Family Caps			Initial Sanctions		
Treatment Group	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL
Treatment	0.098	0.295**	0.305**	0.065	0.274*	0.201	-0.117	0.320	0.276	-0.199	0.214	0.119
	(0.136)	(0.132)	(0.124)	(0.119)	(0.143)	(0.129)	(0.192)	(0.224)	(0.191)	(0.159)	(0.155)	(0.150)
Policy	0.077	0.035	0.037	0.090	0.063	0.164	-0.091	-0.035	-0.112	-0.254	-0.357***	-0.303**
	(0.181)	(0.160)	(0.164)	(0.206)	(0.205)	(0.216)	(0.214)	(0.157)	(0.171)	(0.155)	(0.137)	(0.149)
Treatment*policy	0.000	0.068	-0.051	0.064	0.090	0.110	0.294	0.159	0.131	0.411	0.369	0.358
	(0.178)	(0.175)	(0.139)	(0.165)	(0.187)	(0.143)	(0.208)	(0.294)	(0.215)	(0.297)	(0.270)	(0.231)
Max benefit[a]	-0.725	-1.483	-1.741**	-0.568	-1.346	-1.490	-0.661	-1.048	-1.603*	-2.185	-2.234	-2.258
	(0.754)	(1.014)	(0.856)	(0.800)	(0.997)	(0.909)	(1.030)	(0.852)	(0.922)	(2.272)	(2.093)	(1.773)
Child's age	0.055	0.027	0.015	0.063*	0.041	0.027	0.021	0.015	-0.001	0.011	0.007	-0.003
	(0.036)	(0.032)	(0.029)	(0.035)	(0.034)	(0.030)	(0.055)	(0.051)	(0.044)	(0.051)	(0.047)	(0.046)
Number of siblings	-0.069***	-0.077***	-0.083***	-0.072***	-0.076***	-0.082***	-0.076**	-0.052**	-0.061**	-0.054**	-0.088**	-0.062**
	(0.022)	(0.021)	(0.019)	(0.021)	(0.020)	(0.018)	(0.031)	(0.024)	(0.025)	(0.023)	(0.034)	(0.030)
Male	-0.289***	-0.312***	-0.325***	-0.301***	-0.324***	-0.339***	-0.169**	-0.208***	-0.188***	-0.301***	-0.366***	-0.387***
	(0.065)	(0.058)	(0.060)	(0.063)	(0.056)	(0.059)	(0.086)	(0.066)	(0.065)	(0.100)	(0.092)	(0.101)
White	0.074	0.134	0.128	0.096	0.148	0.144	-0.030	-0.050	-0.043	0.316	0.118	0.185
	(0.167)	(0.118)	(0.142)	(0.164)	(0.116)	(0.138)	(0.228)	(0.144)	(0.191)	(0.195)	(0.188)	(0.181)
Black	-0.419*	-0.461***	-0.441**	-0.394*	-0.442***	-0.419**	-0.572*	-0.640***	-0.617**	-0.166	-0.476*	-0.426*
	(0.219)	(0.170)	(0.188)	(0.212)	(0.163)	(0.180)	(0.308)	(0.238)	(0.243)	(0.248)	(0.268)	(0.238)
Living in a metro area	0.060	0.051	0.077	0.037	0.038	0.068	0.135	0.091	0.132	0.102	0.052	0.132
	(0.073)	(0.093)	(0.081)	(0.073)	(0.089)	(0.076)	(0.110)	(0.119)	(0.108)	(0.136)	(0.163)	(0.140)
Mother 's age	-0.002	-0.005	-0.006	-0.001	-0.004	-0.005	0.003	0.003	0.003	0.007	0.002	-0.001
	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)	(0.008)	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
Mother being a high school dropout		-0.344**	-0.392***		-0.315**	-0.366***		-0.612***	-0.595***		-0.220**	-0.288***
		(0.152)	(0.122)		(0.154)	(0.122)		(0.148)	(0.130)		(0.099)	(0.089)
Mother has post high school degree		0.014	0.005		0.036	0.025		-0.020	-0.001		0.065	0.054
		(0.080)	(0.080)		(0.079)	(0.078)		(0.107)	(0.109)		(0.102)	(0.093)
Unemployment	0.005	-0.029	-0.048	0.026	-0.024	-0.035	0.020	-0.000	-0.036	0.043	0.031	-0.004
	(0.067)	(0.074)	(0.064)	(0.059)	(0.066)	(0.057)	(0.090)	(0.090)	(0.090)	(0.086)	(0.085)	(0.080)

Medicaid coverage	0.012	0.011	0.013	0.014	0.012	0.014	0.031**	0.027**	0.026*	0.021	0.030**	0.031*
	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.009)	(0.015)	(0.012)	(0.013)	(0.018)	(0.015)	(0.016)
Marginal effect of the policy-treatment interaction at the mean (wrt treatment):												
	0.012	0.128	-0.069	0.121	0.177	0.245	0.494	0.233	0.162	0.669	0.397	0.472
	(0.274)	(0.257)	(0.201)	(0.266)	(0.290)	(0.213)	(0.360)	(0.439)	(0.355)	(0.467)	(0.423)	(0.354)
Marginal effect of the policy-treatment interaction at the mean (wrt policy):												
	0.013	0.166	-0.081	0.135	0.233	0.302	0.518	0.329	0.196	0.667	0.564	0.558
	(0.300)	(0.344)	(0.236)	(0.303)	(0.400)	(0.278)	(0.366)	(0.626)	(0.421)	(0.494)	(0.581)	(0.425)
Average marginal effect (wrt treatment):												
	0.013	0.138	-0.075	0.130	0.192	0.267	0.526	0.254	0.177	0.734	0.445	0.523
	(0.293)	(0.277)	(0.220)	(0.287)	(0.315)	(0.236)	(0.401)	(0.478)	(0.387)	(0.540)	(0.488)	(0.412)
Average marginal effect (wrt policy):												
	0.014	0.180	-0.088	0.147	0.255	0.333	0.553	0.359	0.214	0.731	0.635	0.624
	(0.321)	(0.374)	(0.257)	(0.329)	(0.438)	(0.310)	(0.406)	(0.688)	(0.460)	(0.571)	(0.674)	(0.494)
Observations	16556	17992	20777	17200	18672	21543	8485	9235	10676	6805	7324	8520
P-value of Wald test on joint significance of…												
State dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year dummies	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: All models include state and year dummies. Standard errors are adjusted for clustering at the state level.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

a. Max benefit is measured in thousands.

Table I-5. Negative Binomial Estimates of the Effect of Welfare Reform Policies on the Number of Doctor Consultations

Welfare Reform Policies	**Time Limits**			**Work Requirements**			**Family Caps**			**Initial Sanctions**		
Treatment Group	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL
Treatment	-0.028	0.161***	0.094***	-0.014	0.190***	0.114***	-0.030	0.173**	0.075	-0.050*	0.084*	0.044
	(0.055)	(0.049)	(0.034)	(0.043)	(0.040)	(0.023)	(0.083)	(0.076)	(0.049)	(0.029)	(0.045)	(0.027)
Policy	0.000	-0.002	0.019	-0.052	0.001	0.002	-0.008	0.021	0.038	-0.046	-0.052	-0.041
	(0.043)	(0.035)	(0.035)	(0.037)	(0.037)	(0.029)	(0.045)	(0.032)	(0.040)	(0.037)	(0.036)	(0.034)
Treatment*policy	-0.025	-0.140***	-0.097***	-0.038	-0.181***	-0.127***	-0.070	-0.201***	-0.137***	0.051	-0.139*	-0.069
	(0.047)	(0.041)	(0.028)	(0.042)	(0.043)	(0.035)	(0.062)	(0.057)	(0.039)	(0.051)	(0.073)	(0.056)
Max benefit[a]	-0.126	0.187	0.028	-0.191	0.067	-0.080	-0.243	0.158	-0.019	-0.427	0.137	-0.126
	(0.306)	(0.238)	(0.224)	(0.334)	(0.272)	(0.236)	(0.291)	(0.288)	(0.331)	(0.746)	(0.623)	(0.680)
Child's age	-0.038***	-0.034***	-0.035***	-0.037***	-0.033***	-0.034***	-0.040***	-0.038***	-0.039***	-0.038***	-0.037***	-0.037***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)	(0.006)
Number of siblings	-0.137***	-0.151***	-0.143***	-0.136***	-0.149***	-0.142***	-0.151***	-0.147***	-0.141***	-0.146***	-0.177***	-0.159***
	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)	(0.011)	(0.009)	(0.011)	(0.013)	(0.011)
Male	0.046***	0.035**	0.037***	0.046***	0.035**	0.036***	0.047*	0.031	0.031	0.057**	0.029	0.034*
	(0.015)	(0.014)	(0.012)	(0.014)	(0.014)	(0.012)	(0.025)	(0.020)	(0.019)	(0.023)	(0.022)	(0.021)
White	0.249***	0.208***	0.170***	0.256***	0.210***	0.174***	0.253***	0.182***	0.153***	0.265***	0.249***	0.219***
	(0.037)	(0.045)	(0.043)	(0.037)	(0.044)	(0.043)	(0.046)	(0.055)	(0.054)	(0.075)	(0.059)	(0.059)
Black	-0.040	-0.098**	-0.113**	-0.037	-0.099***	-0.112**	-0.053	-0.113*	-0.118*	-0.078	-0.098	-0.126*
	(0.052)	(0.039)	(0.046)	(0.050)	(0.038)	(0.044)	(0.070)	(0.063)	(0.071)	(0.079)	(0.079)	(0.073)
Living in a metro area	0.014	0.042	0.025	0.013	0.041	0.027	0.028	0.068**	0.052	0.019	0.042	0.037
	(0.026)	(0.033)	(0.029)	(0.025)	(0.031)	(0.028)	(0.036)	(0.035)	(0.037)	(0.034)	(0.047)	(0.039)
Mother's age	0.000	-0.002	-0.002	-0.000	-0.002	-0.002	0.000	0.000	-0.000	0.002	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Mother being a high school dropout		-0.140***	-0.143***		-0.138***	-0.139***		-0.148***	-0.154***		-0.091	-0.128**
		(0.039)	(0.037)		(0.037)	(0.037)		(0.056)	(0.052)		(0.062)	(0.062)
Mother has post high school degree		0.202***	0.196***		0.200***	0.194***		0.247***	0.233***		0.199***	0.189***
		(0.026)	(0.025)		(0.025)	(0.024)		(0.027)	(0.032)		(0.034)	(0.032)
Unemployment	0.009	0.023*	0.021	0.014	0.022*	0.020	0.036**	0.048***	0.045***	0.007	0.007	0.011
	(0.014)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.015)	(0.014)	(0.016)	(0.026)	(0.027)	(0.027)

Medicaid coverage	-0.001	-0.002	-0.001	-0.001	-0.003	-0.002	0.000	-0.003	0.001	0.003	-0.001	0.000
	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
Marginal effect of the policy-treatment interaction at the mean (wrt treatment):												
	-0.071	-0.386***	-0.261***	-0.104	-0.500***	-0.348***	-0.190	-0.524***	-0.350***	0.146	-0.373*	-0.183
	(0.137)	(0.112)	(0.075)	(0.126)	(0.121)	(0.093)	(0.172)	(0.149)	(0.098)	(0.142)	(0.193)	(0.146)
Marginal effect of the policy-treatment interaction at the mean (wrt policy):												
	-0.069	-0.397***	-0.263***	-0.098	-0.508***	-0.344***	-0.179	-0.529***	-0.346***	0.144	-0.376*	-0.184
	(0.134)	(0.116)	(0.075)	(0.119)	(0.117)	(0.089)	(0.163)	(0.154)	(0.098)	(0.140)	(0.195)	(0.147)
Average marginal effect (wrt treatment):												
	-0.074	-0.409***	-0.277***	-0.109	-0.530***	-0.369***	-0.200	-0.559***	-0.374***	0.153	-0.398*	-0.195
	(0.143)	(0.120)	(0.081)	(0.132)	(0.130)	(0.101)	(0.182)	(0.163)	(0.107)	(0.149)	(0.207)	(0.156)
Average marginal effect (wrt policy):												
	-0.072	-0.423***	-0.279***	-0.102	-0.540***	-0.366***	-0.189	-0.568***	-0.370***	0.151	-0.404*	-0.197
	(0.140)	(0.125)	(0.081)	(0.125)	(0.127)	(0.096)	(0.172)	(0.169)	(0.107)	(0.147)	(0.210)	(0.157)
Observations	112721	118530	139348	116972	122833	144354	58048	61199	71587	45011	47085	55703
P-value of Wald test on joint significance of…												
State dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year dummies	0.095	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: All models include state and year dummies. Standard errors are adjusted for clustering at the state level.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

a. Max benefit is measured in thousands.

