ESSAYS ON U.S. HEALTH POLICY AND HOSPITAL CARE

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My dissertation consists of three chapters, each of which empirically examines impacts of U.S. health care policies on hospital care for a subgroup of disadvantaged populations. The first chapter studies the impacts of Medicaid coverage expansions for pregnant women on patient reallocation across hospitals. If patients from low-income zip codes, who are likely to gain coverage after expanded public insurance coverage, have limited hospital options due to a lack of payer source, they may be able to receive care at higher quality hospitals once they obtain coverage. Using Florida hospital data and the Nationwide Inpatient Sample (NIS) for 1988-1995, I find that low-income mothers who gained coverage following the expansions gave birth at higher quality hospitals—facilities with neonatal intensive care units and those with low postnatal complication rates. In the second chapter, I continue investigating the effects of expansion, but examine its impact on hospitals' provision of indigent care, along with the impact of the Balanced Budget Act of 1997, with its reductions in Medicare and Medicaid hospital payments, on hospitals' supply of indigent care. The definition of hospital indigent care is, for the purpose of this dissertation, based on uncompensated care costs in dollars, volume of the uninsured, and amounts of unprofitable services provided. Using the Florida hospital data for 1990-2000, I find that these two health care policies reduced hospitals' provision of indigent care, but to different extents, and that the policy impacts differed by hospital ownership type. The third chapter, a joint project with Kosali Simon, examines the impact of the Children's Health Insurance

Program on hospital utilization for low-income children. The expansion of public insurance coverage results in two contrasting effects that could increase or decrease hospital care for low-income children. On the one hand, the gain of public insurance coverage will increase access to primary care, and this may prevent hospitalizations, particularly those with ambulatory care sensitive conditions, to some degree. On the other hand, the coverage gain means lower costs of care and thus may increase hospital care across the board. Using the NIS for 1996-2002, we find that hospitalization rates and intensity of care increased overall, but these increases originated from increased non-ambulatory care sensitive hospitalizations.

BIOGRAPHICAL SKETCH

Eunkyeong Lee was born on September 17, 1978 in Daejeon, South Korea. She graduated from Seo-Daejeon Girls' High School in 1997, and completed her undergraduate education at Yonsei University in Seoul with a Bachelor of Arts in Economics. After college, she joined Bank of Korea, the central bank of Korea, as a junior economist, working in the research department on various issues related to international and financial economics, from 2001 to 2003. In 2003, she began her doctoral work in Economics at Cornell University, and received her Ph.D. in Economics from Cornell University in 2009.

To my parents

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CHAPTER 1

The Impact of Medicaid Expansion on Patient Reallocation Across Hospitals

I. Introduction

During the late 1980s and early 1990s, the U.S. government implemented two major health policies in order to improve health outcomes for low-income mothers. One was to provide more low-income pregnant women with public health insurance coverage, and the other was to provide medical care suppliers with higher payments for treating low-income mothers. A large body of prior research has shown that these policies succeeded in enhancing health outcomes for low-income patients, primarily through increasing the quantity of prenatal care: more visits to physicians and greater utilization of medical services during visits (Marquis and Long, 1999; Epstein and Newhouse, 1998; Currie and Gruber, 2001; Long *et al*, 2005). Despite extensive research on the achievements of the expansion policy, little is known about whether the expansion of public health insurance helps low-income mothers to receive care at higher quality hospitals. If those who obtain coverage also have better access to high-quality hospitals, in addition to better access to prenatal care, this will contribute to enhancing their health outcomes.

Previously, three studies examined how site of care for low-income pregnant women responded to Medicaid policy changes: Baker and Royalty (2000) for physician care; Duggan (2000) and Aizer *et al* (2005) for hospital care. Baker and Royalty (2000) studied impacts of Medicaid expansions and physician fee increases on reallocation of low-income mothers across physicians and showed patient reallocation between public and private physicians. Concerning hospital care, Duggan (2000) and Aizer *et al* (2005) found that increased Medicaid payments through the Medicaid

Disproportionate Share Hospital (DSH) program[1] reallocated low-income mothers from public to private hospitals. With caution, both Baker and Royalty (2000) and Aizer et al (2005) suggested that this movement from public to private care providers enhanced quality of care, and thus should have improved health outcomes: Baker and Royalty (2000) believed that physician care in a private setting allows for more continuity of care, while Aizer et al (2005) assumed that private hospitals are likely to be higher quality because these are mainly used by privately insured patients, who have few constraints on hospital choice. Inspired by these three studies, I explore the impact of Medicaid coverage expansions on patient reallocation across hospitals, comparing several attributes of hospitals utilized by maternity patients before and after the policy change. Studying maternity patients has several advantages. First, virtually all babies are delivered in a hospital, unlike many diseases for which patients may or may not select hospital care. Therefore, we can get almost a full sample of childbirth patients and rule out selection problems. Second, pregnant women have enough time to research hospitals, compared to other patient groups that usually do not have such a long time to decide on their care providers. Third, a more practical reason to study birth is that pregnant women were major beneficiaries of nationwide Medicaid expansion policies in the late 1980s and early 1990s. Increased income thresholds for Medicaid eligibility during this period provided a larger number of low-income pregnant women with public health insurance coverage.

Ideally, I would like to examine whether maternity patients who were previously uninsured but gained public insurance coverage were reallocated between hospitals, and, if they were, whether such changes were associated with improved quality of care, i.e., increased access to higher quality providers. However, the data

[1] Medicaid DSH payments are supplemental payments to hospitals that serve disproportionately large numbers of low-income patients.

sets available to me, Florida hospitals' discharge data and the Nationwide Inpatient Sample (NIS), lack patient income information. Therefore, I use patients' zip code median household income to classify patients into treatment and control groups, and study patient reallocation across zip code income categories.

The objective of this paper is to empirically examine whether maternity patients from low-income zip codes are reallocated to different types of hospitals after Medicaid expansions, and if so, whether these hospitals are higher quality. Those from low-income zip codes are more likely to be uninsured and indigent, so have a higher probability of gaining coverage when the Medicaid program increases eligibility income thresholds. As a result, I expect that those from low-income zip codes are more likely to move to different hospitals after Medicaid expansions, particularly to those of higher quality if lack of coverage restricted their hospital options previously.

Despite ongoing interest in quality of hospital care and a great deal of effort toward inventing a valid measure[2], there is no consensus about which aspects of quality to measure (Jha et al, 2006). In this paper, I categorize hospitals based on hospital attributes and clinical outcomes—ownership type, teaching status, presence of NICU, obstetric volume, bed capacity, urban/rural status, and postpartum complication rates—and compare attributes of hospitals used by maternity patients from low-income zip codes before and after Medicaid expansions. In particular, I focus on two hospital attributes that directly measure quality of hospital care—neonatal intensive care units (NICU) and postnatal complication rates—and examine whether utilization of hospitals with NICU or those with low complication rates increased among those from low-income zip codes after Medicaid expansions. Although hospitals may adjust their quality of care in response to policy implementations, this paper will not discuss

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[2] Hospital Compare (the Center for Medicare and Medicaid Services), Quality Check (the Joint Commission), US News and World Report, the Leapfrog Group Hospital Survey, HealthGrade, New York State Report Card, and so on.

those possible changes in hospital quality, but only discuss changes in sites of hospital care in settings in where hospital quality is not an endogenous variable.

In order to examine the impact of coverage expansions on patient reallocation, I use discharges from all hospitals in Florida as well as 20 percent of community hospitals in the NIS, and select patients aged 15-44 who were hospitalized to give birth during 1988-1995. Without patient income information, I construct my treatment group and control groups based on patient zip code median household income: the treatment group is comprised of those whose zip code income levels were between 100 and 185 percent of the federal poverty level (FPL) (the income range that was above the eligibility income threshold prior to Medicaid expansions and below the income threshold after the expansions); the two control groups are: those whose zip code income levels were below 100 percent of the FPL and those whose zip code income levels were above 185 percent of the FPL.

Conducting two sets of analysis, at the hospital level and at the patient level, I compare types of hospitals used by patients in the treatment group and those in the control groups. In the hospital level analysis, I examine whether the proportion of maternity patients in the treatment group increased at a certain type of hospital after Medicaid expansions. For example, if those in the treatment group obtained coverage and moved to hospitals with a NICU, the proportion of these mothers would increase at NICU hospitals. In the patient level analysis, I use conditional logit models to examine which of the hospital attributes determined patients' choice of hospitals. In the national setting, however, lack of patient zip code information and a sampling nature in the NIS force me to use binary logit or linear probability models. Using each of the hospital attributes as a dependent variable, I separately estimate whether or not those from low-income zip codes chose hospitals with one attribute rather than hospitals without that attribute: for example, whether they chose FP hospitals over

NFP hospitals. Also, the availability of patient race information for some states allows me to investigate racial disparities in access to high-quality hospitals. Since non-whites are over-represented among low-income patients, increased public insurance coverage is expected to reduce racial disparities in both quantity and quality of care.

I find some evidence that Medicaid expansions helped those from low-income zip codes to give birth at higher quality hospitals. In Florida, the two eligibility expansions in 1989 and 1992 reallocated patients across hospitals to different extents. The 1989 expansion, which was the eligibility expansion alone, appeared to increase access to safety-net hospitals (teaching and public hospitals), hospitals with NICU, and those with good clinical outcomes. However, when the eligibility expansion was paired with a physician fee increase in 1992, maternity patients from low-income zip codes had further increased hospital choice sets, including hospitals of private ownership and hospitals with better clinical outcomes. The size of patient reallocation was larger after the 1989 expansion, which was targeted toward extremely indigent patients. In the national setting, my findings are consistent with those in Florida, particularly the results from the 1989 expansion. In other words, maternity patients from low-income zip codes were able to deliver at better safety-net hospitals and those with good clinical outcomes. I also demonstrate that maternity patients of color benefited the most, implying that racial disparities in access to high quality providers were somewhat reduced after coverage expansions.

The outline of this paper is as follows. Section II describes the background of Medicaid policy changes, and Section III provides the conceptual framework. Section IV summarizes the findings of previous literature, and Section V explains empirical strategies and data sets. My results are discussed in Section VI, and Section VII provides further discussion and concludes the paper.

II. Background on the Medicaid Program

Medicaid is an entitlement program under Title XIX of the Social Security Act, jointly funded by state and federal governments. Since its establishment in 1965, the Medicaid program has been a major source of health insurance for low-income individuals who otherwise would not be able to afford private health insurance. States have broad discretion to decide eligibility, scope of services and reimbursements. Before 1984, Medicaid eligibility was closely tied with the Aid for Families to Dependent Children (AFDC) program, so that only indigent, single mothers were eligible for Medicaid, and its income cutoffs were fairly low (Gruber, 1997).

Between 1984 and 1987, however, the restriction on family structure had been lifted, and income cutoffs for Medicaid eligibility were raised significantly. By 1992, all states were required to provide Medicaid coverage to all children under age six and pregnant women with family income up to 133 percent of the federal poverty level (FPL), with the option of extending coverage up to 185 percent of the FPL. As a result, the fraction of women eligible for Medicaid greatly increased, from 20 percent in 1986 to about 45 percent in 1992 (Currie and Gruber, 1996). As in Currie and Gruber (2001), I take advantage of the variations in size and timing of the expansions across states in the study of the national sample.