Table I-6. Negative Binomial Estimates of the Effect of Welfare Reform Policies on the Number of Hospital Stays

Welfare Reform Policies	Time Limits			Work Requirements			Family Caps			Initial Sanctions		
Treatment Group	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL
Treatment	0.919***	0.942***	0.751***	0.751***	0.699***	0.626***	0.783***	0.686**	0.729**	0.319*	0.400**	0.393*
	(0.148)	(0.268)	(0.177)	(0.192)	(0.209)	(0.162)	(0.270)	(0.318)	(0.286)	(0.166)	(0.190)	(0.205)
Policy	0.216	0.296	0.230	0.046	0.030	-0.057	-0.197	0.236*	0.111	-0.204	-0.122	-0.163
	(0.174)	(0.183)	(0.159)	(0.175)	(0.179)	(0.136)	(0.242)	(0.143)	(0.148)	(0.161)	(0.187)	(0.180)
Treatment*policy	-0.476***	-0.599**	-0.424**	-0.243	-0.250	-0.277	-0.153	-0.236	-0.395	0.112	0.106	-0.145
	(0.178)	(0.273)	(0.186)	(0.230)	(0.275)	(0.207)	(0.343)	(0.351)	(0.296)	(0.190)	(0.284)	(0.244)
Max benefit[a]	-1.436	-0.106	-0.691	-1.610	-0.234	-1.019	-1.421	0.775	-0.080	2.152	5.945*	2.391
	(1.754)	(1.679)	(1.384)	(1.733)	(1.658)	(1.403)	(1.794)	(2.026)	(1.781)	(3.726)	(3.489)	(3.448)
Child's age	-0.086***	-0.085***	-0.092***	-0.086***	-0.084***	-0.091***	-0.104***	-0.104***	-0.114***	-0.065***	-0.070***	-0.067***
	(0.013)	(0.011)	(0.012)	(0.013)	(0.011)	(0.012)	(0.020)	(0.016)	(0.016)	(0.017)	(0.014)	(0.013)
Number of siblings	-0.192***	-0.243***	-0.222***	-0.193***	-0.226***	-0.210***	-0.154***	-0.232***	-0.209***	-0.230***	-0.278***	-0.238***
	(0.033)	(0.041)	(0.031)	(0.032)	(0.038)	(0.030)	(0.042)	(0.055)	(0.042)	(0.033)	(0.058)	(0.045)
Male	0.231**	0.174*	0.139	0.241**	0.187*	0.150	0.178	0.138	0.060	-0.017	-0.103	-0.147
	(0.111)	(0.099)	(0.098)	(0.105)	(0.095)	(0.096)	(0.132)	(0.134)	(0.140)	(0.118)	(0.091)	(0.111)
White	0.212*	0.186	0.153	0.248*	0.208	0.173	0.007	0.121	0.126	0.414	0.634***	0.628***
	(0.128)	(0.176)	(0.173)	(0.128)	(0.176)	(0.173)	(0.184)	(0.169)	(0.199)	(0.267)	(0.210)	(0.202)
Black	0.155	0.088	0.182	0.223	0.191	0.258	-0.141	0.151	0.182	0.323	0.572*	0.615**
	(0.166)	(0.215)	(0.206)	(0.164)	(0.220)	(0.212)	(0.246)	(0.276)	(0.286)	(0.313)	(0.299)	(0.310)
Living in a metro area	0.001	0.097	0.042	0.000	0.092	0.036	0.181	0.222	0.225*	0.017	0.003	0.103
	(0.097)	(0.090)	(0.078)	(0.095)	(0.093)	(0.080)	(0.158)	(0.171)	(0.132)	(0.182)	(0.153)	(0.125)
Mother 's age	-0.014	-0.011	-0.006	-0.012	-0.010	-0.006	-0.010	-0.006	-0.001	-0.030**	-0.021**	-0.025***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.014)	(0.011)	(0.011)	(0.012)	(0.009)	(0.009)
Mother being a high school dropout		0.063	0.091		0.064	0.095		0.272**	0.187*		0.216	0.221
		(0.099)	(0.087)		(0.094)	(0.085)		(0.132)	(0.110)		(0.159)	(0.144)
Mother has post high school degree		-0.074	-0.023		-0.081	-0.032		0.113	0.098		0.055	0.078
		(0.119)	(0.105)		(0.117)	(0.104)		(0.160)	(0.135)		(0.111)	(0.088)
Unemployment	0.047	0.074	0.032	0.028	0.048	0.018	0.129	0.198*	0.081	-0.049	-0.014	-0.038
	(0.098)	(0.092)	(0.071)	(0.093)	(0.091)	(0.072)	(0.109)	(0.115)	(0.089)	(0.080)	(0.128)	(0.084)

Medicaid coverage	-0.016	-0.019*	-0.018	-0.018	-0.021*	-0.020*	-0.010	-0.025**	-0.025*	-0.011	-0.031*	-0.021
	(0.011)	(0.012)	(0.011)	(0.012)	(0.012)	(0.012)	(0.021)	(0.012)	(0.014)	(0.019)	(0.018)	(0.019)
Marginal effect of the policy-treatment interaction at the mean (wrt treatment):												
	-0.062**	-0.063	-0.053*	-0.040	-0.037	-0.054*	-0.053	-0.016	-0.054	0.008	0.009	-0.035
	(0.028)	(0.042)	(0.032)	(0.035)	(0.037)	(0.033)	(0.061)	(0.047)	(0.049)	(0.038)	(0.048)	(0.045)
Marginal effect of the policy-treatment interaction at the mean (wrt policy):												
	-0.091**	-0.102	-0.070*	-0.054	-0.052	-0.060*	-0.064	-0.028	-0.067	0.011	0.014	-0.039
	(0.036)	(0.062)	(0.039)	(0.047)	(0.050)	(0.036)	(0.077)	(0.071)	(0.058)	(0.045)	(0.065)	(0.052)
Average marginal effect (wrt treatment):												
	-0.094**	-0.094	-0.077	-0.057	-0.051	-0.074	-0.077	-0.024	-0.082	0.011	0.013	-0.046
	(0.047)	(0.067)	(0.049)	(0.053)	(0.053)	(0.047)	(0.099)	(0.071)	(0.079)	(0.052)	(0.068)	(0.061)
Average marginal effect (wrt policy):												
	-0.117**	-0.131	-0.088*	-0.068	-0.065	-0.076	-0.085	-0.038	-0.092	0.014	0.018	-0.051
	(0.052)	(0.085)	(0.052)	(0.060)	(0.065)	(0.047)	(0.106)	(0.097)	(0.083)	(0.058)	(0.085)	(0.071)
Observations	112721	118530	139348	116972	122833	144354	58048	61199	71587	45011	47085	55703
P-value of Wald test on joint significance of…												
State dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year dummies	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00

Note: All models include state and year dummies. Standard errors are adjusted for clustering at the state level.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

a. Max benefit is measured in thousands.

Table I-7. Nonlinear Estimates of the Effect of Welfare Reform on Health

Health measures	Child's Health Status			Days in Bed			Doctor Consultations			Hospital Stays		
Treatment Group	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL	at most HS	100% FPL	200% FPL
Treatment	1.337***	1.170***	1.042***	-0.042	0.304*	0.248*	-0.013	0.175***	0.106***	0.750***	0.686***	0.691***
	(0.158)	(0.146)	(0.114)	(0.163)	(0.165)	(0.137)	(0.043)	(0.039)	(0.029)	(0.206)	(0.177)	(0.130)
Waivers	-0.165	0.011	-0.028	-0.344	0.025	-0.031	0.053	0.064	0.052	-0.240	-0.232	-0.185
	(0.270)	(0.245)	(0.221)	(0.338)	(0.214)	(0.193)	(0.057)	(0.048)	(0.048)	(0.320)	(0.266)	(0.239)
Treatment*Waivers	-0.070	-0.202	-0.171	0.200	0.043	0.089	-0.041	-0.008	-0.009	0.240	0.131	-0.093
	(0.133)	(0.144)	(0.113)	(0.171)	(0.191)	(0.134)	(0.043)	(0.065)	(0.051)	(0.166)	(0.238)	(0.168)
TANF	0.244	0.204	0.137	0.094	-0.027	-0.068	-0.005	0.052	0.048	0.452*	0.613***	0.357**
	(0.160)	(0.200)	(0.152)	(0.169)	(0.228)	(0.177)	(0.053)	(0.047)	(0.034)	(0.248)	(0.184)	(0.162)
Treatment*TANF	-0.217	-0.358***	-0.319***	0.067	0.019	-0.029	-0.015	-0.171***	-0.121***	-0.415**	-0.353	-0.335**
	(0.145)	(0.127)	(0.114)	(0.183)	(0.176)	(0.139)	(0.040)	(0.042)	(0.031)	(0.194)	(0.224)	(0.149)
Max benefit[a]	-2.187**	-0.395	-0.787	-0.894	-1.410	-1.629*	-0.101	0.163	0.010	-1.818	-0.384	-0.996
	(0.855)	(1.102)	(1.102)	(0.842)	(1.063)	(0.918)	(0.311)	(0.263)	(0.245)	(1.846)	(1.790)	(1.485)
Child’s age	0.000	0.003	-0.001	0.065*	0.041	0.028	-0.037***	-0.033***	-0.034***	-0.085***	-0.084***	-0.090***
	(0.006)	(0.006)	(0.006)	(0.035)	(0.034)	(0.030)	(0.003)	(0.003)	(0.003)	(0.013)	(0.011)	(0.012)
Number of siblings	-0.001	-0.003	-0.012	-0.072***	-0.076***	-0.081***	-0.136***	-0.149***	-0.142***	-0.194***	-0.229***	-0.212***
	(0.022)	(0.022)	(0.019)	(0.020)	(0.020)	(0.018)	(0.009)	(0.011)	(0.009)	(0.031)	(0.038)	(0.030)
Male	0.237***	0.162***	0.207***	-0.301***	-0.325***	-0.339***	0.046***	0.035**	0.037***	0.235**	0.182*	0.152
	(0.064)	(0.060)	(0.052)	(0.062)	(0.056)	(0.060)	(0.014)	(0.014)	(0.012)	(0.103)	(0.094)	(0.094)
White	-0.270**	-0.164	-0.185	0.107	0.149	0.143	0.256***	0.211***	0.173***	0.248*	0.225	0.177
	(0.110)	(0.123)	(0.120)	(0.153)	(0.114)	(0.138)	(0.037)	(0.045)	(0.043)	(0.127)	(0.172)	(0.173)
Black	0.025	0.088	0.167	-0.373*	-0.446***	-0.419**	-0.038	-0.095**	-0.110**	0.230	0.200	0.257
	(0.131)	(0.142)	(0.130)	(0.199)	(0.165)	(0.184)	(0.050)	(0.038)	(0.044)	(0.161)	(0.213)	(0.209)
Living in a metro area	-0.123	-0.156*	-0.169**	0.035	0.038	0.066	0.013	0.040	0.026	-0.001	0.086	0.035
	(0.077)	(0.094)	(0.076)	(0.074)	(0.089)	(0.076)	(0.025)	(0.031)	(0.028)	(0.097)	(0.092)	(0.081)
Mother ‘s age	0.006**	0.008**	0.011***	-0.001	-0.004	-0.005	-0.000	-0.002	-0.002	-0.013	-0.010	-0.006
	(0.003)	(0.004)	(0.003)	(0.005)	(0.006)	(0.005)	(0.002)	(0.002)	(0.002)	(0.008)	(0.007)	(0.007)
Mother being a high school dropout		0.452***	0.424***		-0.315**	-0.368***		-0.139***	-0.139***		0.076	0.091
		(0.084)	(0.083)		(0.155)	(0.124)		(0.038)	(0.037)		(0.090)	(0.084)

Mother has post high school degree		-0.341***	-0.360***		0.037	0.026		0.200***	0.194***		-0.076	-0.034
		(0.074)	(0.067)		(0.079)	(0.078)		(0.025)	(0.024)		(0.116)	(0.104)
Unemployment	-0.089	-0.058	-0.065	0.026	-0.026	-0.039	0.015	0.022*	0.020	0.032	0.055	0.022
	(0.063)	(0.054)	(0.051)	(0.059)	(0.065)	(0.057)	(0.014)	(0.012)	(0.012)	(0.088)	(0.086)	(0.070)
Medicaid coverage	0.002	0.000	0.007	0.014	0.012	0.014	-0.001	-0.002	-0.001	-0.018	-0.023**	-0.020*
	(0.008)	(0.011)	(0.010)	(0.011)	(0.010)	(0.010)	(0.004)	(0.003)	(0.002)	(0.012)	(0.012)	(0.011)
Marginal effect of the policy-treatment interaction at the mean (wrt treatment):												
waiver	-0.005	-0.003	-0.004	0.285	0.085	0.139	-0.122	-0.014	-0.022	0.022	0.004	-0.027
	(0.005)	(0.003)	(0.002)	(0.293)	(0.363)	(0.254)	(0.125)	(0.177)	(0.139)	(0.039)	(0.034)	(0.026)
TANF	0.00004	-0.004	-0.005**	0.126	0.018	-0.082	-0.041	-0.454***	-0.320***	-0.027	-0.005	-0.030
	(0.003)	(0.003)	(0.002)	(0.294)	(0.301)	(0.237)	(0.117)	(0.110)	(0.083)	(0.031)	(0.031)	(0.022)
Marginal effect of the policy-treatment interaction at the mean (wrt policy):												
waiver	-0.007	-0.006	-0.005*	0.301	0.107	0.161	-0.119	-0.015	-0.023	0.033	0.009	-0.031
	(0.007)	(0.004)	(0.003)	(0.311)	(0.460)	(0.288)	(0.121)	(0.181)	(0.140)	(0.048)	(0.048)	(0.030)
TANF	-0.002	-0.007*	-0.007***	0.140	0.247	-0.089	-0.040	-0.472***	-0.324***	-0.053	-0.025	-0.043
	(0.004)	(0.004)	(0.003)	(0.332)	(0.381)	(0.262)	(0.114)	(0.116)	(0.083)	(0.043)	(0.049)	(0.027)
Average marginal effect (wrt treatment):												
waiver	-0.006	-0.005	-0.005	0.307	0.092	0.152	-0.127	-0.015	-0.024	0.033	0.007	-0.037
	(0.006)	(0.004)	(0.003)	(0.327)	(0.393)	(0.279)	(0.130)	(0.190)	(0.150)	(0.053)	(0.049)	(0.037)
TANF	-0.001	-0.005	-0.007**	0.135	0.019	-0.089	-0.042	-0.480***	-0.339***	-0.045	-0.013	-0.044
	(0.004)	(0.004)	(0.003)	(0.314)	(0.326)	(0.261)	(0.121)	(0.119)	(0.090)	(0.047)	(0.046)	(0.033)
Average marginal effect (wrt policy):												
waiver	-0.007	-0.006	-0.006*	0.313	0.117	0.176	-0.124	-0.015	-0.024	0.042	0.011	-0.039
	(0.008)	(0.004)	(0.003)	(0.341)	(0.502)	(0.317)	(0.127)	(0.193)	(0.148)	(0.061)	(0.061)	(0.040)
TANF	-0.002	-0.008*	-0.008**	0.153	0.027	-0.098	-0.041	-0.502***	-0.344***	-0.067	-0.032	-0.054
	(0.004)	(0.005)	(0.003)	(0.360)	(0.415)	(0.288)	(0.118)	(0.126)	(0.090)	(0.056)	(0.062)	(0.036)
Observations	125468	130810	152806	17200	18672	21543	116972	122833	144354	116972	122833	144354
P-value of Wald test on joint significance of…												
State dummies	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Year dummies	0.00	0.00	0.00	0.00	0.05	0.00	0.27	0.00	0.00	0.00	0.00	0.00

Note: All models include state and year dummies. Standard errors are adjusted for clustering at the state level.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

a. Max benefit is measured in thousands.

Essay II : Hospital Treatment Rates and Spillover Effects: Does Ownership Matter?

1. Introduction

The quality and cost effectiveness of the health care system in the U.S. are two of the major concerns of the Affordable Care Act (ACA). According to World Health Organization (WHO), the total health expenditure of the U.S. accounted for 17.9% of the national GDP in 2010, which was the highest in the world. Despite spending this high expenditure on health, the health outcomes were not significantly better than those of other countries. In this paper we focus on ownership of the hospitals and their treatment rates. We distinguish between three types of hospital ownership: For-profit, not-for-profit, and government owned hospitals. There is an extensive literature focusing on hospital ownership, see for example Sloan (2000), McClellan and Staiger (2000), Sloan et al. (2001), Kessler and McClellan (2002), Horwitz and Nichols (2009), Bayindir (2012), to mention a few. A brief review of the different ownership theories and the empirical evidence is given in section 2. The empirical studies have mixed results. Both not-for-profit and government hospitals enjoy tax exemptions and financial advantages. They may have the luxury of using their profits to finance less profitable services. Sloan (2000) finds that not-for-profit hospitals provide better overall quality to the community. Bayindir (2012) suggests that not-for-profit hospitals are more likely to treat uninsured patients and patients with public health insurance than for-profits hospitals. Some studies indicate that for-profits are profit-seeking and have more financial incentives to provide better treatment and attract patients, while other studies suggest that there is no difference in quality between not-for-profits and for-profits hospitals. On the demand side, Jung, Feldman, and Scanlon (2011) find that hospitals with better reputation and higher quality of health care tend to increase patients' willingness to revisit. Moscone, Tosetti, and Vittadini (2012) suggest that information from neighbors along with patients' previous experience and hospital characteristics play important roles in their choice of hospitals in Italy. Porell and Adams (1995) survey the literature and report that patients are more likely to choose hospitals with better health outcomes. The health care market is based on the interactions between hospitals and patients. We explore how this market generates externalities among hospitals. In particular, we study how the treatment rates of one hospital may be affected by the treatment rates and competition from other neighboring hospitals.

The competition level of the market may be affected by the distance between hospitals, the hospital's reputation and the quality of hospitals[1]. Tay (2003) suggests that patients have a tradeoff between the quality of the hospital and the distance to other hospitals[2]. Hospitals improve their quality to attract patients from other neighborhoods[3]. Horwitz and Nichols (2009) find that not-for-profit hospitals are more likely to provide relatively profitable services in a market with a higher proportion of for-profit admissions. Government hospitals are the least likely to offer profitable services and the most likely to offer unprofitable services.

Knowledge spillovers may also contribute to externalities of health care**.** "A large medical literature has documented the important role of social networks in physician adoption of new technologies, suggesting that knowledge externalities are the source of the productivity spillovers." See Chandra and Staiger (2007, p.133). Physicians may learn from each other and possibly transfer to another hospital, especially when a new technology or equipment is introduced. Hence, it is important to take into account the possible spillovers from one hospital to its neighboring hospitals.

---

[1] We do not argue that price of medical services is negligible, but most patients have insurance (Tay, 2003). Insurance companies cover a major part of medical expense. Moreover, patients who are aged 65 and above are most likely covered by Medicare. The out-of-pocket payments from patients are relatively low (Sloan, 2000). Porell and Adams (1995) indicate that studies do not find significant price effects when they use gross charges as the price measure.

[2] While almost half of acute myocardial infarction (AMI, or heart attack) patients are admitted to the closest hospital from home, more than 50% of the patients are willing to travel four to five miles further on average for better quality health care.

[3] However, using mortality rates, other empirical studies show mixed results of the effects of the competition on quality (see Gaynor, 2006).

These spillovers create a spatial correlation of quality, which is presented in Figure II-1. The maps present the geographic distribution of the summary Hospital Compare quality scores by hospital referral region[4] (HRR) in the United States in 2005 (The Dartmouth Atlas of Health Care). The scores indicate the average percentages of heart attack, heart failure, and pneumonia clinical processes that are given to patients in the HRR. Figure 1a shows the spatial patterns of the overall score. The treatment rates are above 90% in many HRRs in the middle and north eastern United States. One may argue that these HRRs are wealthier urban areas. Therefore, their overall medical quality is higher than the national average. The geographic clusters suggest heterogeneity of health care across the country. However, we also find geographic clusters of high treatment rates in some less wealthy HRRs, such as those in North Carolina. This confirms the results by Skinner (2012) that demographic variables cannot fully explain the geographic variations in health care. The clusters may also indicate that the medical quality of one HRR is correlated with that of its neighboring HRRs. Focusing on the treatment rates by illness condition, we find the geographic patterns of heart attack and heart failure treatments in Figures 1b and 1c to be similar to that of the overall treatments. The geographic pattern of pneumonia treatments in Figure 1d is slightly different from heart disease treatments, but a spatial correlation persists.

When examining the interaction among hospitals, most studies utilize the Herfindahl-Hirschman Index (HHI) or similar market share variables as measures of competition level or market structure. While these indices are good measures of the aggregate competition level of the market, they do not take distances between hospitals into consideration. A market with three

[4] Dartmouth Atlas defines the hospital referral regions by the regional market of health care. Patients are able to transfer or be referred to another hospital for major cardiovascular surgical procedures and for neurosurgery in the same HRR. One HRR can cross different counties and states.

hospitals close to each other is considered to have the same competition as one with three hospitals spread out.

In this paper, we utilize a spatial Durbin model of hospital treatment rates. This spatial model is able to identify the intensity of geographic correlations**.** Other studies using spatial analysis in health care include Mobley et al. (2006) who studied elderly access to primary care services. They use the spatial lag model, which includes the spatial lagged dependent variable to model spillovers. They find a strong and positive spatial correlation for hospital treatments. However, they do not consider hospital ownership as an aspect of quality disparity.