Before examining the policy impacts with the national sample, I extensively study hospitals and patients in the state of Florida[3]. Following the federal requirements, Florida extended Medicaid coverage three times in October 1987, July 1989, and May 1992[4]. Although the first event in 1987 was the largest increase in the eligible income limit from 47 to 100 percent of the FPL, I can only examine the last

[3] I choose the state of Florida because of many interesting features in its health care market, as well as the availability of the hospital universe and detailed data. Florida has the second highest uninsured rates in the nation—19.2 percent of the non-elderly population—and the fourth largest Medicaid population.
[4] Table 1.1 summarizes the Medicaid policy changes related to obstetric care in Florida for 1987-1995.

two expansions (1989 and 1992) because data collection began only in 1988. In July 1989, the income eligibility threshold was raised from 100 to 150 percent of the FPL, and then it was raised further, up to 185 percent of the FPL, in May 1992. Figure 1.1 shows Medicaid enrollment growth and the trend of Medicaid deliveries in Florida. Although I cannot separate the enrollment of pregnant women from total enrollment, the growing Medicaid enrollment, along with increased number of Medicaid deliveries in the late 1980s and the early 1990s, confirms that the Medicaid expansion policy effectively helped low-income mothers to gain coverage and seek health care[5].

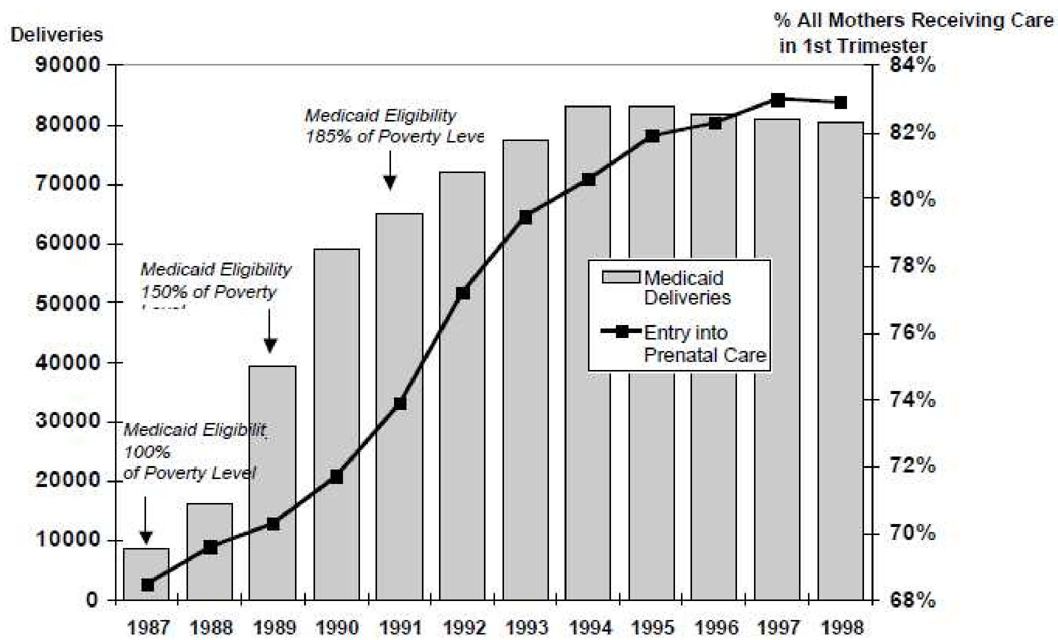
In addition to the increased income limits, Medicaid physician fee for obstetric care also increased in the nation (Currie et al, 1995): on average, the Medicaid to private fee ratio increased from 0.52 in 1989 to 0.80 in 1993. Also, the Florida government twice raised Medicaid physician fees for obstetric care. Firstly, in 1988, there was a large fee increase for global obstetric care[6] from \$315 to \$800 (\$1100 for high-risk patients)[7]. Secondly, in 1992, the global fee structure was switched to a separate fee system, under which physicians were paid \$800 (\$1100 for high-risk patients) for a delivery only, with an additional fee of \$50 for a prenatal or postnatal care visit. For example, if a pregnant woman with Medicaid made 8.7 prenatal visits and one postnatal visit, i.e., the average number of prenatal and postnatal visits (Currie *et al*, 1995), the physician who treated her would receive \$485[8] in addition to \$800, the fee for a non-high-risk delivery. Compared to the physician fee before 1992, the global obstetric fee increased 60 percent per patient (Norton, 1995): as a percentage of private payers' average charges, Medicaid physician fees increased from 47 percent in 1989 (Schwartz, 1991) to 66 percent[9] in 1992.

[5] Since researchers did not find any increasing trend in births among Medicaid-eligible mothers (DeLeire *et al*, 2007), this increase in enrollment is not attributed to an increase in fertility.
[6] Global obstetric care includes prenatal care, delivery, and postnatal care.
[7] In Florida, the Medicaid physician fees for vaginal deliveries and c-sections were the same.
[8] $(8.7+1)\times\$50=\$485$.
[9] I estimate this value based on the method discussed in Section VI.

[Table 1.1] Florida Medicaid Policies During 1987-1995

Medicaid Eligibility Expansions	Effective Date
Income eligibility expanded from 47% to 100% of FPL	October 1987
Income eligibility expanded from 100% to 150% of FPL	July 1989
Income eligibility expanded from 150% to 185% of FPL	May 1992
Medicaid Obstetrical Fee Increases	Effective Date
Raising obstetrical global fees from $315 to $800	1988
Instituting a new global fee for $1100 for high-risk pregnant women	
Global obstetrical fees eliminated: new delivery-only fees of $800 and $1100 established for low- and high-risk deliveries, respectively.	July 1992
New per visit fee of $50 created for prenatal care, capped at 10 visits per pregnancy for low-risk women and 14 visits for high-risk women	
New per visit fee of $50 created for postpartum care, capped at two visits per pregnancy.	
New fee of $50 created for administration of Healthy Start risk assessment screen; $100 if completed in first trimester	

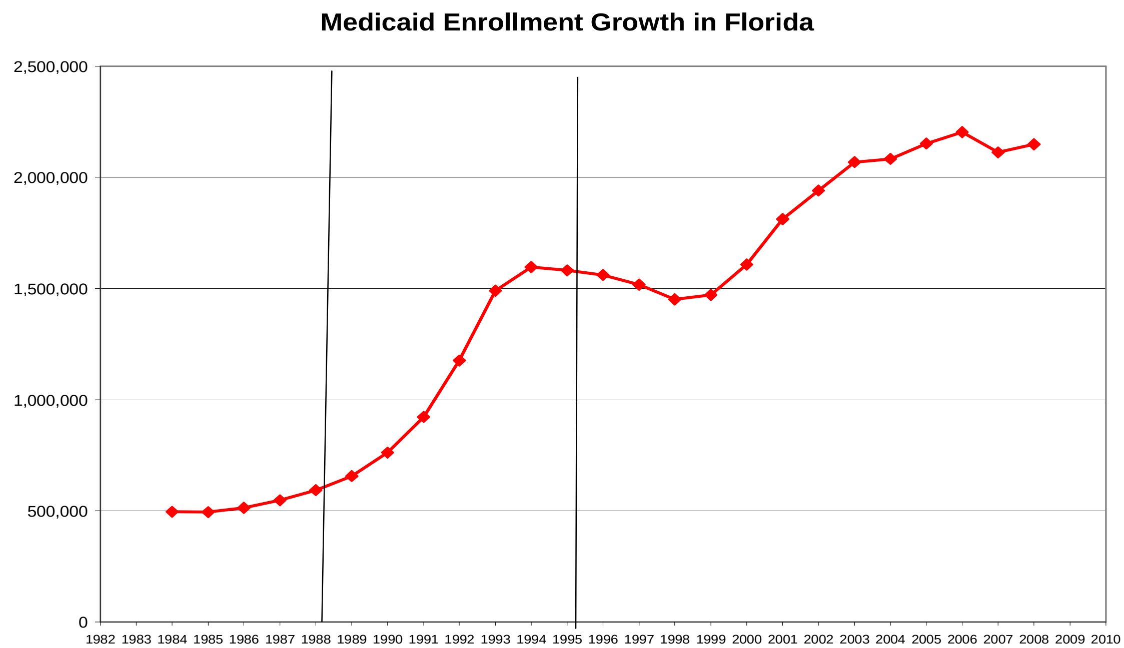
Source: Hill *et al* (1998)



Source: Medicaid delivery data from "The Effects of the Florida Medicaid Eligibility Expansion for Pregn: Women," by RAND (adjusted); ACHA Health Policy and Analysis. Early prenatal care from DOH Annual Statistics Report, 1987-1998.

A. Medicaid Eligibility Income Threshold and Delivery

[Figure 1.1] Florida Medicaid Eligibility, Delivery, and Enrollment



Source: Social Services Estimating Conference, various years. Downloaded from http://collinsinstitute.fsu.edu/research/table/71#http://collinsinstitute.fsu.edu/research/table/71

B. Medicaid Enrollment
[Figure 1.1] continued

III. Conceptual Framework

Hospital Care Decision

Traditionally, low-income uninsured patients have limited hospital options to the extent that they have to depend primarily on safety-net hospitals, i.e., public or major teaching hospitals. These hospitals take care of the majority of low-income patients under an obligation to provide care for the indigent in return for receiving government funds. By contrast, non-safety-net hospitals, particularly high-quality institutions, may be reluctant to accept low-income uninsured patients due to uncertainty about receiving payment for providing care.

The site of hospital care is determined by patients, physicians, and hospitals: patients demand hospital care, hospitals supply the care, and physicians link these two sides. Once a patient chooses her physician, her hospital options are restricted to those which the physician has admitting privileges with. In that sense, patients' hospital choices are influenced by their physicians to a great extent (Luft et al, 1990; Burns and Wholey, 1992). However, patients can play a major role in selecting hospitals by choosing treatment physician-hospital bundles (McGuirk and Porell, 1984; Tay, 2003), and by actively expressing their preferences to physicians (Wolinsky and Kurz, 1984). If physicians, as agents, take into account patients' preference for hospitals, or if physicians' hospital choice depends on many of the same factors that influence patients' hospital choice, physicians' choice of hospitals will reflect the outcomes as if patients maximize utility by independently choosing hospitals (Porell and Adam, 1995). In this paper, whether patients themselves or their agents (physicians) choose hospitals is not an important issue. What matters is that whoever selects a hospital has relative preferences for one hospital attribute over the other (e.g. teaching hospital over non-teaching hospital) when all other attributes are constant, and these relative preferences should be systemically reflected in hospital admissions.

I conjecture that Medicaid expansions provide incentives for both the supply side (hospitals) and the demand side (low-income patients) to change their behavior with regard to hospital admission and selection patterns, respectively. The rationale behind this conjecture is based on the following two assumptions: first, hospitals, maximizing profits or some combination of profits and other elements, prefer paying patients; second, all else being equal, patients will choose the highest quality hospitals among those available to them.

On the supply side, hospitals can rank patients based on profitability: according to the Lewin Group (2005), hospitals' payment-to-cost ratio is 1.22 for the privately insured (most profitable), 0.14 for indigent and uninsured patients who usually incur uncompensated care (the least profitable), and the profitability of

Medicaid patients is between these two (Medicaid hospital payments including DSH cover 92% of the costs). Due to hospitals' preference for profitable patients, I conjecture that a level of access to different types of hospitals varies according to the profitability of their payer source, i.e., patients' coverage types. In particular, opportunity costs of treating those without coverage may be greater for high-quality hospitals, which can attract a large number of privately insured patients. As a result, low-income uninsured patients are expected to have the most difficulty in accessing high-quality care, in addition to have the least access to care in overall. Despite low reimbursement, hospitals receive guaranteed payments for treating Medicaid patients. The certainty of Medicaid payments, as well as higher amounts than those received from average uninsured patients, suggests that Medicaid patients are more profitable than low-income uninsured patients, who mostly end up paying a significantly small amount (14% of the costs), or paying nothing at all (uncompensated care). Therefore, Medicaid expansions, by changing insurance status of nearly poor mothers from uninsured to Medicaid, create more profitable patients for hospitals and consequently increase the pool of patients with a reliable payer source. With the increased profitability of low-income mothers, I hypothesize that coverage expansions would increase hospitals' willingness to provide care to low-income mothers, including high-quality institutions. Obviously, the underlying assumption is that hospitals have extra capacity to admit additional patients, and marginal revenue from a low-income patient is greater than marginal cost of treating her. Considering low occupancy rates in the 1990s—59 percent in Florida[10] and no more than 65 percent in the nation (Bazzoli *et*

[10] I calculate this occupancy rate based on obstetric care only for Florida hospitals, which is total inpatient days divided by total available bed days corresponding obstetric care. 59 percent is the average of the occupancy rates for 1988-1995.

al, 2003)[11]—I conjecture that hospitals did have room for additional patients as long as the marginal revenue of care is larger than the marginal cost.