In addition to spillover effects, the spatial Durbin model allows us to examine whether the market structure affects the treatment rates. The market of medical services is composed of hospitals with different characteristics, such as ownership and size. As suggested by Horwitz and Nichols (2009), hospitals have different treatment decisions based on the market structure they are facing. We cannot assume the spillover effects are the same for all types of markets. Operational strategies of hospitals may not only differ by the type of ownership but may also respond to the type of ownership of neighbors.

We use clinical process treatment rates from Hospital Compare as our dependent variable. Compared to other measures, like the mortality rate or the length of hospital stays, the process treatment rates are less noisy and reflect real hospital medical services. Our study finds strong and positive spillover effects among hospitals for heart attack patients. The spillover effects are even stronger for less acute illness conditions like heart failure and pneumonia. We find some evidence that not-for-profit hospitals provide better medical services than government and for-profit hospitals, but the treatments also differ by the market structure. Hospitals in a market with stronger intensity of not-for-profit hospitals are more likely to provide medications at discharge but less likely to perform percutaneous coronary intervention (PCI) in time. Moreover, the treatment rates of hospitals decrease if they are surrounded by large hospitals. The overall effect depends on the characteristics of the hospital, the spillover effects, and the market structure.

2. Literature Review

Unlike most of the industries that are composed of for-profit firms, about 60% of the non-federal hospitals in the United States were not-for-profit and only 20% were for-profit in 2010. As Horwitz and Nichols (2009, p.925) summarize in their Table 1, there are four theories of not-for-profit hospitals: (1) maximizing own output (Newhouse, 1970): not-for-profits are profit-seeking and maximize profitable services as for-profits do. They will offer more health care until profits are driven to zero; (2) maximizing the community output (Lee and Weisbrod, 1977): the goal of not-for-profits is to benefit the whole community and to maximize market output including unprofitable services; (3) for-profit in disguise (Pauly and Redisch, 1973): nonprofits would be essentially identical to for-profit hospitals in equilibrium, with economic profits counted as costs (salaries or perquisites accruing to staff physicians); and (4) a mixture of (1) and (2) (Hirth, 1997): not-for-profits behave depending on the competition level of the market. They are profit-seeking when facing competition.

The empirical studies have mixed results. Tax exemptions allow not-for-profit and government hospitals to provide better quality to the community or more medical care to uninsured patients (Sloan, 2000; Bayindir, 2012). Clement et al. (2002) note that for-profit hospitals provide less charity care than not-for-profits. Sloan et al. (2001) find that for-profit hospitals are more likely to use high-tech procedures with higher costs, while Kessler and McClellan (2002) find that areas with for-profit hospitals have lower hospital expenditures, but virtually the same patient health outcomes. They conclude that for-profit hospitals have important spillover benefits for medical productivity. Geweke, Gowrisankaran, and Town (2003) use a Bayesian model to estimate hospital quality in Los Angeles County. Focusing on elderly pneumonia patients, they find that there is not a definitive difference in mortality rates by hospital ownership. This is in line with the results of Sloan et al. (2001) and Sloan and Taylor (1999). These studies find weak evidence that the mortality rate of Medicare patients and the probability of readmission differ by hospital ownership.

However, when competition and market structure are taken into consideration, several studies suggest that the first or the last theory has more support. Horwitz and Nichols (2009) find not-for-profit hospitals are more likely to provide profitable services in a high for-profit market (15% of for-profit admissions or higher). The spillovers of medical services provided make not-for-profit hospitals behave more like for-profits in a high for-profit market. The role of hospital ownership is less important when the competition level increases. Not-for-profits compete with for-profit hospitals by providing better quality of health care (Sloan, 2000). McClellan and Staiger (2000) also suggest that the growing difference in mortality rates of the elderly AMI patients between for-profit and not-for-profit hospitals may be attributed to various factors, including location. The treatment decisions may depend on the competition level of the market hospitals are located in.

Besides competition, knowledge spillovers among physicians could also cause spatial correlations. Physicians are more likely to practice intensive treatments in a market with advanced medical technologies. Chandra and Staiger (2007) find that spillovers of technology increase the treatment rate in the market. Cardiac catheterization rate of AMI patients is higher in a market with a higher propensity for intensive treatments. Physicians learn practice skills from other physicians, and possibly transfer these skills to other hospitals due to job movement or due to these physicians working at multiple hospitals. About 40% of physicians with inpatient duty work at more than one hospital (Fisher et al., 2007). This mobility increases the probability of exchanging knowledge among physicians. Therefore, interactions and spatial correlations of treatments among hospitals should not be neglected when we examine hospital treatment rates.

Mobley et al. (2006) study this geographic correlation of health care in the U.S. They use Admissions for Ambulatory Care Sensitive Conditions (ACSCs) among elderly patients in the late 1990s as the preventive care utilization measure. ACSCs are preventable admissions and therefore can be an indicator of *poor quality*. They use a spatial lag model with both maximum likelihood and two stage least squares methods. They find strong and positive spatial correlations. More ACSCs in neighboring hospitals are associated with an increase in ACSCs for the hospital itself. The utilization rates are not significantly different between the elderly living in poor rural areas and those living in urban areas.

3. Data and methodology

We model hospital treatment rates using the spatial Durbin panel model given by

$$y_t = \lambda W y_t + H_t \gamma_1 + X_t \beta + W H_t \gamma_2 + \varepsilon_s + \tau_t + u_t \qquad t=1,2,..,T$$

$$u_{it} = \mu_i + v_{it} \qquad i=1,2,..,N$$

where y_t is an (Nx1) vector of treatment rates for N hospitals at time t. W is an (NxN) spatial weight matrix, whose diagonal elements are zero and whose off diagonal elements are the normalized inverse distance from hospital i to hospital j. This weight matrix is row-normalized, i.e., the elements in each row sum to one, $\sum_{j=1}^{N} w_{ij} = 1$. Wy_t is the spatial lagged dependent variable, which presents the weighted average treatment rates of neighboring hospitals. λ thus measures the spillover effect of hospital treatment rates. H_t is an (Nxk) matrix of hospital characteristics, and X_t is an (Nxc) matrix of county demographic variables where hospital i is located. ε_s and τ_t are state and year fixed effects. u_t is an (Nx1) vector of error component disturbances. As the second equation shows, the typical element of u_{it} is the hospital random effect μ_i and a remainder classical disturbance v_{it}. μ_i is assumed to be i.i.d. $(0, \sigma_\mu^2)$ and v_{it} is assumed to be i.i.d. $(0, \sigma_v^2)$. μ_i and v_{it} are independent of each other and the regressors H_t and X_t.

Our panel data consists of all hospitals in the 48 continental states that reported their treatment rates every year from 2005 to 2008. Neighboring hospitals are those within a 30 miles radius. Thirty miles may seem arbitrary, but Horwitz and Nichols (2007) indicate that 90% of the discharges are from a mean radius of 21.5 miles of non-rural hospitals, compared to 25.2 miles for rural hospitals. Therefore, 30 miles seems reasonable to cover the potential market.

Our dependent variables are the treatment rates from Hospital Compare of the Centers for Medicare and Medicaid Services. This data set was released in 2004. The treatment rates are the percentages of the eligible adult patients who were actually given seven clinical processes of care for heart attack treatments[5]. Instead of examining the spillover effects on each of the seven AMI clinical processes separately, we combine them into four categories: (1) overall treatment rate; (2) giving aspirin and/or beta blockers at arrival; (3) prescribing aspirin/beta blockers/angiotensin converting enzyme (ACE) inhibitors at discharge; and (4) giving percutaneous coronary intervention (PCI) within 120 minutes of arrival[6]. The first category refers to the average of all treatments offered to AMI patients. The medications are similar in the

[5] Hospital Compare includes 17 clinic processes of care in total for heart attack, heart failure, and pneumonia.
[6] Smoking consultation is also included in the overall treatment receiving rate.

second and third categories, but the timing of prescriptions indicates different treatment purposes. The second category indicates timely treatments that can relieve the conditions. The third category implies preventive treatments to reduce the probability of readmissions. These three categories are obtained using a weighted average where the weights are the number of cases in each process. PCI is a coronary angioplasty. It is a relatively high intensity treatment, which requires skilled staff and equipment.

A heart attack is a very acute condition, and patients need immediate medical care. They are most likely to be taken to hospitals in distinct local markets[7]. This precludes patients from travelling long distances to seek care and in turn being less likely to select the hospital they like. In addition, hospitals need to treat patients who check in to the emergency room, regardless of their insurance type. Focusing on heart attack processes allow us to reduce the selection issue between patients and hospitals. As Chandra and Staiger (2007, p.117) put it: “markets for heart attack treatment are geographically distinct…mobility is limited, and it is possible to observe production in many distinct local markets.”

There are several advantages of using Hospital Compare as our quality measures. First, the processes reflect the real medical services that are delivered to patients in a timely manner. Even though using health outcomes, such as mortality rate, as quality measures can cover unobservable factors, they could be noisy due to relatively low mortality probability (McClellan and Staiger, 2000). The processes in Hospital Compare are timely and effective for patients. Many of the processes for AMI patients are recommended in the ACC/AHA Guidelines for the Management of Patients with Acute Myocardial Infarction (1999). Second, most of these processes are not intensive or require advanced technologies. Hospitals should be able to provide

[7] Even if patients travel four to five miles for better treatments as suggested by Tay (2003), these hospitals may still be within one market according to our definition of neighborhood.

the treatments regardless of the size and the specialization of the hospital. We acknowledge that these are the basic treatments, which can be achieved easily. One hospital with lower treatment rates may not guarantee a worse overall quality. It may focus on other medical and non-medical services that are not included in the data, such as open heart surgery. However, these non-intensive treatments, such as giving beta blockers, serve as a marker of the quality of non-intensive medical management in a hospital, see Chandra and Staiger (2007, p.118). Heidenreich and McClellan (2001) and Rogers et al. (2000) find that giving aspirin/beta blockers/ACE inhibitors is the major reason for increasing survival rate following AMI. Third, these measures only include patients who are appropriate for the treatments. One limitation of our data is that it is at the hospital level. Without patient-level data, we have no information about the characteristics and illness severity of patients.

Data for the hospital characteristics are taken from the AHA Guide and Provider of Services File, which includes: indicators of not-for-profit hospitals, for-profit hospitals, teaching hospitals[8], and locating in an MSA; number of beds; number of nurses per bed; and HHI. Herfindahl-Hirschman Index (HHI) is the sum of squares of each hospital's market share based on the number of beds within its neighborhood. HHI is an indicator of market concentration/competition. A larger index indicates a lower concentration of the health care market. The market may be dominated by one large hospital and few small hospitals. The spatial lagged hospital characteristics, WH_t, include indicators of for-profit, not-for-profit, and teaching hospitals; number of beds; and number of nurses per bed. γ_2 represents the spillover effects of neighboring hospitals' characteristics.

[8] Teaching hospitals include hospitals with Council of Teaching Hospitals designation, hospitals approved to participate in residency and/or internship training by the Accreditation Council for Graduate Medical Education, and those with medical school affiliation reported to the American Medical Association.