On the demand side, patients' hospital choice depends on various factors, such as preference, convenience, knowledge, experience, insurance coverage, quality of care, hospital reputation, and recommendations by friends and physicians. In this paper, I am only able to examine the relationship between changes in insurance coverage and hospital choice, assuming that all else is constant, or other effects are averaged out. Medicaid expansions provide indigent mothers with not only low-cost health insurance coverage, but also possibly more and better hospital options. As a result, those who gain coverage are expected to reoptimize their utility functions and thereby select the best hospital given a new, expanded choice set.

Combining the effects on the demand and supply sides of hospital care, I hypothesize that the expansion of the Medicaid program would have reallocated low-income mothers between hospitals, and that the hospitals used by low-income mothers who gained coverage would be of higher quality than those used by uninsured low-income patients.

My hypotheses above are based on several assumptions. On the supply side, the underlying assumption is that hospitals available to low-income uninsured patients are different from those available to paying patients, including Medicaid patients, and the latter may be of higher quality than the former. However, if hospitals do not view Medicaid and uninsured patients very differently due to low Medicaid payments, I will find little reallocation effects after the expansion. For the robustness check, I will use variations in Medicaid payments across states and examine whether states with lower Medicaid payments had smaller reallocation effects. On the demand side, the

[11] Although there are regional and seasonal variations in hospital occupancy rates (higher occupancy rates in regions with larger black populations and during the winter) (Chiswick, 1975), occupancy rates had been universally low across the nation until the mid 1990s.

underlying assumption is that patients who gain coverage, in order to move to different hospitals, should be able to access physicians who have admitting privileges at the hospitals to which they want to move. This implies that patients with Medicaid coverage may see a different set of physicians than they could without coverage, and these new physicians have admitting privileges with higher quality hospitals. Alternatively, the patients may see the same set of physicians, but the gain of Medicaid coverage can help them to be referred to their preferred hospitals in the following process: on the patient side, those who gained coverage may make more visits to physicians or increase interactions with physicians during a visit, which improve physicians' understanding of patient health and preference, and thereby enhance matching processes between patients and hospitals; on the physician side, expected Medicaid payments may provide a greater incentive to increase interactions with patients and accommodate their preferences. If this intermediate process fails, we may see little effect on patient reallocation.

On the demand side, there are at least four other factors that could potentially reduce policy impacts on patient reallocation: low take-up rates, crowding-out effects, low elasticity of demand for high-quality care, and residential segregation. First, not all of the Medicaid-eligible population takes up Medicaid: even if a larger number of low-income individuals become eligible for Medicaid, only those who actually enroll in the program can take advantage of its benefits. Considering that a high percentage of births (35-40%) have been financed by Medicaid, however, low take-up rates may be less of a problem. Second, the crowding-out group are those who previously had private or other forms of coverage but switched to Medicaid. Since private insurance payers provide more generous reimbursements (Currie and Gruber, 2001), the crowding out group are likely to receive lower quantity and quality of care if they switch to Medicaid. I will address concern about crowding-out effects in Section V.

Third, low-income patients who face lower costs of care and better hospital options as a result of the coverage expansion may not be very responsive to the quality of hospital care: for those with low socioeconomic status, their marginal costs (in terms of time and money) of searching new (high-quality) hospitals may be extremely high compared to their marginal benefits. Fourth, they actually may be willing to move to higher quality hospitals but unable to do so if they reside in areas where high-quality hospitals are too far away (Currie and Thomas, 1995; Aizer et al, 2005). There is some evidence that hospital racial segregation is partly due to residential segregation (Smith, 1998; Sarrazin et al, 2009). If the same logic is applied to disparities in access to high quality care between low-income and high-income patients, low-income patients may have more constraints on access to high-quality care because their residence is geographically isolated from high-quality hospitals.

<u>Hospital Quality</u>

Hospital quality is a complex, multi-dimensional concept, which can range from clinical outcomes to resource utilization, treatment intensity, patient safety, and satisfaction. Recently, a great deal of attention has been paid to hospital quality with regard to patients' choice of hospitals (Luft *et al*, 1990; Burns and Wholey, 1992; Phibbs *et al*, 1993; Hodgkin, 1996; Chernew *et al*, 1998; Tay, 2003; Howard, 2005). Despite limited information in hospital administrative data, previous studies widely used clinical outcomes as a direct quality measure (mortality or complication rates), and considered hospital attributes such as hospital ownership, teaching status, high-tech services, patient volume, medical staff level, or bed capacity as an indirect quality measure. Particularly for obstetric care, possible outcome quality measures are neonatal mortality rates (Phibbs *et al*, 1993), complication rates (Romano *et al*, 2005), adverse outcomes (Epstein *et al*, 2008), and other procedure and patient safety indicators invented by the HCUP. In this paper, I use the risk-adjusted postpartum complication rates for the clinical outcome measure.

Unlike the direct quality measure, how to interpret the indirect measures is debatable. Among those indirect quality measures, hospitals with NICU are unambiguously considered higher quality providers than hospitals without a NICU. For the rest of hospital attributes, however, it is not clear whether a hospital with one attribute is better than the one without it. In particular, the relationship between hospital ownership and quality of care is highly controversial (Eggleston *et al*, 2006). Some argue that FP hospitals provide higher quality care in order to attract profitable patients (Mukamel, 1999; Taylor et al, 1999; Sloan, 2003), while others claim the opposite: FP hospitals provide lower quality of care because profit maximizers only care about profits, but not the quality of care (Shen, 2002; McClellan and Staiger, 1999; Norton, 1998). Another argument is that the quality of care does not differ by hospital ownership type (Sloan et al, 2001), or at least not between private FP and private NFP hospitals.

Similarly, the relationship between teaching status and quality of care is uncertain. Generally, teaching hospitals are known to provide high-quality care for heart diseases and other surgical procedures (Kupersmith, 2004), but there is no such evidence for obstetric care (Finkelstein *et al*, 1998). In fact, Phibbs *et al* (1993) found that privately insured patients preferred non-teaching hospitals because they provide a more private environment during delivery. Larger and higher volume hospitals seem to offer more efficient and better-quality care, but again, there is no consensus about the relationship between hospital size (or volume) and the quality of care: the hospital size reflects a level of services available, and larger facilities can produce economies of scale, which improves resource allocation; some studies showed that a higher patient volume is positively correlated with lower infant mortality (Rogowski *et al*, 2004; Phibbs *et al*, 2007), and HealthGrades (2007) take obstetric volume into account when they determine hospital rankings.

IV. Literature Review

Prior research on Medicaid policy can be categorized into two groups: studies on coverage expansions and studies on payment increases. The coverage expansions directly provide health insurance coverage for a larger number of low-income, medical care consumers, whereas the payment increase creates financial incentives for medical service providers to offer more care to them.

A substantial amount of research has been devoted to the costs and benefits of the Medicaid expansion policy. In particular, previous literature has highlighted the achievements of this policy for the demand side: increased access to care, and enhanced health status for low-income mothers and newborns (Marquis and Long, 1999; Epstein and Newhouse, 1998; Curie and Fahr, 2001; Currie and Gruber, 1996 and 2001; Kaestner et al, 1999; Long *et al*, 2005; Dafny and Gruber, 2005). However, the impact of this policy on the supply side has been overlooked, although Medicaid expansions can also alter suppliers' motivation in relation to the provision of medical care for low-income patients. More specifically, Medicaid expansions increase hospitals' expected payments for treating those who were previously uninsured but became eligible for Medicaid. The certainty of payments for treating these patients may motivate hospitals and physicians to accept more low-income patients. If higher quality providers become more available to the new Medicaid population, this increased access to higher quality of care will be another channel that leads to improved health outcomes for low-income patients. However, this mechanism has not been discussed as the impact of coverage expansions.

For policies concerning payment increases, the following three policies have been discussed at length: first, changes in Medicaid hospital reimbursements (Dranove and White, 1988; Dafny, 2005); second, the Medicaid DSH program (Aizer *et al*, 2005; Baicker and Staiger, 2005; Coughlin, 1998, 2000, 2001 and 2005; Duggan, 2000); and third, changes in Medicaid physician fees (Currie *et al*, 1995; Cohen and Cunningham, 1995; Baker and Royalty, 2000; Gray, 2001; Cunningham and Nicholas, 2005; Decker, 2007). Except for Baker and Royalty (2000), Duggan (2000), and Aizer *et al* (2005), all of these studies focused on the increase in quantity and intensity of care in response to one of the three policy changes.

Among the few exceptions, Baker and Royalty (2000) examined the impacts of Medicaid expansions and obstetric physician fee increases on reallocation of maternity patients in terms of physician care. Using the 1987 and 1991 Survey of Young Physicians, they found some intriguing results as follows: Medicaid expansions increased access to physicians who worked in public settings such as hospital clinics and emergency rooms, but not to those working in private offices; however, increased physician fees made those private physicians available to low-income patients. Since their study assumed that private physicians provided higher quality care, their findings suggest that low-income mothers received better physician care after the fee increase. If this increased access to higher quality physicians led them to give birth at higher quality hospitals, one can expect greater improvements in their health outcomes. However, they did not discuss the policy impacts on hospital care.

As for hospital care, both Duggan (2000) and Aizer *et al* (2005), using California hospital data from the early 1990s, examined the impact of the Medicaid DSH program on patient reallocation and health outcomes. The findings of these two studies imply that low hospital payments might have put Medicaid patients at a disadvantage, with restricted hospital options, but the extra DSH payments enabled them to receive treatment at hospitals of the same quality as those used by the privately insured. Duggan (2000) showed that Medicaid mothers, who became more profitable due to the DSH payments, were reallocated from public to private hospitals, but he did not find evidence for improvement in their health outcomes. However, Aizer *et al* (2005) found that the DSH program did improve health outcomes for Medicaid mothers by moving them to the same hospitals used by privately insured mothers. Although Duggan (2000) studied the impact of the DSH program on reallocation of Medicaid mothers in California for 1988-1995, when Medicaid coverage was greatly expanded as well, he did not take into account possible effects of the coverage expansions. Also, he examined the reallocation with regard to hospital ownership type alone, but not with regard to overall quality of hospitals. In this paper, I use several hospital characteristics to determine quality of hospitals, and examine the impact of Medicaid expansions on reallocation of low-income mothers. Unlike Aizer *et al* (2005), who implicitly assumed the reallocation of Medicaid mothers towards higher quality hospitals after the increase in Medicaid DSH payments and mainly discussed their improved health outcomes, I explicitly study the reallocation mechanism through which the expansion policy may lead to improved health outcomes, examining the switch to higher quality of hospitals among low-income mothers.