The characteristics of potential patients are controlled by county demographic variables, which are from the American Community Survey of the U.S. Census Bureau. This data set includes only counties with a population of 65,000 and above in 2005 and 2006. Therefore, hospitals in our data are located in relatively more urbanized areas. We control for percentages of never married individuals age 15 and above, high school dropouts, high school graduates, male, Hispanic, black, and elderly (age 65 and above); median earnings; and population density per square mile. One may argue the disparity of health care quality is due to geographic heterogeneity. Patients receive better treatment because they are located in an area with better medical care resources. These county demographic variables are good proxies for geographical heterogeneity.

Table II-1 presents the descriptive statistics of our data. The treatment rates of the four heart attack treatment categories have large means and small minimum values. This suggests that the distributions of treatment rates are skewed. Out of 2342 hospitals in our sample, 18.5% are for-profit, 68.7% are non-profit hospitals. The proportion of non-profit hospitals is slightly higher than the national average but closer to that in the non-rural areas (Horwitz and Nichols, 2007). Of these hospitals, 41.2% have teaching status and 89.4% are located in MSAs. The average number of beds is 263 and the average number of nurses per bed is 1.1. The average (median earnings) is $33,790 and the average population density is 2,230 individuals per square mile. Among the potential patients, 30.9% are never-married, 44% have at most a high school degree, 12.5% are elderly, 14.5% are Hispanic and 12.5% are black.

4. Empirical Results

We estimate our spatial Durbin panel data model using the generalized moments (GM) estimator[9] with random effects. See LeSage and Pace (2009) for a nice introduction of the spatial Durbin model and Kapoor, Kelejian and Prucha (2007) for details on the GM methodology. Also, Mutl and Pfaffermayr (2010) for an extension of the GM methodology to the spatial lag model and Debarsy (2012) for the spatial Durbin model. See also Elhorst (2003) for maximum likelihood estimation of spatial lag panel models, and Lee and Yu (2010) and Baltagi (2011) for recent surveys of spatial panels.

Table II-2 presents the spillover effects of the heart attack treatment rates using a GM estimator. Some of the diagnostics performed include testing the joint significance of the state dummies as well as the time dummies. These were jointly significant for all models considered. Similarly, the hospital random effects are significant for all models. The first two columns show the GM estimation of the overall heart attack treatment rate. Without controlling for the market structure in the first column, we find that not-for-profit hospitals provide better health care to heart attack patients than government hospitals. Surprisingly, the treatments in for-profit hospitals are not significantly different from government hospitals. The number of beds, the number of nurses per bed, and being a teaching hospital are all positively associated with hospital quality. These are in line with the studies of Keeler et al. (1992) and Geweke, Gowrisankaran, and Town (2003). Yuan et al. (2000) also find that teaching not-for profit hospitals have lower mortality rates and infer that they provide over-all better quality of care. Aiken et al. (2002) report that a higher patient-per-nurse ratio increases the mortality rate of

[9] We use the full set of moment conditions, see Millo and Piras (2012) for details. We also estimate the model using maximum likelihood estimation (MLE) using XSMLE: Stata module for spatial panel data model estimation, see Belotti, Hughes, and Mortari (2013). The MLE results were similar to those using the GM estimator except for smaller estimates of lambda. However, all the lambda estimates were statistically significant at the 1% significance level. These results are presented in Appendix Table II-1 and Appendix Table II-2.

AMI. We find little evidence that demographic variables affect hospital treatments. Hospitals provide better quality in an area with a higher never-married population, and lower quality in an area with more blacks and higher population density.

The estimate of lambda indicates the magnitude of spillover effects among hospitals. For the overall treatment rate in column (1), the spatial correlation coefficient estimate is 0.414 without the measures of market structure. This suggests that when the average heart attack treatment rate of neighboring hospitals increases by 1%, the hospital's treatment rate also increases by 0.414%. This effect is large and close to the results found by Mobley et al. (2006).

After adding the market structure variables in column (2), the estimation results are similar to those in column (1). However, the effects of blacks and population density are no longer significant. The lambda estimate increases to 0.5. Ownership of neighboring hospitals does not impact its own quality, while the effect of its own not-for-profit status becomes weaker. Hospitals provide fewer treatments in a market with teaching hospitals and larger neighboring hospitals. The significance of market structure variables suggest that ignoring these may generate biased results. In addition, these results suggest that the treatment decisions of hospitals may be associated with a higher quality of neighbors rather than the distribution of hospital ownership in the market. Larger hospitals provide more health care, but when a hospital is close to larger hospitals, its treatment rates are lower. Columns (3) to (8) decompose the overall treatment into more specific heart attack treatments. Focusing on the estimation with market structure variables, we find weak evidence that for-profit hospitals provide fewer medications to patients after they arrive than government hospitals. Not-for-profit hospitals have a higher PCI treatment rate than government hospitals. We find that number of beds, number of nurses per bed, and teaching status are positively associated with the medication treatment rates at both arrival and discharge, but not with PCI. The number of nurses per bed has relatively strong effects, but the number of beds is not significant. Teaching hospitals are more likely to give medications to heart attack patients. This is in line with the suggestion of Sloan (2000) that major teaching hospitals have better quality and non-teaching government hospitals have the worst outcome for elderly patients. What is interesting is that teaching status is negatively associated with the PCI treatment rate. This could be because teaching hospitals have longer waiting time to perform PCI than other hospitals (Nallamothu et al, 2005).

Hospitals provide more medications but fewer PCI treatments in areas with a more never-married population. The percentage of high school graduates has a negative relationship with medications at discharge and PCI. Hospitals give more medications at discharge in an area with an older population and a higher population density.

The lambda estimates range from 0.4 to 0.48. Focusing on estimation with market structure, a 1% increase in average treatment rate of each category in neighboring hospitals is associated with an increase of 0.45%, 0.48%, and 0.41%, respectively, in the hospital’s own treatment rate. The spillover effect of PCI is relatively smaller than other treatments. This may be due to a technology specialty, and proficiency of doctors and nurses. However, the strong and positive spatial correlation of PCI confirms the results of Chandra and Staiger (2007). Hospitals are more likely to perform these treatments in a market with a high propensity of intensive treatments.

Except for the number of beds, market structure has different impacts on each treatment category. With not-for-profit hospitals in the market, a hospital is more likely to prescribe medications at discharge but less likely to perform PCI. All the treatments decrease when there are larger hospitals nearby. Interestingly, a hospital prescribes fewer medications at discharge when there are teaching hospitals in its neighborhood.

5. Spillover Effects on Other Illness Conditions

Hospital Compare also includes four processes of heart failure and six processes of pneumonia[10]. These two illness conditions are less acute in the sense that patients have more likelihood to travel further for treatments, or for preferred physicians, or for insurance reasons. Hence, we expect the effects of competition among hospitals and the geographic heterogeneity to be stronger. We combine these treatments for each illness condition and apply the previous spatial panel Durbin model to the average treatment rates of heart failure and pneumonia.

The GM estimation results are presented in Table II-3. The first two columns are the estimation of heart failure treatments and the latter two columns are for pneumonia treatments. Focusing on the estimation with market structure, the results in column (2) suggest that not-for-profit hospitals provide more treatments than government hospitals. Both the number of beds and the number of nurses per bed increase the treatment rates of heart failure patients. The lambda estimate indicates that when neighboring hospitals increase their heart failure treatment rate by 1% on average, it increases its own hospital treatment rate by around 0.67%. Similar to heart attack treatments, larger hospitals in the neighborhood decrease the treatment rates of own hospital.

Column (4) suggests that both for-profit and not-for-profit hospitals provide more pneumonia treatments than government hospitals. Teaching hospitals, however, are less likely to

[10] The processes of heart failure include an evaluation of the left ventricular systolic function, ACE inhibitor, discharge instructions, and smoking cessation advice during a hospital stay. The processes of pneumonia include giving initial antibiotic within 4 hours of arrival, screening for pneumococcal vaccination status, giving oxygenation, performing blood culture prior to the first hospital dose of antibiotics, giving smoking cessation advice, and giving appropriate initial antibiotics to immune-competent patients with pneumonia during the first 24 hours after arrival.

provide these pneumonia treatments. Hospitals also provide fewer treatments to areas with high minority populations. The lambda estimate indicates that when neighboring hospitals increase their pneumonia treatment rates by 1% on average, it increases its own hospital treatment rate by around 0.56%. Hospitals have lower treatment rates when they have for-profit, not-for-profit and teaching hospitals in their neighborhoods.

6. Discussion

Our results suggest that not-for-profit hospitals provide better quality, especially for cardiac treatments. McClellan and Staiger (2000) also suggest that not-for-profit hospitals treat elderly patients with heart diseases slightly better than for-profits. One of the possible explanations is that for-profit hospitals are more aggressive on cost control. Eggleston and Shen (2011) find that the mortality rate for elderly heart attack patients is higher in for-profit hospitals, because they have more restrictive budget constraints. McKay and Deily (2008) also suggest that reductions in costs are associated with adverse consequences on health outcomes. In addition, not-for-profit hospitals enjoy tax exemptions. They are able to transfer the profit to services that are beneficial to patients. If the not-for-profit hospitals provide better services due to tax exemption, charitable obligations may benefit heart attack patients.

However, the effect of ownership depends on treatments and market structure. The results on PCI treatments suggest that not-for-profit hospitals provide better quality of heart attack treatments in an inter-sectoral market. When a market has only for-profit or only not-for-profit hospitals, there is no significant effect or the effects are traded off. However, when a not-for-profit hospital is located in a high for-profit market, the PCI treatment rate is significantly higher. According to the study of Horwitz and Nichols (2009), PCI is a relatively profitable service. This result is in line with their study that not-for-profits provide more profitable services in a high for-profit market. We also do not find strong evidence that hospitals provide different quality by ownership on heart attack treatments other than PCI. Not-for-profit hospitals provide better heart failure treatment regardless of the ownership composition in the market. Ownership of neighboring hospitals offset the high pneumonia treatment rates of for-profit and not-for-profit hospitals. Therefore, our results on hospital ownership are mixed.

Our results support the competition hypothesis. Hospitals have lower treatment rates when they compete with hospitals of better quality. Competition may generate both positive and negative externalities at the same time. Hospitals compete by providing better quality, while improving quality can be very costly (Morey et al., 1992). Fournier and Mitchell (1992) and Robinson and Luft (1985) suggest that the level of competition is associated with increasing cost. The overall effect could be in line with studies of Propper, Burgess, and Green (2004) that competitions lower hospital quality[11]. Also, when a hospital has a larger neighbor, there is a higher probability of empty beds which is costly (Gaynor and Anderson, 1995). Hospitals with more beds have diseconomy of scale. The cost may increase with increasing beds (Keeler, Melnick, and Zwanziger, 1999). Hospitals may offer fewer treatments for financial reasons.

As expected, we also find that the spillover effect is stronger for less acute illness treatments than heart attack treatments. Less acute illnesses allow patients to travel further, making the competition among hospitals to increase. Positive externalities from competition and knowledge spillover improve medical services in the whole market.

Our results corroborate similar findings for France by Gobillon and Milcent (2012). These authors find that local composition of ownership and demographic variables have limited effects

[11] There are other studies that suggest competitions improve cost-effectiveness and generate economy of scale (Dranove, Shanley, and Simon, 1992; Kessler and McClellan, 2000, Zwanziger and Melnick, 1988). In addition, Bloom et al. (2010) find that competition increases management quality of the public hospitals in the UK.

on spatial disparity of innovative treatments in France. They also find strong spillover effects and suggest that regional unobservable factors account for 20% of spatial disparities.

Since the overall effect depends upon the characteristics of the hospital itself, spillovers and market structure, this may explain why Gaynor (2006) suggests a mixed result for the effect of competition on hospital quality. Vickers and Yarrow (1988) also conclude that the competition level in the market could be a more important determinant of performance than type of ownership.

7. Conclusion

Our study employs a spatial Durbin panel data model to control for geographic correlation of treatments among hospitals. Our results suggest strong and positive spillover effects among hospitals. Our results should be tempered by the fact that we included basic treatments which were limited by data availability. Some hospitals may perform other effective treatments which are not available in our data set. In addition we only focused on three illness conditions. Some hospitals may provide better quality care treatments for other illness conditions not reported in our data set.

Our results on hospital ownership are mixed. While we find some evidence that hospitals have different operation strategies by ownership, this also depends on the market structure where the hospital is located. One thing that policy makers should not ignore is the effect of spillovers which we found to be strong and significant.

References

Aiken, Linda H., Sean P. Clarke, Douglas M. Sloane, et al. 2002. “Hospital Nurse Staffing and Patient Mortality, Nurse Burnout, and Job Dissatisfaction.” *The Journal of the American Medical Association* 288(16):1987-1993.

Baltagi, Badi H. 2011. “*Spatial Panels*,” Chapter 15 in *The Handbook of Empirical Economics and Finance*, Aman Ullah and David E.A. Giles, editors, Chapman and Hall, pp. 435-454.

Bayindir, Esra Eren. 2012. “Hospital Ownership Type and Treatment Choices.” *Journal of Health Economics* 31: 359-370.

Bloom, Nicholas, Carol Propper, Stephan Seiler, and John Van Reenen. 2010. “The Impact of Competition on Management Quality: Evidence from Public Hospitals.” National Bureau of Economic Research (NBER) Working Paper No. 16032.

Belotti F., Hughes G., and Piano Mortari A. 2013. XSMLE: Stata module for spatial panel data models estimation, Statistical Software Components S457610, Boston College Department of Economics.

Chandra, Amitabh, and Douglas O. Staiger. 2007. “Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks.” *Journal of Political Economy* 115(1): 103-140.

Clement, Jan P., Kenneth R. White, and Vivian Valdmanis. 2002. “Charity Care: Do Not-For-Profits Influence For-Profits?” *Medical Care Research and Review* 57(1): 59-78.

Debarsy, Nicolas. 2012. “The Mundlak Approach in the Spatial Durbin Panel Data Model.” *Spatial Economic Analysis* 7: 109-131.

Dranove, David, Mark Shanley, and Carol Simon. 1992. “Is Hospital Competition Wasteful?” *The RAND Journal of Economics* 23(2): 247-262.

Eggleston, Karen, and Yu-Chu Shen. 2011. “Soft Budget Constraints and Ownership: Empirical Evidence from US hospitals.” *Economics Letters* 110: 7-11.

Elhorst, J. Paul. 2003. “Specification and Estimation of Spatial Panel Data Models.” *International Regional Science Review* 26(3):244-268.

Fisher, Elliott S., Douglas O. Staiger, Julie P.W. Bynum, and Daniel J. Gottlieb. 2007. “Creating Accountable Care Organizations: The Extended Hospital Medical Staff.” *Health Affairs* 26(1): 44-57.

Fournier, Gary M., and Jean M. Mitchell. 1992. “Hospital Costs and Competition for Services: A Multiproduct Analysis.” *The Review of Economics and Statistics* 74(4): 627-634.

Gaynor, Martin. 2006. “What Do We Know About Competition and Quality In Health Care Markets?” National Bureau of Economic Research (NBER) Working Paper No. 12301.

Gaynor, Martin, and Gerard F. Anderson. 1995. “Uncertain Demand, the Structure of Hospital Costs, and the Cost of Empty Hospital Beds.” *Journal of Health Economics* 14: 291-317.

Geweke, John, Gautam Gowrisankaran, and Robert J. Town. 2003. “Bayesian Inference for Hospital Quality in a Selection Model.” *Econometrica* 71(4): 1215-1238.

Gobillon, Laurent, and Carine Milcent. 2012. “Spatial Disparities in Hospital Performance.” Forthcoming in: *Journal of Economic Geography*.

Heidenreich, Paul A., and Mark McClellan. 2001. “Trends in Treatment and Outcomes for Acute Myocardial Infarction: 1975-1995.” *The American Journal of Medicine* 110(3): 165-174.

Hirth, Richard A. 1997. “Competition between For-Profit and Not-For-Profit Health Care Providers: Can It Help Achieve Social Goals.” *Medical Care Research and Review* 54: 414-438.

Horwitz, Jill R., and Austin Nichols. 2007. “What Do Nonprofits Maximize? Nonprofit Hospital Service Provision and Market Ownership Mix.” National Bureau of Economic Research (NBER) Working Paper No. 13246.

Horwitz, Jill R., and Austin Nichols. 2009. “Hospital Ownership and Medical Services: Market Mix, Spillover Effects, and Nonprofit Objectives.” *Journal of Health Economics* 28: 924-937.

Jung, Kyoungrae, Roger Feldman, and Dennis Scanlon. 2011. “Where Would You Go For Your Next Hospitalization?” *Journal of Health Economics* 30: 832-841.

Kapoor, M., Kelejian, H.H., Prucha, I.R. 2007. “Panel Data Models with Spatially Correlated Error Components.” *Journal of Econometrics* 140(1): 97-130.

Keeler, Daniel P. and Mark B. McCleallan. 2000. “Is Hospital Competition Socially Wasteful?” *The Quarterly Journal of Economics* 115(2): 577-615.

Keeler, Emmett B., Glenn Melnick, and Jack Zwanziger. 1999. “The Changing Effects of Competition on Non-Profit and For-Profit Hospital Pricing Behavior”. *Journal of Health Economics* 18: 69-86.

Keeler, Emmett B., Lisa V. Rubenstein; Katherine L. Kahn, et al. 1992. “Hospital Characteristics and Quality of Care.” *The Journal of the American Medical Association* 268(13): 1709-1714.

Kessler, Daniel P., and Mark B. McClellan. 2002. “The Effects of Hospital Ownership on Medical Productivity.” *The RAND Journal of Economics* 33: 488-506.

Lee, A. James, and Burton Allen Weisbrod. 1977. “Collective Goods and the Voluntary Sector: The Case of the Hospital Industry.” In: Burton Allen Weisbrod, editor . *The Voluntary Nonprofit Sector*. Lexington Books, Lexington, MA.

Lee, Lung-fei, and Jihai Yu. 2010. “Some Recent Developments in Spatial Panel Data Models.” *Regional Science and Urban Economics* 40: 255–271.

LeSage, J., and Pace, R.K., 2009. An Introduction to Spatial Econometrics. CRC Press, Taylor & Francis Group, Boca Raton, London, New York.

McClellan, Mark, and Douglas Staiger. 2000. “Comparing Hospital Quality at For-Profit and Not-For-Profit Hospitals.” In: David M. Cutler, editor. *The changing hospital industry: comparing not-for-profit and for-profit institutions.* Chicago: The University of Chicago Press.

McKay, Niccie L., and Mary E. Deily. 2008. “Cost Inefficiency and Hospital Health Outcomes.” *Health Economics* 17: 833-848.

Millo, Giovanni, and Gianfranco Piras. 2012. “splm: Spatial Panel Data Models in R.” *Journal of Statistical Software* 47(1): 1-38.

Mobley, Lee R., Elisabeth Root, Luc Anselin, et al. 2006. “Spatial Analysis of Elderly Access to Primary Care Services.” *International Journal of Health Geographics*: 5-19.

Morey, Richard C., David J. Fine, Stephen W. Loree, et al. 1992. “The Trade-Off between Hospital Cost and Quality of Care: An Exploratory Empirical Analysis.” *Medical Care* 30(8): 677-698.

Moscone, Francesco, Elisa Tosetti, and Giorgio Vittadini. 2012. “Social Interaction in Patients’ Hospital Choice: Evidences from Italy.” *Journal of the Royal Statistical Society* 175(2): 453-472.

Mutl, J. and M. Pfaffermayr. 2010. “The Hausman Test in a Cliff and Ord Panel Model.” *Econometrics Journal*, 10: 1-30.

Nallamothu, Brahmajee K et al. 2005. “Times to Treatment in Transfer Patients Undergoing Primary Percutaneous Coronary Intervention in the United States.” *Circulation* 111: 761-767.

Newhouse, Joseph P. 1970. “Toward a Theory of Not-For-Profit Institutions: An Economic Model of a Hospital.” *The American Economic Review* 60: 64-74.

Pauly, Mark, and Michael Redisch. 1973. “The Not-For-Profit Hospital as Physicians’ Cooperative.” *The American Economic Review* 63: 87-99.

Porell, Frank W., and E. Kathleen Adams. 1995. “Hospital Choice Models: A Review and Assessment of Their Utility for Policy Impact Analysis.” *Medical Care Research and Review* 52(2): 158-195.

Propper, Carol, Simon Burgess, and Katherine Green. 2004. "Does Competition Between Hospitals Improve the Quality of Care? Hospital Death Rate and the NHS Internal Market." *Journal of Public Economics* 88: 1247-1272.

Robinson, James C., and Harold S. Luft. 1985. "The Impact of Hospital Market Structure on Patient Volume, Average Length of Stay, and the Cost of Care." *Journal of Health Economics* 4: 333-356.

Rogers, William J., John G. Canto, Costas T. Lambrew, et al. 2000. "Temporal Trends in the Treatment of Over 1.5 Million Patients with Myocardial Infarction in the U.S. from 1990 through 1999." *Journal of the American College of Cardiology* 36(7): 2056-2063.

Ryan, Thomas J., Elliott M. Antman, Neil H. Brooks, et al. 1999. "1999 Update: ACC/AHA Guidelines for the Management of Patients with Acute Myocardial Infarction: Executive Summary and Recommendations: A Report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines." *Circulation* 100: 1016–1030.

Skinner, Jonathan. 2012. "Causes and Consequences of Regional Variations in Health Care." in Thomas G. McGuire, Mark V. Pauly, and Pedro P. Baros, editors. *Handbook of Health Economics Vol. 2.* Elsevier Science B.V.

Sloan, Frank A. 2000. "Not-For-Profit Ownership and Hospital Behavior." in Culyer, A.J. and Newhouse, J.P., editors. *Handbook of Health Economics.* Elsevier Science B.V.

Sloan, Frank A., Gabriel A. Picone, Donald H. Taylor Jr., Shin-Yi Chou. 2001. "Hospital Ownership and Cost and Quality of Care: Is There a Dime's Worth of Difference?" *Journal of Health Economics* 20: 1-21.

Sloan, Frank A., and Donald H. Taylor. 1999. "Does Ownership Affect the Cost of Medicare?" In: Rettenmaier, A.J., Saving, T. R., editors. *Medicare Reform: Issues and Answers.* University of Chicago Press, Chicago, IL: 99-129.

Tay, Abigail. 2003. "Assessing Competition in Hospital Care Markets: The Importance of Accounting for Quality Differentiation." *The RAND Journal of Economics* 34(4): 786-814.

The Dartmouth Atlas of Health Care. Available at www.dartmouthatlas.org. Last accessed February 2013.

Vickers, John, and George K. Yarrow. 1988. "Privatization: An Economics Analysis." MIT Press, Cambridge, MA.

Yuan, Zhong, Gregory S. Cooper, Douglas Einstadter, et al. 2000. "The Association between Hospital Type and Mortality and Length of Stay: A Study of 16.9 Million Hospitalized Medicare Beneficiaries." *Medical Care* 38(2): 231-245.