Patients' choice of hospital has been widely discussed in many different settings. To my knowledge, however, no study has related the Medicaid expansion policy to hospital choice behavior of low-income patients. Though not very recent, Porell and Adams *et al* (1996) produced an excellent review of hospital choice models. Based on their study, I find that previous studies have several features in common. Firstly, the majority of them have restricted their samples to Medicare patients hospitalized with heart disease, because they have identical hospital choice sets and out-of-pocket costs of care. Phibbs *et al* (1993) and Gaskin *et al* (2001) are the only two studies that examined Medicaid mothers' hospital choice. Phibbs *et al* (1993) used cross section data of California in 1985, so they were unable to examine changes in hospital admissions or selection patterns over time. Gaskin *et al* (2001) did examine the change in the type of hospitals used by low-income mothers in response to increased price competition, but they did not relate Medicaid policies to hospital choice. Moreover, their binary logit models can explain only one of many aspects of hospital quality, so they examined whether or not low-risk Medicaid mothers went to safety-net hospitals. As a result, they did not provide a comprehensive explanation for how other hospital attributes influenced patients' hospital choice. Secondly, prior research has focused on the role of patient characteristics such as race, severity of illness, income, or insurance type in the hospital choice model (Nichols, 2005; Aizer *et al*, 2005). However, this paper focuses more on how hospital attributes, particularly quality of hospitals, influenced patients' hospital selection decisions.

Admittedly, patients' hospital choices are influenced by their physicians to a certain degree. Like most previous research, except for Burns and Wholey (1992), lack of data is the reason that I cannot control for physician characteristics in my hospital choice model. As explained in Section III, However, I agree with Tay (2003) that patients do play a major role in selecting hospitals by choosing physicians who are more likely to have the same preferences as to hospitals or to accommodate their tastes (Dranove *et al*, 1992), and by letting their preferences be known to physicians. Ultimately, it is the patient who makes the final decision, based on the best information available from her physician and all other possible sources.

Finally, literature in epidemiology and public health provides some explanations for how well aggregate level income variables such as zip code income predict individual income levels. Using zip code income as a proxy for individual income could be problematic, and the magnitude of biases resulting from using this aggregate income level varies by the size of the zip code and the year in which the zip code was established[12]. I expect a correlation between individual household income and zip code income for the 1990 Census to be between 0.3 and 0.5 because of the following reasons: Soobader *et al* (2001) presented the correlation between individual income and 1990 census tract/block income as 0.43-0.44, by merging the National Health Interview Survey (NHIS), which includes individuals' family income information, with census tract/block income in the 1990 Census. Considering that zip code and census tract income levels are highly correlated (0.78-0.88), the correlation between zip code income in the 1990 Census and individual household income is expected to be lower than 0.44, but above 0.30. This is consistent with the correlation for the 1980 Census: Geronimus *et al* (1996) showed that the correlation between zip code income in the 1980 Census and personal income is about 0.4, linking two data sources, the Panel Study of Income Dynamics (PSID) in 1985 and the National Maternal and Infant Health Survey (NMIHS) in 1988, to the 1980 Census data (the correlation was 0.39 for the PSID and 0.35 for the NMIHS). Since the correlation between zip code income and individual income level, 0.4, is quite modest, I study policy effects across zip code income groups, instead of using zip code income as a proxy for patient income.

[12] I consult with Nancy Krieger, who is an expert in the relationship between aggregate level and individual level socioeconomic variables.

V. Data and Empirical Strategy

(1) Data

To examine whether Medicaid expansions reallocated low-income mothers across hospitals, ideally, I would like to use longitudinal data sets for women who gave birth at least twice during my study period, the first time when they were uninsured and the second after they obtained coverage. Then I would be able to compare their site of care before and after the coverage change. Unfortunately, such data set does not exist. My main data sources are Florida hospital data and the Nationwide Inpatient Sample (NIS): both are pooled cross-section. The Florida data sets, provided by the Florida Agent for Health Care Administration (AHCA), consist of hospital discharge and financial data files, and include the universe of Florida hospitals. The discharge data sets contain patient information such as age, race[13], sex, residential county and zip code[14], payer source, DRG code, principle diagnosis and procedure code, type and source of admission, and total charges. The hospital financial data sets contain hospital information such as ownership type, teaching status, bed capacity (number of licensed beds), presence of neonatal intensive care units, obstetric volume (number of labor/delivery procedures), and hospital location (county and zip code). Using hospital identifiers, I merge these hospital variables with the discharge data sets.

The NIS is the counterpart of the Florida inpatient discharge data sets in the national setting. Since 1988, the Healthcare Cost and Utilization Project (HCUP) has annually released all inpatient discharges of a 20 percent sample of U.S. community

[13] Patients' race information in Florida is available from 1992 onwards.
[14] In my analysis, patient zip code information serves two purposes: first, I use patient zip code income as a proxy for patient household income, so that I identify my treatment and control groups based on the zip code income levels; second, distance to hospital from patient residence is the distance between patient zip code and hospital zip code.

hospitals[15] from participating states. The NIS provides patient information similar to the Florida discharge data, but limited hospital information: hospital location (state, county, and zip code), ownership type, teaching status, bed capacity, and urban/rural status are included, but NICU variable is not available. The weakness of the NIS is lack of patients' zip code information, but the NIS includes two indicator variables for the range of zip code income levels: ZIPINC4 breaks down zip codes into four income categories, while ZIPINC8 breaks down zip codes into eight categories. The advantage of using the NIS is that the availability of patient race information for several states[16] in some years enables me to examine racial disparities in the policy effects.

From the Census 1990 and 2000, I obtain zip code level data such as household median income, longitude, latitude, and historical poverty thresholds.

(2) Sample Construction and Identification Strategy

My sample is restricted to pregnant women aged 15-44 who were hospitalized for childbirth[17] during 1988-1995 in the Florida discharge data sets, as well as those in the NIS (8 states for 1988 and 19 states for 1995). Patients admitted through emergency rooms are not included in the main analysis, but separately analyzed in a later section. Transferred patients from other hospitals/institutions are dropped along with those treated at hospitals where fewer than ten deliveries were performed in a year[18].

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[15] Community hospitals are defined as short-term, non-Federal, general and other hospitals, excluding hospital units of other institutions (e.g., prisons). They include OB-GYN, ENT, orthopedic, cancer, pediatric, public, and academic medical hospitals; however, long-term care, rehabilitation, psychiatric, and alcoholism and chemical dependency hospitals are excluded, unless these types of discharges are from community hospitals (HCUP, 2008).

[16] Patients' race information is available for California, Iowa, Massachusetts, and New Jersey (1988-95); Colorado, Connecticut, Kansas, Maryland, New York, and South Carolina (1993-95); Florida and Wisconsin (1992-95).

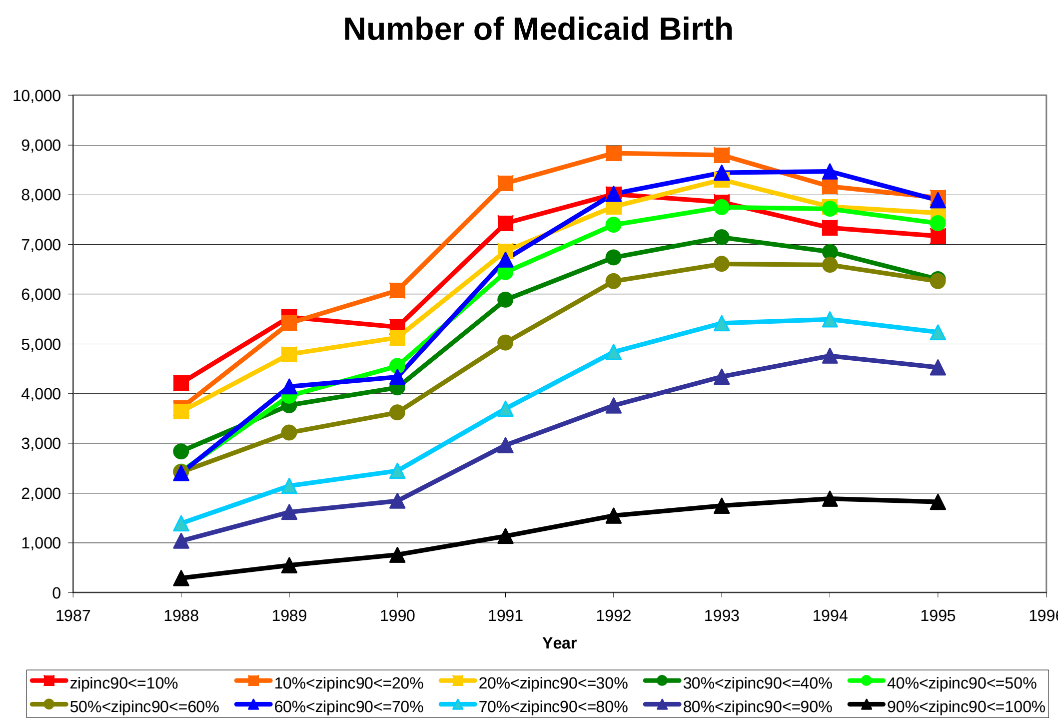
[17] Childbirth patients are identified by their DRG codes (370-375).

[18] Ten and seven percent of the discharges in Florida and in the NIS report admissions through emergency room, respectively.

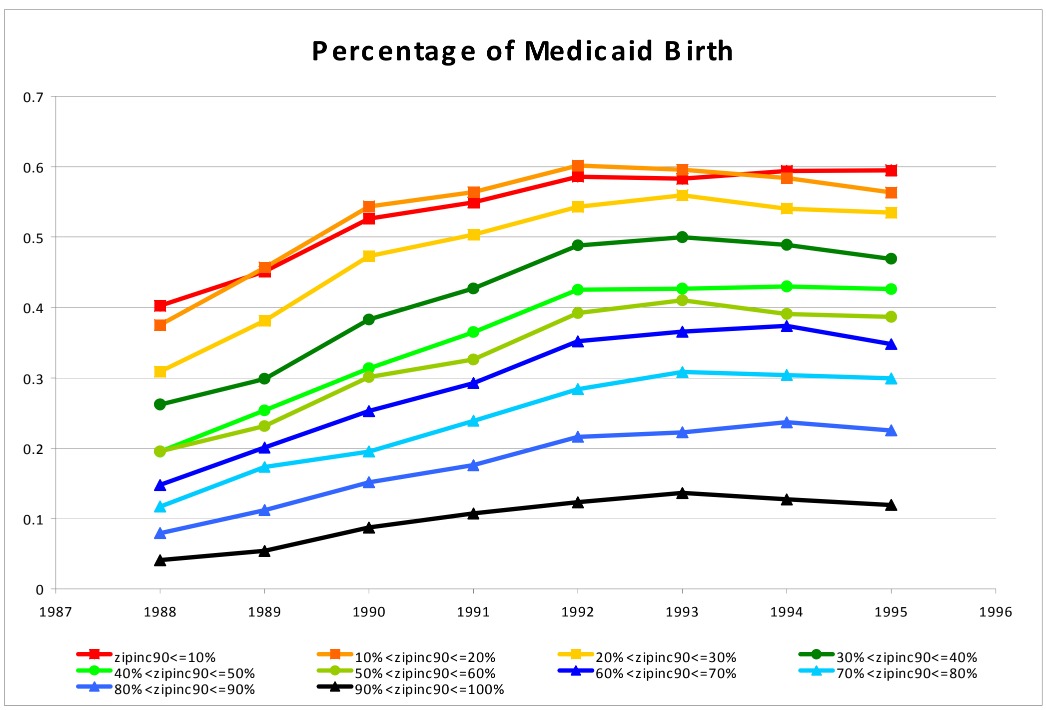
Now, I need to identify low-income patients who obtained coverage after the expansion policy. As mentioned above, with the ideal (longitudinal) data unavailable, the other method to identify new Medicaid-eligible patients is to use patients' household income and examine whether their income levels were between 100 and 185 percent of the FPL (the old and new income threshold for Medicaid). The challenging task is to identify this patient subgroup with patients' income information unavailable: neither the Florida data nor the NIS do not provide patients' household income information[19].