Zwanziger, Jack, and Glenn A. Melnick. 1988. "The Effects of Hospital Competition and the Medicare PPS Program on Hospitals Cost Behavior in California." *Journal of Health Economics* 7: 301-320.

Figure II-1. Geographic Distribution of the Summary Hospital Compare Quality Score in Hospital Referral Regions

Figure 1a. Overall

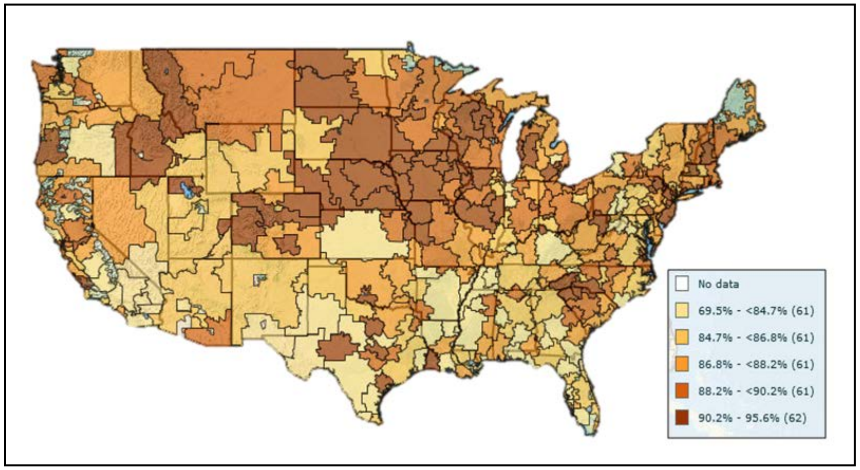


Figure 1b. Heart Attack

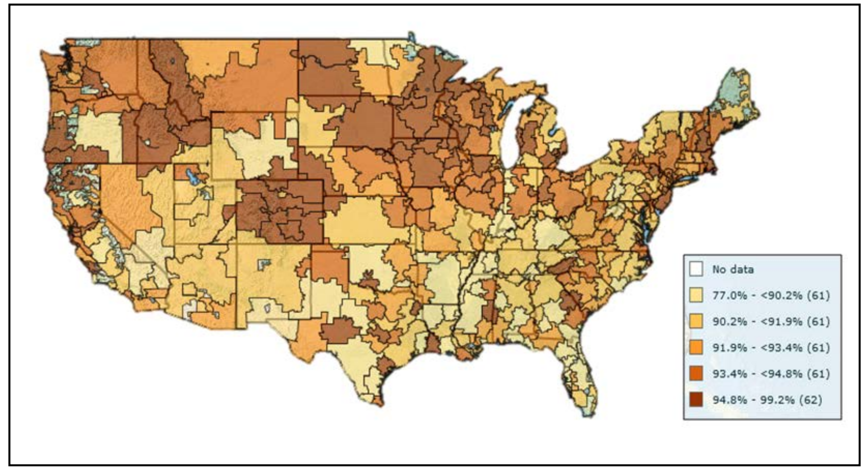


Figure 1c. Heart Failure

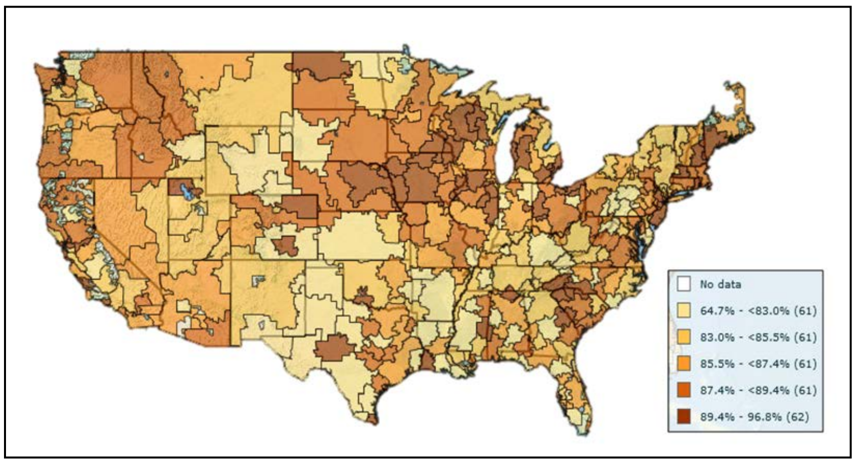
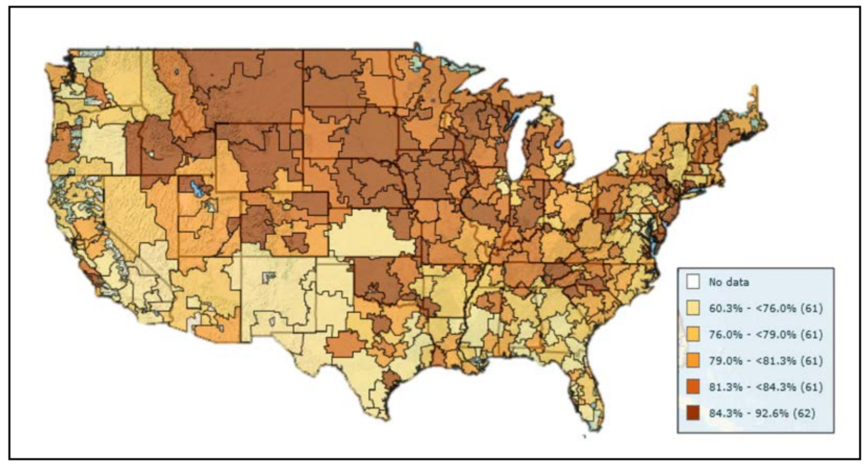


Figure 1d. Pneumonia



Source: The Dartmouth Atlas of Health Care (The Dartmouth Institute for Health Policy and Clinical Practice).

Table II-1. Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Dependent Variables:				
Heart Attack Treatments:				
Overall	0.921	0.065	0.257	1
Medication at arrival	0.934	0.063	0.28	1
Medication at discharge	0.917	0.086	0	1
PCI	0.627	0.197	0	1
Heart Failure Overall Treatments:	0.797	0.129	0.05	1
Pneumonia Overall Treatments:	0.835	0.082	0.447	1
Independent Variables:				
For-profit	0.185	0.389	0	1
Not-for-profit	0.687	0.464	0	1
Number of beds (in 100's)	2.632	2.103	0.04	22.07
Nurses per bed	1.102	0.522	0.2	7.04
Teaching Status	0.412	0.49	0	1
Located in an MSA	0.894	0.308	0	1
HHI	0.137	0.172	0.001	0.971
% never married	0.309	0.06	0.166	0.557
% HS dropouts	0.151	0.059	0.018	0.418
% HS grads	0.29	0.067	0.116	0.55
Median earnings (in 10,000's)	3.379	0.061	1.741	6.09
% male	0.49	0.011	0.445	0.58
% Hispanic	0.145	0.159	0	0.951
% black	0.126	0.129	0	0.668
% elderly	0.125	0.033	0.046	0.335
Population density (in 10,000's)	0.223	0.668	0.001	0.716

Table II-2. Estimates of Spillover Effects and Hospital Characteristics on Heart Attack Treatments

Treatment	Overall		Medication at arrival		Medication at discharge		PCI	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
For-profit	-0.005	-0.005	-0.008**	-0.007*	-0.008	-0.007	0.010	0.013
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.018)	(0.018)
Not-for-profit	0.007**	0.006*	0.003	0.003	0.005	0.003	0.058***	0.058***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.016)	(0.016)
Number of beds	0.004***	0.005***	0.004***	0.004***	0.007***	0.007***	0.003	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Nurses per bed	0.008***	0.008***	0.008***	0.008***	0.008***	0.008***	0.038***	0.036***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.009)	(0.009)
Teaching Status	0.011***	0.013***	0.011***	0.013***	0.018***	0.020***	-0.019*	-0.019*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.010)	(0.010)
Located in an MSA	0.003	0.005	0.001	0.003	0.006	0.008	0.030	0.031
	(0.005)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.033)	(0.033)
HHI	-0.010	-0.010	-0.011	-0.012	-0.013	-0.012	-0.009	-0.001
	(0.009)	(0.010)	(0.009)	(0.009)	(0.012)	(0.013)	(0.050)	(0.050)
% never married	0.061**	0.064**	0.051*	0.053*	0.076**	0.077**	-0.286*	-0.280*
	(0.028)	(0.029)	(0.028)	(0.028)	(0.038)	(0.039)	(0.153)	(0.153)
% HS dropouts	-0.037	-0.033	-0.030	-0.032	-0.060*	-0.045	-0.080	-0.118
	(0.032)	(0.032)	(0.031)	(0.031)	(0.044)	(0.044)	(0.175)	(0.176)
% HS grads	-0.015	-0.019	-0.018	-0.022	-0.054	-0.057*	-0.256*	-0.236*
	(0.025)	(0.025)	(0.025)	(0.025)	(0.034)	(0.034)	(0.133)	(0.133)
Median earnings	0.003	0.004	0.003	0.004	0.001	0.004	-0.010	-0.010
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.017)	(0.017)
% male	0.013	-0.026	0.094	0.064	0.035	-0.026	0.606	0.688
	(0.111)	(0.112)	(0.111)	(0.112)	(0.151)	(0.154)	(0.640)	(0.639)
% Hispanic	-0.016	-0.003	-0.004	0.005	-0.031*	-0.010	-0.069	-0.068
	(0.014)	(0.014)	(0.013)	(0.013)	(0.018)	(0.019)	(0.075)	(0.075)
% black	-0.029*	-0.019	-0.018	-0.009	-0.031	-0.018	-0.134*	-0.119
	(0.015)	(0.015)	(0.015)	(0.015)	(0.020)	(0.021)	(0.081)	(0.008)
% elderly	0.071	0.078	0.078	0.083	0.122*	0.132*	-0.010	-0.091
	(0.052)	(0.053)	(0.050)	(0.051)	(0.070)	(0.070)	(0.271)	(0.271)
Population density	-0.004**	-0.004	-0.003*	-0.003	-0.006**	-0.005*	-0.008	-0.007
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.011)	(0.011)
Spatial (λ)	0.414***	0.500***	0.424***	0.452***	0.350***	0.476***	0.401***	0.414***
	(0.067)	(0.076)	(0.071)	(0.079)	(0.068)	(0.080)	(0.087)	(0.082)

Market Structure:								
For-profit		-0.001		-0.0004		0.005		-0.001
		(0.007)		(0.007)		(0.010)		(0.028)
Not-for-profit		0.007		0.007		0.015*		-0.056**
		(0.006)		(0.006)		(0.008)		(0.024)
Number of beds		-0.004***		-0.003***		-0.005***		-0.007**
		(0.001)		(0.001)		(0.002)		(0.003)
Nurses per bed		0.003		0.005		0.004		-0.022
		(0.004)		(0.004)		(0.005)		(0.016)
Teaching Status		-0.008**		-0.005		-0.011**		0.020
		(0.004)		(0.004)		(0.005)		(0.015)
State fixed effect?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test for state fixed effects	3.33***	2.92***	3.68***	3.11***	3.50***	3.10***	3.37***	3.42***
F-test for year fixed effects	63***	62***	77***	77***	90***	89***	21***	22***
Number of hospitals	2,094	2,094	2,094	2,094	2,094	2,094	941	941
Observations	8,376	8,376	8,376	8,376	8,376	8,376	3,764	3,764