Here, I identify the treatment group and the control groups, using patients' zip code household median income as a proxy for patients' household income: the zip code income data from Census 1990 are linked to patients' zip codes in the Florida discharge records. In Figure 1.2, I examine number of Medicaid births across zip code income percentiles, as well as proportion of Medicaid births within each of the zip code income categories. The figure shows that Medicaid births increased when the Medicaid expansions took place. The increase was larger in lower income zip code groups, and most of the increase occurred in the lower 50 percent of the zip code distribution. Figure 1.3 shows births by coverage type in Florida in the same period. The percentage of Medicaid births was below 20 percent in 1988, but increased to 30 percent in 1990 and to 41 percent in 1993.

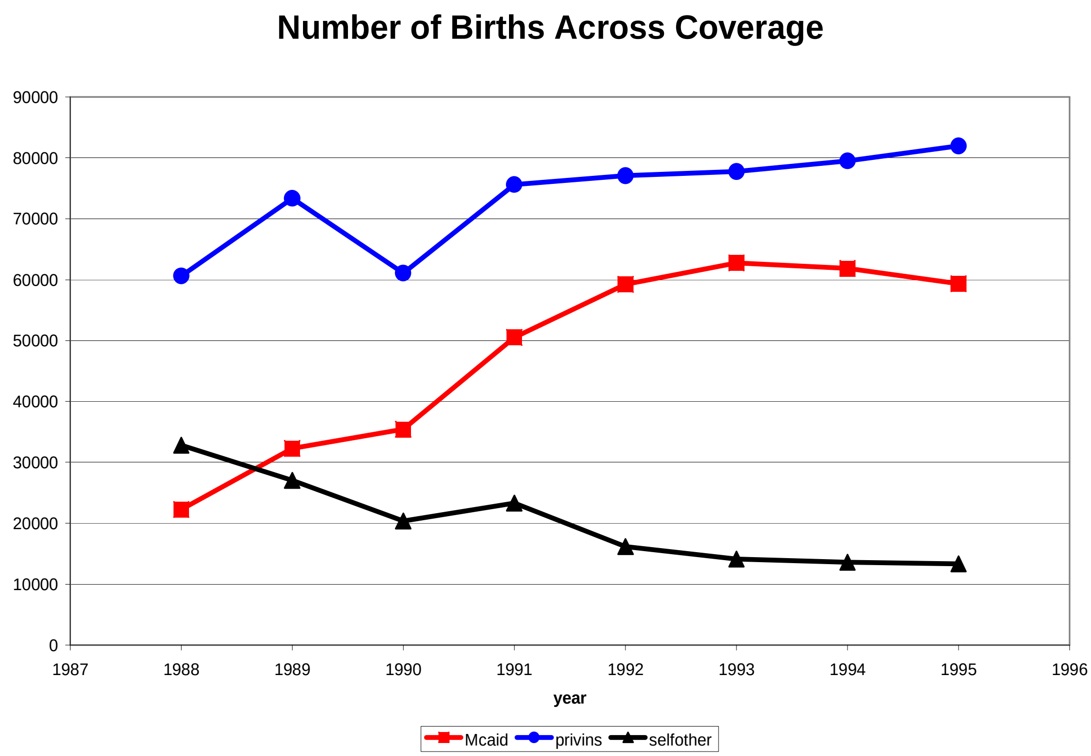
[19] If I had patients' income information, I would construct a treatment group with those who were previously uninsured but became eligible for Medicaid due to the eligibility rule changes, and examine their choice of hospitals before and after the expansions. Then I would compare this treatment group with two control groups whose coverage type should not have been affected by the expansions such as an always Medicaid-eligible group (extremely indigent mothers, who should have gained Medicaid coverage before the expansions and continuously had it throughout my sample period) and a never Medicaid-eligible group (high-income patients probably with private coverage, who should never have been eligible for Medicaid during the sample period).

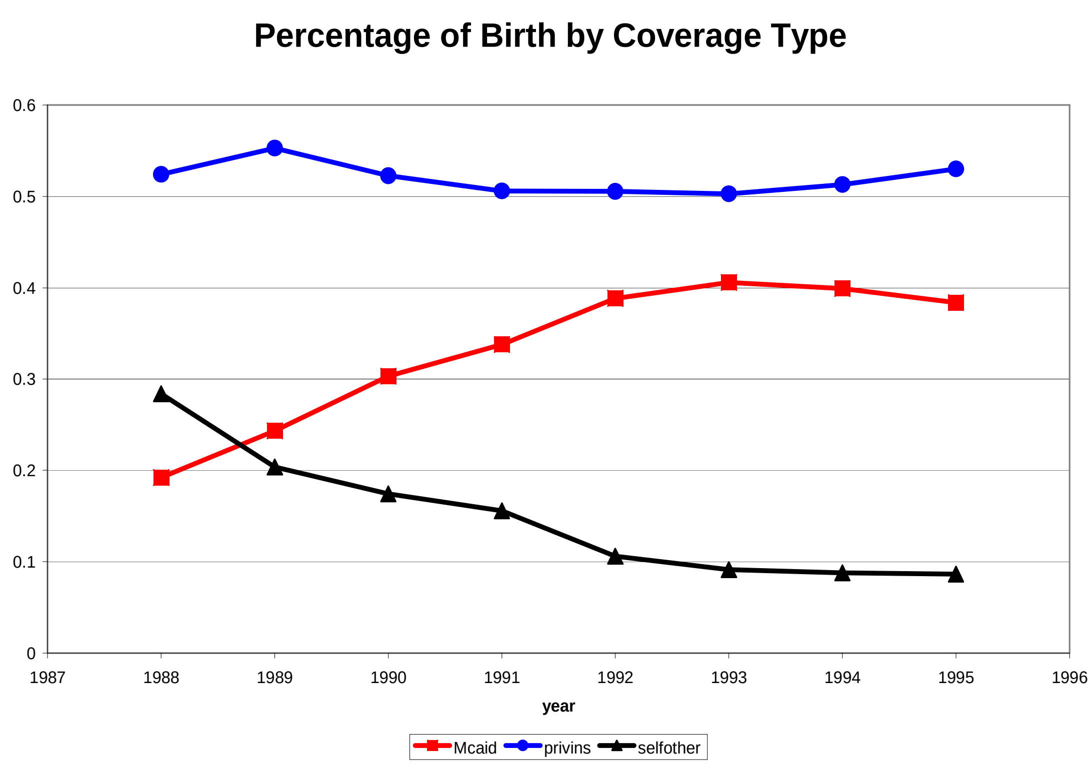


Note: zipinc90=zip code median household income in the 1990 Census
zipinc90 is broken down into 10 categories based on the distribution of the zip code income (%).



[Figure 1.2] Medicaid Birth across Zip Code Income Categories in Florida





[Figure 1.3] Birth by Coverage Type in Florida

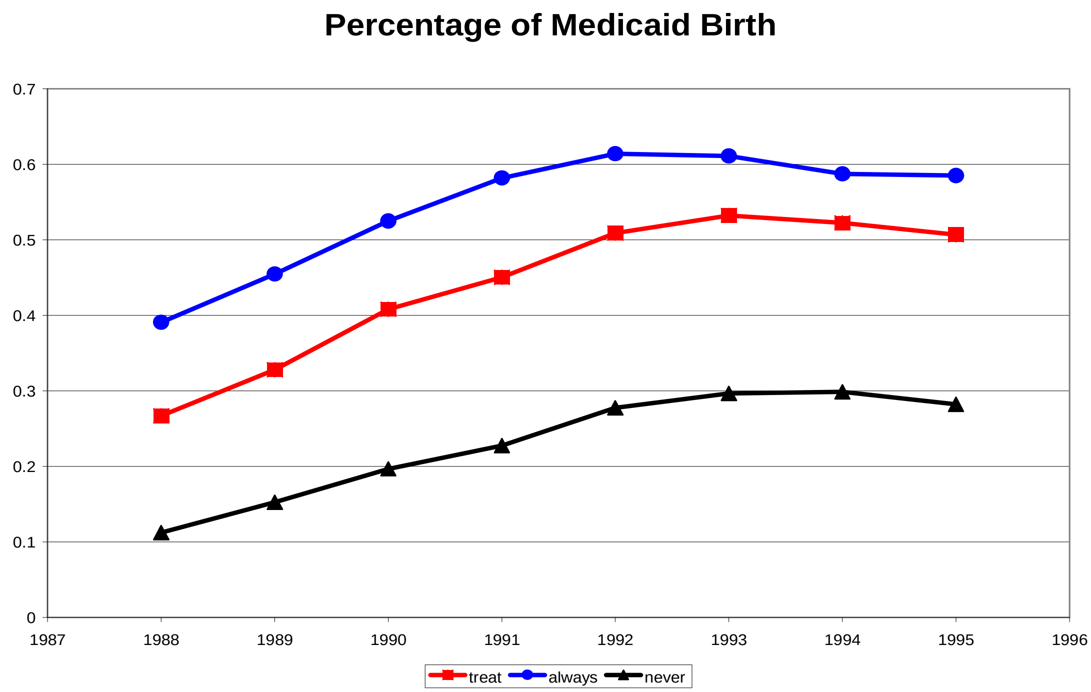
Based on the zip code income levels, I define a treatment group for the 1989 expansion as all patients who resided in zip codes whose income levels were in the lower 10 to 30 percent of the income distribution (corresponding to 100-150 percent of the FPL), while a treatment group for the 1992 expansion is defined as those who resided in zip codes whose income levels were in the lower 30 to 45 percent of the distribution[20] (corresponding to 150-185 percent of the FPL). I separately look at maternity patients from extremely low-income zip codes (those residing in zip codes whose median income levels were in the bottom 10 percent of the zip code distribution), and maternity patients from high-income zip codes (those residing in zip codes where the income levels were in the upper 55 percent of the distribution). Graph (a) in Figure 1.4 presents proportions of Medicaid births across the patient subgroups: the proportions of Medicaid births significantly increase for maternity patients in the treatment group and those from the extremely poor zip codes[21].

For the NIS data, which do not contain patients' zip codes, I use ZIPINC8 and ZIPINC4, the indicator variables for zip code income brackets. Figure 1.5 presents proportions of Medicaid births over time across the eight zip code income categories (ZIPINC8). The proportion increased to a great degree among the first three zip code income groups, which account for about 30 percent of the discharges. Therefore, I define the treatment group as patients from zip codes whose median household income levels were between \$15,000 and \$25,000, the income range that is above the old

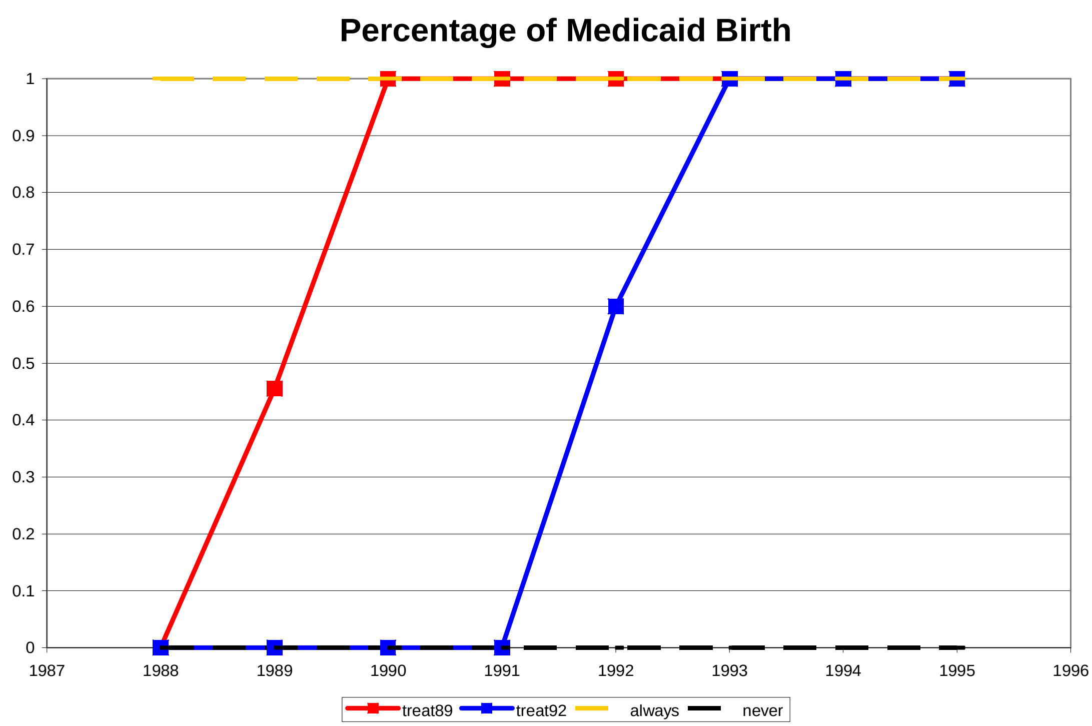
[20] Based on poverty thresholds for a four-member family in the Census guideline, the zip code income cutoff for 100 percent of the FPL was \$15,000 in 1989; the income cutoff for 185 percent of the FPL was \$25,000; the income cutoff for 300 percent of the FPL was \$40,000.

[21] If individual income levels are homogeneous within zip codes, i.e., everyone within the same zip code has the same income level as the zip code median income level, proportion of Medicaid births across the patient subgroups for each expansion should look like those in Graph (b) in Figure 1.4: the proportion of Medicaid births in the treatment group jumps from zero to one when one of the expansions took place (red and blue solid lines). Since everyone from extremely low-income zip codes (zip code income less than 100 percent of the FPL) should have Medicaid, the proportion of Medicaid births in these zip codes should be constant at one (orange dotted line). On the contrary, no one from high-income zip codes (zip code income above 185 percent of the FPL) should have Medicaid, which means that the Medicaid proportion in the richest zip codes should stay at zero (black dotted line).

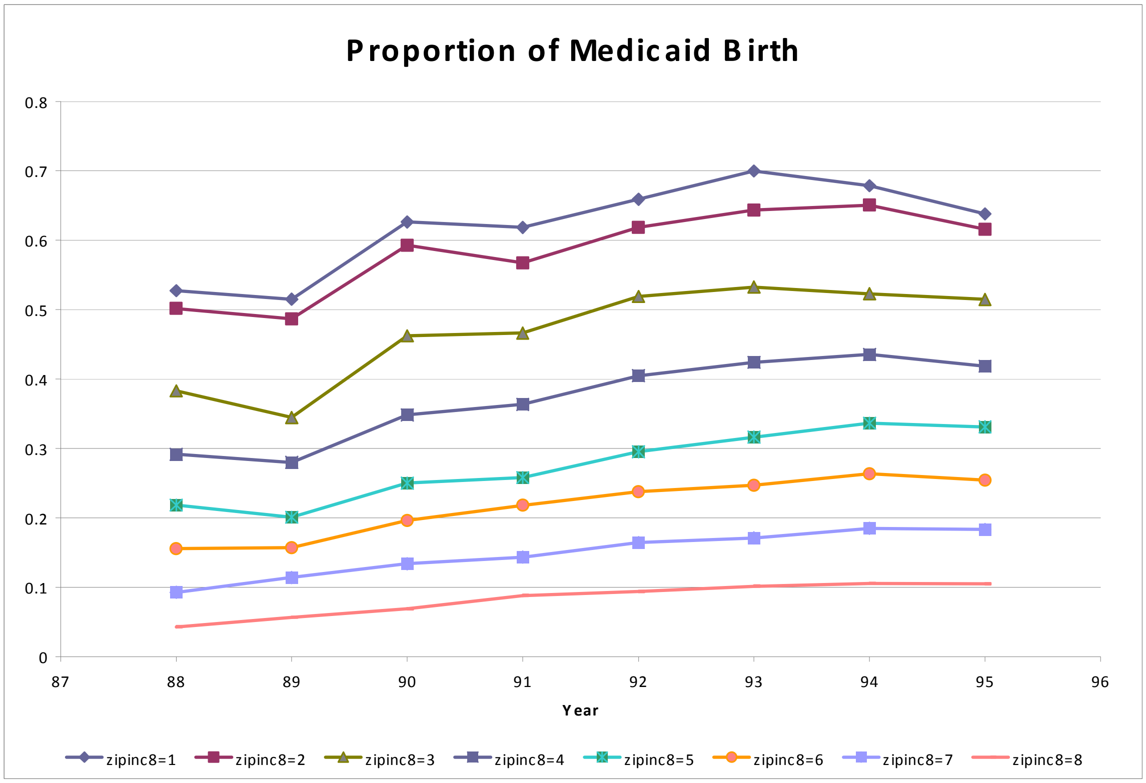
(a) Actual Case



(b) Ideal Case



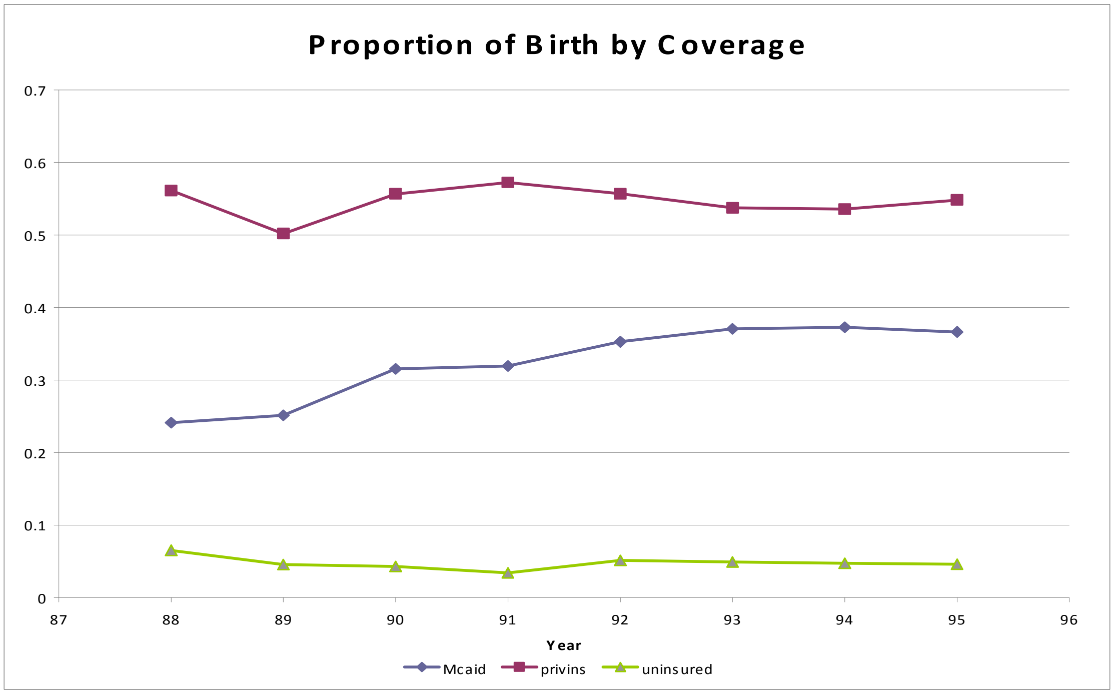
[Figure 1.4] Proportion of Medicaid Birth (Florida)



[Figure 1.5] Proportion of Medicaid Birth by Zip Code Income Category (NIS)

eligibility income threshold but below the new threshold: these are corresponding to the lower second and third categories of ZIPINC8. I also separately examine maternity patients from extremely low-income zip codes and those from high-income zip codes: zip code income levels below $15,000 (the lowest income category in ZIPINC8) are defined as extremely poor zip codes, and zip code income levels above $25,000 (the upper five categories in ZIPINC8) are considered high-income zip codes. Then in Figure 1.6, I break down patients by coverage type: the figure shows that the proportion of Medicaid births increased by 13 percentage points from 1988 to 1995, from 24 to 37 percentages, which is a moderate increase compared to Florida.

In addition to whether she has health insurance coverage and what kind of coverage she has, a patient's risk level may play a role in her hospital choice decision, According to Phibbs *et al* (1993), high-risk patients are more sensitive to quality of



[Figure 1.6] Proportion of Birth by Coverage Type (NIS)

care and thereby show different hospital selection patterns, and high-risk mothers with Medicaid are less able to deliver at high-quality hospitals (those with NICU) than those with private coverage. If Medicaid mothers are discriminated because of their payer source, which gives low reimbursement to hospitals than private payers, we can infer that high-risk, uninsured mothers would have even lower chances to receive care at high-quality hospitals. Therefore, the coverage gain may be more beneficial for high-risk patients among the indigent. However, there are several possibilities that may reduce the policy effects for high-risk patients: first, the barrier to high-quality providers for Medicaid mothers may be as high as that of uninsured patients; second, if most of newly eligible mothers are high-risk due to the lack of a regular source of care before pregnancy, they can be sorted into high-quality hospitals regardless of the coverage gain; third, the coverage gain may decrease the risk-level through increased care to prenatal care.

In order to check whether and how patients' risk levels influence the choice of hospitals for maternity patients, I further break down the treatment and the control groups into high-risk and non-high-risk groups. High-risk pregnancies are determined by patients' diagnosis codes: if a patient has at least one of the general comorbidities listed in Elixhauser *et al* (1998) or the specific obstetric complications listed in Gregory *et al* (2002), she is defined as high-risk. According to Elixhauser *et al* (1998), chronic heart disease, liver disease, diabetes, and renal failure are examples of high-risk diagnoses, while Gregory *et al* (2002) defined advanced maternal age (over 35 years old), preterm, malpresentation, and maternal soft tissue condition as high-risk obstetric conditions, which potentially require elective primary cesarean section.

(3) Model Specification

My main objective is to evaluate whether maternity patients from low-income zip codes, who are more likely to gain Medicaid coverage, move to different types of hospitals after Medicaid expansions, and if so, whether their new choice represents higher quality of care. In doing so, I conduct two sets of analyses at the hospital level and at the patient level, separately. At the hospital level, I examine proportion of maternity patients from low-income zip codes (treatment group), and it relation with each of hospital attributes: if the proportion increased at FP hospitals after the expansion, I interpret that those in the treatment group moved to FP hospitals. The advantage of conducting this hospital level analysis is that the availability of hospital identifiers allows me to construct hospital-level panel structure and examine changes in the proportion of low-income mothers within the same hospitals over time. Moreover, I can indirectly test crowding-out effects at the hospital level. However, the weakness of this hospital level analysis is that we cannot control for distance to hospital, which is considered one of the important determinants in hospital choice decision. Therefore, I conduct a patient level analysis, controlling for zip code distance between patient and hospital. Here, I use a discrete choice model to study how each hospital attribute influences patients' hospital choice.

Hospital Level Analysis

Taking advantage of the hospital panel structure, I estimate hospital fixed-effect models, in which I can control for unobserved, time-invariant heterogeneity across hospitals. The baseline econometric models are as follows:

[Model 1] $Y_{htg} = \beta_0 + \beta_1 \cdot POST_t \times X_{h88} + Hosp_h + Year_t + \varepsilon_{ht}$

[Model 2] $Y_{htg} = \beta_0 + \beta_1 \cdot ELIG_{st} + \beta_2 \cdot ELIG_{st} \times X_{h88} + Hosp_h + Year_t + \varepsilon_{ht}$

Model 1 is applied to the Florida hospitals and Model 2 to the hospitals in the NIS. The dependent variable, Y_{htg}, is a proportion of patient subgroup g at hospital h in year t, where the patient subgroups consist of the treatment group (those from low-income zip codes), those from extremely poor zip codes, and those from high-income zip codes. The proportion of maternity patients from low-income zip codes is the number of patients in the treatment group divided by the total number of patients who came to hospital h in year t.