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Table II-3. Estimates of Spillover Effects and Hospital Characteristics on Heart Failure and Pneumonia Treatments

Treatment	Heart Failure		Pneumonia	
	(1)	(2)	(3)	(4)
For-profit	0.002	0.003	0.011***	0.010***
	(0.007)	(0.007)	(0.004)	(0.004)
Not-for-profit	0.024***	0.024***	0.020***	0.020***
	(0.006)	(0.006)	(0.003)	(0.003)
Number of beds	0.005***	0.005***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Nurses per bed	0.011***	0.010***	0.000	0.000
	(0.004)	(0.004)	(0.002)	(0.002)
Teaching Status	0.002	0.004	-0.008***	-0.007***
	(0.004)	(0.004)	(0.002)	(0.002)
Located in an MSA	0.006	0.009	-0.001	0.001
	(0.009)	(0.009)	(0.004)	(0.004)
HHI	-0.025	-0.026	-0.010	-0.012
	(0.018)	(0.018)	(0.008)	(0.009)
% never married	-0.047	-0.036	-0.003	0.001
	(0.055)	(0.056)	(0.027)	(0.027)
% HS dropouts	-0.030	-0.036	0.007	0.004
	(0.059)	(0.060)	(0.029)	(0.029)
% HS grads	0.004	-0.008	0.015	0.012
	(0.048)	(0.049)	(0.024)	(0.024)
Median earnings	0.002	0.002	0.004	0.004
	(0.006)	(0.006)	(0.003)	(0.003)
% male	-0.310	-0.354*	-0.046	-0.057
	(0.210)	(0.212)	(0.105)	(0.105)
% Hispanic	0.013	0.023	-0.022*	-0.025*
	(0.025)	(0.026)	(0.013)	(0.013)
% black	-0.011	0.002	-0.028*	-0.031**
	(0.029)	(0.030)	(0.014)	(0.015)
% elderly	0.039	0.039	-0.002	-0.003
	(0.101)	(0.102)	(0.049)	(0.051)
Population density	-0.002	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.002)	(0.002)
Spatial (λ)	0.694***	0.669***	0.777***	0.555***
	(0.078)	(0.077)	(0.073)	(0.067)

Market Structure:				
For-profit		-0.015		-0.017**
		(0.014)		(0.007)
Not-for-profit		-0.010		-0.013**
		(0.012)		(0.006)
Number of beds		-0.006**		-0.001
		(0.002)		(0.001)
Nurses per bed		0.001		-0.001
		(0.007)		(0.003)
Teaching Status		-0.007		-0.006*
		(0.007)		(0.004)
State fixed effect?	Yes	Yes	Yes	Yes
Year fixed effect?	Yes	Yes	Yes	Yes
F-test statistic for state fixed effects	5.74***	5.39***	8.72***	8.20***
F-test statistic for year fixed effects	244.7***	244***	634***	636***
Number of hospitals	2,192	2,192	2,134	2,134
Observations	8,768	8,768	8,536	8,536

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Appendix Table II-1: ML Estimates of Spillover Effects and Hospital Characteristics on Heart Attack Treatments

	Overall		Medication at arrival		Medication at discharge		PCI	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
For-profit	-0.005	-0.005	-0.007	-0.007	-0.006	-0.006	0.005	0.008
	(0.005)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.021)	(0.021)
Not-for-profit	0.008**	0.008**	0.004	0.004	0.007	0.006	0.051***	0.050***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.018)	(0.017)
Number of beds	0.004***	0.005***	0.004***	0.004***	0.007***	0.007***	0.002	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Nurses per bed	0.009***	0.009***	0.009***	0.008***	0.009***	0.008***	0.036***	0.035***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.010)	(0.010)
Teaching Status	0.012***	0.012***	0.012***	0.012***	0.019***	0.020***	-0.017*	-0.017
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.010)	(0.010)
Locate in a MSA	0.005	0.007	0.003	0.004	0.009	0.010	0.034	0.039
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.027)	(0.027)
HHI	-0.017	-0.019	-0.021*	-0.022*	-0.021	-0.022	0.015	0.021
	(0.012)	(0.012)	(0.011)	(0.011)	(0.015)	(0.015)	(0.049)	(0.049)
% of never married	0.066**	0.065**	0.062**	0.060**	0.084**	0.081**	-0.368**	-0.366**
	(0.027)	(0.027)	(0.028)	(0.028)	(0.035)	(0.035)	(0.158)	(0.158)
% of HS dropouts	-0.074**	-0.075**	-0.059*	-0.059*	-0.115**	-0.115**	-0.083	-0.125
	(0.035)	(0.035)	(0.034)	(0.034)	(0.047)	(0.047)	(0.179)	(0.179)
% of HS grads	-0.026	-0.029	-0.030	-0.031	-0.068**	-0.071**	-0.294**	-0.274**
	(0.025)	(0.025)	(0.026)	(0.026)	(0.033)	(0.034)	(0.129)	(0.128)
Median earnings	0.002	0.002	0.003	0.004	-0.002	-0.001	-0.018	-0.018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.017)	(0.017)
% of male	0.045	0.027	0.115	0.100	0.089	0.070	0.777	0.836
	(0.138)	(0.138)	(0.135)	(0.136)	(0.185)	(0.184)	(0.725)	(0.720)
% of Hispanic	-0.029**	-0.020	-0.013	-0.003	-0.048**	-0.036*	-0.112	-0.104
	(0.014)	(0.014)	(0.014)	(0.014)	(0.020)	(0.019)	(0.079)	(0.080)
% of black	-0.026*	-0.019	-0.014	-0.008	-0.024	-0.017	-0.176**	-0.158*
	(0.016)	(0.016)	(0.016)	(0.016)	(0.021)	(0.021)	(0.084)	(0.084)
% of elderly	0.051	0.056	0.063	0.069	0.106	0.113*	-0.137	-0.207
	(0.053)	(0.052)	(0.052)	(0.051)	(0.069)	(0.068)	(0.284)	(0.282)
Population density	-0.004**	-0.004*	-0.003*	-0.003	-0.006***	-0.006**	-0.007	-0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.009)	(0.009)
Spatial (λ)	0.104***	0.104***	0.081***	0.079***	0.068***	0.068***	0.111***	0.100***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.018)	(0.020)

Market Strucure:								
For-profit		-0.002		-0.002		0.004		-0.012
		(0.008)		(0.008)		(0.010)		(0.028)
Not-for-profit		0.012*		0.012*		0.021***		-0.054**
		(0.006)		(0.007)		(0.008)		(0.023)
Number of beds		-0.002*		-0.003**		-0.002		-0.008**
		(0.001)		(0.001)		(0.001)		(0.004)
Nurses per bed		0.006*		0.008**		0.009*		-0.007
		(0.004)		(0.004)		(0.004)		(0.017)
Teaching Status		-0.004		0.001		-0.005		0.015
		(0.004)		(0.004)		(0.005)		(0.015)
sigma2	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.015***	0.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Invlogit(theta)	-0.573***	-0.563***	-0.474***	-0.465***	-0.468***	-0.460***	-0.257***	-0.248***
	(0.053)	(0.053)	(0.057)	(0.058)	(0.054)	(0.054)	(0.061)	(0.062)
Observations	8,376	8,376	8,376	8,376	8,376	8,376	3764	3764
R-squared	0.214	0.221	0.183	0.189	0.212	0.218	0.200	0.207
Number of id	2,094	2,094	2,094	2,094	2,094	2,094	941	941

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

Appendix Table II-2: Estimates of Spillover Effects and Hospital Characteristics on Heart Failure and Pneumonia Treatments

	Heart Failure		Pneumonia	
VARIABLES	(1)	(2)	(3)	(4)
For-profit	0.002	0.002	0.009**	0.009**
	(0.009)	(0.009)	(0.004)	(0.004)
Not-for-profit	0.027***	0.027***	0.020***	0.020***
	(0.007)	(0.007)	(0.003)	(0.003)
Number of beds	0.005***	0.005***	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Nurses per bed	0.010**	0.010**	0.000	-0.000
	(0.004)	(0.004)	(0.002)	(0.002)
Teaching Status	0.003	0.004	-0.009***	-0.008***
	(0.004)	(0.004)	(0.002)	(0.002)
Locate in a MSA	0.013	0.015	-0.003	-0.001
	(0.009)	(0.009)	(0.004)	(0.004)
HHI	-0.058***	-0.061***	-0.007	-0.011
	(0.018)	(0.018)	(0.008)	(0.009)
% of never married	-0.064	-0.064	-0.007	-0.002
	(0.059)	(0.059)	(0.028)	(0.028)
% of HS dropouts	-0.065	-0.063	-0.001	-0.004
	(0.066)	(0.065)	(0.032)	(0.032)
% of HS grads	0.013	0.008	0.023	0.018
	(0.048)	(0.048)	(0.024)	(0.024)
Median earnings	0.001	0.002	0.003	0.003
	(0.006)	(0.006)	(0.003)	(0.003)
% of male	-0.331	-0.367	-0.013	-0.040
	(0.293)	(0.294)	(0.109)	(0.109)
% of Hispanic	-0.011	-0.003	-0.046***	-0.043***
	(0.030)	(0.030)	(0.014)	(0.014)
% of black	-0.015	-0.011	-0.049***	-0.045***
	(0.030)	(0.030)	(0.015)	(0.015)
% of elderly	0.035	0.037	0.003	0.000
	(0.099)	(0.099)	(0.048)	(0.048)
Population density	0.000	0.001	-0.001	-0.000
	(0.005)	(0.005)	(0.003)	(0.003)
Spatial (λ)	0.107***	0.107***	0.155***	0.154***
	(0.014)	(0.014)	(0.013)	(0.013)

Market Structure:				
For-profit		-0.016		-0.014*
		(0.014)		(0.007)
Not-for-profit		0.002		-0.008
		(0.012)		(0.006)
Number of beds		-0.002		-0.001
		(0.002)		(0.001)
Nurses per bed		0.003		-0.002
		(0.006)		(0.003)
Teaching Status		-0.004		-0.009**
		(0.008)		(0.004)
sigma2	0.005***	0.005***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Invlogit(theta)	-0.457***	-0.454***	-0.559***	-0.558***
	(0.040)	(0.040)	(0.033)	(0.033)
Observations	8,768	8,768	8,536	8,536
R-squared	0.233	0.235	0.512	0.513
Number of id	2,192	2,192	2,134	2,134

Standard errors are in parentheses.
* Significant at 10%.
** Significant at 5%.
*** Significant at 1%.

VITA

NAME OF AUTHOR: Yin-Fang Yen

PLACE OF BIRTH: Tainan, Taiwan

DATE OF BIRTH: April 17, 1981

GRADUATE AND UNDERGRADUATE SCHOOLS ATTENED:

National Chung Cheng University, Chiayi, Taiwan
The University of Mississippi, Oxford, MS

DEGREES AWARDED:

Master of Arts in Economics, 2008, The University of Mississippi
Bachelor of Arts in Finance, 2003, National Chung Cheng University

AWARDS AND HONORS:

Syracuse University Graduate Assistantship, Fall 2008 – Present
University of Mississippi Graduate Assistantship, Fall 2007 – Spring 2008

PROFESSIONAL EXPERIENCE:

Teaching Assistant, Department of Economics, Syracuse University, 2008 – Present
Teaching Assistant, Department of Economics, University of Mississippi, 2008
Research Assistant, Department of Economics, University of Mississippi, 2007