X_{h88} is a vector of hospital dummy variables measured by the value of 1988, which will rule out endogeneity problems: private for-profit (FP), public, teaching, high-volume, large (in terms of number of licensed beds), presence of NICU[22], low complication rates, and urban hospitals construct each dummy variable that takes the value of one, while hospitals without such attribute—private not-for-profit (NFP), non-teaching, low-volume, small, lack of NICU facilities, high complication rates, and

[22] The NICU variable is included only in the Florida analysis.

rural hospitals—take the value of zero, respectively. I will explain how I construct these hospital dummy variables in the next section.

In the Florida analysis, I estimate Model 1 for the 1989 expansion (with *POST89*) and the 1992 expansion (with *POST92*), separately. *POST89* takes a value of one for the years after the 1989 expansion (1990-1995), and zero for the pre-expansion period (1988-1989). *POST92* takes a value of one for the post 1992 expansion period (1993-1995), and zero, otherwise. $POST_t \times X_{h88}$ is a vector of interaction terms between each of the hospital attributes in X_{h88} and the policy indicator. The coefficient of the interaction term β_1 captures whether the proportion of those from low-income zip codes increased at hospitals with each attribute in X compared to those without it after the policy changes. For example, the coefficient of (POST89×NICU) indicates whether the proportion of those from low-income zip codes increased after 1989 at hospitals with NICU relative to those without a NICU.

In the national analysis, I estimate Model 2, which is the same set-up as Model 1, but replaces the binary policy indicator ($POST_t$) with a simulated fraction of women eligible for Medicaid in state s and year t ($ELIG_{st}$). Using the Current Population Survey (CPS) data of 1987-1996, I take a random sample of women aged 15-44 in each year, and use this same sample across states to calculate the fraction of women who would have been eligible for Medicaid if they lived in the state during that year and became pregnant. This simulated fraction only captures the generosity of the Medicaid program across states, eliminating other confounding effects such as state-specific economic conditions and different demographic compositions.

Another set of dependent variables is constructed based on patients' health insurance coverage. Medicaid expansions should increase the proportion of Medicaid patients at the hospital level, particularly at hospitals which admit more low-income mothers after the expansions, while the proportion of the uninsured should decrease.

The comparison between the proportion of maternity patients from low-income zip codes (treatment group) and the proportion of Medicaid patients enables me to indirectly test crowding-effects. Since the crowding out group should have had access to their preferred hospitals before switching to Medicaid, there should be little reallocation across hospitals for these patients. In the extreme case, if all new beneficiaries are the crowding-out group, they would have little incentive to move to different hospitals, which means no patient reallocation across hospitals. In this case, the proportion of Medicaid patients will increase at the hospital level because of the change in their insurance status, while the proportion of those from low-income zip codes will stay the same. As a result, an increase in the proportion of Medicaid patients without accompanying an increase in the proportion of patients from low-income zip codes indicates crowding-out effects.

Patient Level Analysis

In the patient level analysis, I use McFadden's conditional logit model in order to examine how each of hospital attributes influenced patients' hospital choice. Unlike OLS regression or binary logit models, the conditional logit, one of discrete choice models, can deal with dependent variables that have unordered, choice-specific multiple categorical values. This conditional logit model focuses on explaining how attributes of the choice (e.g. hospital ownership type, teaching status, etc) influence choosers' decision, as opposed to multinomial logit model, an alternative family of the discrete choice models, which examines how attributes of the chooser (e.g. patient's age, sex, income, etc) influence the choice behavior. Using hospital attributes in the year of 1988 as the explanatory variables, I compare hospital choice behavior for the treatment and control groups before and after the expansions. Again, Model 1 is for the Florida data and Model 2 for the NIS data.

$$P_{ijg} = \Pr(Y_{ij} = j) = e^{V} / \sum_j e^{V} \qquad j = 1, \ \ldots \ , J \text{ (the number of hospital options)}$$

$$\text{Model 1: } V_{ijg} = \alpha + \beta \cdot X_{ij88} + \gamma \cdot X_{ij88} \times POST_t + \varepsilon_{ij}$$

$$\text{Model 2: } V_{ijg} = \alpha + \beta \cdot X_{ij88} + \gamma \cdot X_{ij88} \times ELIG_{st} + \varepsilon_{ij}$$

V_{ijg} is the level of utility for patient *i* in a subgroup g choosing hospital *j* among *J* alternatives. The chosen hospital must give the patient greater utility compared to other hospitals in her choice set. This utility is a linear function of hospital attributes as well as the interaction terms between each of the hospital attributes and the policy indicator: *POST*[23] for the Florida data and *ELIG* for the NIS data. The β coefficients are the natural log of the odds ratio of a patient initially being treated at a hospital with the attribute in X to a hospital without that attribute. The coefficients of the interaction terms (γ) capture the impact of Medicaid expansion on changes in patients' hospital choice. The hospital attributes (X_{ij88}) include distance to hospital from a patient's residence, as well as the explanatory variables used in the hospital-level analysis: ownership, teaching status, the presence of NICU, hospital capacity, obstetric volume, urban/rural status, and clinical outcomes at the 1988 level. The error terms are assumed to follow Type I extreme value distribution.

To estimate this conditional logit model, I construct a hospital choice set for each patient in the following way. First, I calculate distance to hospital from patient residence based on patient and hospital zip code centroids[24]. Then I drop those who delivered babies at hospitals located more than 30 miles away from home[25]. Finally,

[23] In the patient level analysis, I use both year and quarter to determine the policy variables: POST89=1 for the discharges from the 3rd quarter of 1989, and POST92=1 for the discharges after the 2nd quarter of 1992.
[24] I use the Great Circle Distance Formula.
[25] Since about 95 percent of the patients in my Florida sample chose hospitals within thirty miles from their residence, the extremely large distance values in the upper five percent were likely to be coding errors or represent those admitted to local hospitals while they were away from home.

each patient is assigned to her hospital choice set which contains all hospitals in her zip code as well as those chosen by other patients residing in the same zip code as hers (Nichols, 2005).

The limitation of this conditional logit model is that it is not applicable to those with only one hospital option or when one cannot identify a full set of hospital options. Therefore, I cannot conduct the conditional logit analysis for Florida patients who had only one hospital option, as well as the patient sample in the NIS: since the NIS lacks patient zip code information and includes a subset of hospitals in each state (only 20 percent of the community hospitals), one's hospital choice set, no matter how well constructed, does not include all of her possible hospital options. These data limitations prevent me from constructing a complete hospital choice set for patients, threatening viability of the conditional logit model. Therefore, for patients in the NIS as well as Florida patients with a single hospital option, I use linear probability models (LPM)[26] as follows:

Model 3: $Y_{is88} = \alpha + \beta \cdot X_{ist} + \gamma \cdot ELIG_{ts} + YEAR_t + STATE_s + \varepsilon_{its}$

The dependent variables are binary indicators for each attribute of the hospitals chosen by patient i in state s. This binary dependent variable model can serve as a simplified version of a discrete choice model (Gaskin *el al*, 2001)[27]. The vector X controls for patient characteristics: age and high-risk status. For patients' age, I include two indicator variables (*Age_l25* and *Age_g34*): *Age_l25* has a value of one for those aged below 25; and *Age_g34* has a value of one for those aged above 34; those aged between 25 and 34 are the reference group. High-risk status is also

[26] I also use a binary logit model, but it produces qualitatively similar results as the LPM.
[27] The caveat to this alternative approach is that I can examine only one dimension of hospital quality at a time. However, this approach, without a construction of hospital choice sets, can still provide some insight into hospital admission and selection patterns.

controlled for by a dummy variable. Including both year and state fixed-effects, I control for unobserved year-specific and state-specific factors. For the Florida sample, I estimate the same model, replacing ELIG with POST, and STATE with county fixed-effects.

(4) Construction and Interpretation of Hospital Variables

Construction of Hospital Quality Variables

In the hospital and the patient level analysis, I include hospital attribute variables, which can be interpreted as indirect and direct quality measures: six observable characteristics (ownership, teaching status, presence of neonatal intensive care units, hospital capacity, obstetric volume, and urban/rural status) and one clinical outcome measure for maternity care (risk-adjusted complication rates). All the hospital variables in the main analysis are constructed as binary variables: FP=1 for private, for-profit hospitals; Public=1 for public hospitals; private, not-for-profit hospitals are the reference group; Teaching=1 for a hospital with a residency program to train obstetricians; NICU=1 if a hospital has a neonatal intensive care unit; Bed_Large = 1 if a hospital has a large capacity, i.e., a number of licensed beds is above 200 for urban hospitals and 75 for rural hospitals; Vol_High=1 if a hospital has a higher obstetric volume, i.e., a number of labor/delivery procedures is greater than its median value in a given year; Urban=1 if a hospital is located in an urban area.

The risk-adjusted complication rate, a ratio of actual to expected complications[28], at the hospital level is generated based on patients' adverse health outcomes after birth. The actual complications are the number of patients who suffered

[28] Post-obstetrical complications and adverse outcomes are defined by HealthGrade (Exhibit B in Hospital Report Cards Maternity Care and Women's Health 2007-2008 Methodology White Paper) and the Delta Group (Table 1 in Forthman *et al*, 2005).

from adverse outcomes after birth at a given hospital. The expected complications are aggregated predicted probabilities of a patient having adverse outcomes to the hospital level. The predicted probability is estimated by binary logit models in which the dependent variable is the indicator for whether a patient had postpartum complications (clustered by hospital units). The explanatory variables in the models are patient characteristics such as age, presence of chronic illness[29], a number of comorbidities[30], emergency room admissions, and DRG dummy variables. The higher value of RATIO, i.e., the actual complications greater than the expected complications, means poorer clinical outcomes. I assign a binary indicator for lower complication rates at the hospital level: RAT_LOW=1 if RATIO is less than the value of one, i.e., the number of actual complications is less than the number of expected complications. For some analysis, I divide RATIO into four tiers at its quartiles and use those four indicator variables: Rat_q1 has a value of one for hospitals whose RATIO is in the first quartile (the group of hospitals with the best clinical outcomes), whereas Rat_q4 has a value of one for hospitals whose value of RATIO is in the highest quartile (the group of hospitals with the worst clinical outcomes)[31].

In order to avoid endogeneity concerns, all of the hospital variables are constructed as time-invariant, fixed values at the initial year of 1988[32]. If hospitals adjust their quality in response to policy changes in order to attract a certain type of patients, seeing more patients from low-income zip codes receiving care at higher

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[29] I use chronic condition indicators, provided by the HCUP.

[30] I use the number of secondary diagnosis codes for the number of comorbidities.

[31] Alternatively, as in Epstein *et al* (2008), I use linear probability model with hospital fixed-effect estimates included. With patient characteristics as well as their risk factor controlled in this model, the remaining effects on patient health outcomes, captured by the hospital fixed-effect estimates, imply overall hospital quality. Since the correlation between these fixed-effect estimates and the complication ratio (RATIO) is significantly high (above 0.8), the results reported in this paper are based on the RATIO.

[32] Ideally, I would like to use hospital variables before 1988. However, since the earliest year of data available is 1988 in both Florida and the national sample, all hospital variables including the clinical outcome measure are based on the hospital samples in 1988. For hospitals that entered after 1988, I use the first available year in the calculation.

quality hospitals may be attributed to hospitals' change in characteristics, not the patient reallocation to higher quality hospitals.

Interpretation of Hospital Variables

Now, I would like to associate the above hospital attributes with the quality of hospitals. As explained in Section II, without a consensus on the relationship between hospital attributes and quality of care, I examine the association between my clinical outcome measure and other hospital characteristics. Regressing RATIO on the other hospital attributes (FP, Public, teaching, NICU, high-volume, large bed, and urban status), however, I do not find any statistically significant association between the clinical outcome measure and the rest of the hospital attributes. Therefore, except for NICU and the clinical outcome measure, I do not attach the level of quality to the hospital variables. Instead, I interpret them as hospital attributes or types that each patient subgroup may or may not prefer. For example, I expect those from low-income zip codes to be reallocated toward FP hospitals if a lack of coverage before the expansion was the constraint for them to choose FP hospitals.

VI. Results

Descriptive Statistics

Table 1.2 presents descriptive statistics of the Florida and NIS data: the second to fourth columns for the Florida data, and the last three columns for the NIS data. The Florida hospital sample consists of 872 observations during 1988-1995: thirty-one percent private, for-profit hospitals; fifty-three percent private, not-for-profit hospitals; and fifteen percent public hospitals. Eight percent were teaching hospitals, which had

[Table 1.2] Summary Statistics (1988-1995)

A. Patient and Hospital Variables

Patients Characteristics	Florida			NIS		
Variable	Mean	Std.	Obs.	Mean	Std.	Obs.
Age (years)	26.9	5.81	1,029,801	27.1	5.82	4,568,817
Zip Code Distance (miles)	7.47	6.07	1,029,801	-	-	-
Length of Stay	2.47	2.11	1,029,801	2.49	2.36	4,568,817
High-risk	0.41	0.49	1,029,801	0.28	0.45	4,568,817
c-section	0.26	0.44	1,029,801	0.23	0.42	4,568,817
Household Median Income	$30746	11624	1,029,801	30924	9951	4,568,817
Medicaid	0.31	0.46	1,029,801	0.32	0.46	4,568,817
Private coverage	0.55	0.50	1,029,801	0.59	0.49	4,568,817
Other (Self-pay+Other)	0.12	0.33	1,029,801	0.04	0.20	4,568,817
Hospital Attributes	**Florida**			**NIS**		
Private, for-profit	0.31	0.46	872	0.09	0.29	5216
Private, not-for-profit	0.53	0.50	872	0.70	0.46	5216
Public	0.15	0.36	872	0.21	0.41	5216
Teaching	0.08	0.27	872	0.15	0.35	5216
Bed_large	0.69	0.46	872	0.35	0.48	5216
NICU	0.39	0.49	872	-	-	-
Rat_low (RATIO<1)	0.61	0.49	872	0.60	0.49	5216
Vol_high	0.50	0.50	872			
Annual number of delivery procedure	3381.5	9636.7	872	1077.10	1392.49	5216
Urban	0.93	0.26	872	0.61	0.49	5216

B. Construction of Treatment and Control Group

Zip Code Income Group	Florida	NIS
100 ≤ zip code income ≤ 185% of the FPL	42%	23%
100 ≤ zip code income ≤ 150%	28%	-
150 ≤ zip code income ≤ 185%	14%	-
zip code income<100% of the FPL	9%	2%
zip code income > 185% of the FPL	50%	75%
185 ≤ zip code income ≤ 300% of the FPL	-	47%
300% of the FPL < zip code income	-	28%
Number of Observations	1,029,801	4,568,817

[Table 1.2] Continued

C. Breakdown of Zip Code Income in the NIS Data

NIS Data (1988-1995)				
Income range	**ZIPINC8**	Freq.	%	**ZIPINC4**
$0-15000	1	89,856	1.96	1
$15000-20000	2	332,615	7.29	
$20000-25000	3	734,380	16.01	
$25000-30000	4	841,222	18.34	2
$30000-35000	5	954,487	16.45	3
$35000-40000	6	550,312	12.00	4
$40000-45000	7	392,368	8.55	
$45000+	8	590,892	12.88	
Missing	.	300,685	6.56	
Total		4,586,817	100	

D. Breakdown of Patients by Race in the NIS Data

Race	Freq.	%
White	1,804,673	65.1
Black	318,717	11.5
Hispanic	462,718	16.7
Other race	185,054	6.7
Total	2,771,162	100

residency programs in obstetrics and gynecology, and thirty-nine percent hospitals had NICU. Sixty-one percent of the hospitals had RATIO whose value is less than one, and sixty-nine percent were grouped into large hospitals based on the number of licensed beds. A half of the hospital sample were high-volume hospitals, while ninety-three percent were located in urban areas. The occupancy rates during the sample period were between 53% (for 1994) and 61% (for 1988).

The size of patient sample, pregnant women aged 15-44 who were admitted to hospitals for childbirth, except for the emergency room admissions, is 1,029,801. Based on the zip code income classification, the treatment for the 1989 expansion (those whose zip code income levels were between 100 and 150 percent of the FPL) was 28 percent, while the treatment group for the 1992 expansion (those whose zip code income levels were between 150 and 185 percent of the FPL) was 14 percent. Fifty percent of the patient sample resided in zip codes whose median income levels were above 185 percent of the FPL, while nine percent of the total discharges belong to the zip codes whose median income levels were below 100 percent of the FPL. The breakdown of the patients by health insurance coverage is as follows: 31 percent had Medicaid, 55 percent had private insurance, and 12 percent were either self-pay or had other coverage.

The NIS started with eight states[33] in 1988, but eleven states entered between 1989 and 1995[34]. The NIS hospital sample consists of a total of 5216 hospitals[35] for 1988-1995: 70 percent are NFP hospitals, 21 percent public hospitals, and only 9 percent FP hospitals. Fifteen percent of the hospitals were teaching hospitals, and sixty-one percent were located in urban areas. The patient sample in the NIS consists of more than 4.5 million discharges[36], but observations with race information shrink to 2.8 millions (about 60% of the total discharges). The treatment group accounts for 23 percent of the patient sample, while those whose zip code income was less than 100 percent of the FPL consist of only 2 percent of the sample. The remaining 75 percent of the patient sample resided in high income zip codes: 47 percent of them came from zip codes whose income ranged between 185 and 300 percent of the FPL, while 28 percent came from zip codes whose income levels were above 300 percent of the FPL. The breakdown of the patient sample across insurance coverage shows a pattern similar to that in the Florida data. The breakdown of the patient sample by race is as

[33] California, Colorado, Florida, Illinois, Iowa, Massachusetts, New Jersey, and Washington

[34] In 1989, three states (Arizona, Pennsylvania and Wisconsin) entered the NIS, six states (Connecticut, Kansas, Maryland, New York, Oregon and South Carolina) were added in 1993, and two more states (Missouri and Tennessee) were included in 1995.

[35] Five states—California, Florida, Illinois, Iowa and Wisconsin—take up more than sixty percent of the hospital sample.

[36] California and Florida are the two largest states which make up forty-three percent of the patient sample.

follows: 65 percent Whites, 12 percent Blacks, 17 percent Hispanics, and 7 percent other race.

<u>Results from the Florida Data</u>

Table 1.3 and Table 1.4 report the results of the hospital level analysis in Florida: Table 1.3 for the 1989 expansion and Table 1.4 for the 1992 expansion. The first two columns show the results for the treatment group (the first column for the simple OLS regression model and the second column for the hospital fixed-effect model), while the last two columns report the same results for the Medicaid patient group. Since time-invariant hospital variables are dropped out in the fixed-effect model setting, I start with a simple OLS regression model with year and county (for Florida) or state (NIS) dummy variables included.

The OLS regression results show attributes of the hospital used by maternity patients from low-income zip codes (the treatment group) before and after the expansions. In the pre-expansion period, the proportion of those in the treatment group was 7 percentage point lower at hospitals with NICU than those without it, while this proportion was 33 percentage point lower at urban hospitals. Teaching hospitals had a 6 percentage point higher proportion of these mothers than non-teaching hospitals, albeit not statistically significantly from zero at the 10 percent level. The proportion of maternity patients from low-income zip codes was smaller by 6 and 4 percentage points at FP and public hospitals, respectively, than NFP hospitals. After the 1989 expansion, this proportion increased at public hospitals by 4 percentage points. The hospital fixed-effect model produces qualitatively similar results to the OLS regressions, with the increase in the proportion at urban hospitals and clinically better performing hospitals statistically significant at the 5 percent level.

[Table 1.3] Hospital Level Analysis for the 1989 Expansion in Florida

Y=Proportion of Patient Subgroup	Treatment 89 (100≤ZIPINC≤150%)		Medicaid	
	OLS	Fixed-Effect	OLS	Fixed-Effect
FP	-0.06		-0.18***	
	(0.04)		(0.05)	
Public	-0.04		0.04	
	(0.04)		(0.07)	
Teaching	0.06		0.22***	
	(0.04)		(0.07)	
Large_bed	-0.02		-0.04	
	(0.04)		(0.06)	
NICU	-0.07*		-0.01	
	(0.04)		(0.05)	
Rat_low	0.02		0.09**	
	(0.03)		(0.04)	
High_Vol	0.02		0.02	
	(0.05)		(0.06)	
Urban	-0.33***		-0.07	
	(0.12)		(0.10)	
FP×POST89	0.02	0.01	0.09**	0.04
	(0.03)	(0.02)	(0.03)	(0.03)
Public×POST89	0.04*	0.04*	0.03	0.01
	(0.02)	(0.02)	(0.04)	(0.04)
Teaching×POST89	0.02	0.01	-0.07**	-0.08***
	(0.02)	(0.02)	(0.03)	(0.03)
largebed×POST89	0.01	0.01	0	-0.02
	(0.02)	(0.02)	(0.04)	(0.03)
NICU×POST89	-0.02	-0.01	0	0.02
	(0.01)	(0.01)	(0.03)	(0.03)
Rat_low×POST89	0.03	0.04**	0	0.02
	(0.02)	(0.02)	(0.03)	(0.03)
High_Vol×POST89	0.01	0	0.03	0
	(0.02)	(0.01)	(0.04)	(0.03)
Urban×POST89	0.04	0.07**	-0.15**	-0.11**
	(0.03)	(0.03)	(0.06)	(0.06)
constant	0.71***	0.26***	0.24	0.19***
	(0.13)	(0.01)	(0.18)	(0.01)
Year F.E.	YES	YES	YES	YES
County F.E.	YES	-	YES	-
Hospital F.E.	-	YES	-	YES
Observations	872	872	872	872
R-square	0.85	0.06	0.54	0.51
F test	468491.2	1.7	57.56	27.12
p value	0	0.06	0	0

Now, I compare the proportion of those in the treatment group with the proportion of Medicaid patients. Before the coverage expansion, the proportion of Medicaid mothers was 18 percentage points smaller at FP hospitals than NFP hospitals, but 22 percentage points larger at teaching hospitals than non-teaching hospitals. Also, hospitals with good clinical outcomes had a 9 percentage point larger proportion of Medicaid mothers than those with poor clinical outcomes. After the expansion, the proportion of Medicaid mothers increased at FP hospitals by 9 percentage points, while it decreased by 7 percentage points at teaching hospitals. As explained above, the change in the Medicaid proportion without a change in the proportion of those from low-income zip codes can be interpreted as crowding-out effects. For example, the increase in the Medicaid proportion at FP hospitals was not paired with an increase in the proportion of those in the treatment group: the latter was smaller (0.02) and not statistically significant at the 10 percent level. This could imply that FP hospitals provided care to the same zip code income group of patients, who only changed their insurance status to Medicaid. However, I am cautious about interpreting my results for the crowding out effects, because I am using zip code income levels instead of individual income levels.

Table 1.4 continues to report the results of the hospital level analysis for the 1992 expansion. Based on the OLS regressions, I do not find any particular pattern for the type of hospitals chosen by my treatment group in the pre-expansion period. After the 1992 expansion, the proportion of those from low-income zip codes increased 2 percentage points at public hospitals and 1 percentage point at large hospitals, but none of the coefficients is statistically significant. Again, the proportion of Medicaid mothers increased at FP hospitals by 11 percentage points, while it decreased by 21 percentage points at urban hospitals.

[Table 1.4] Hospital Level Analysis for the 1992 Expansion in Florida

Y=Proportion of Patient Subgroup	Treatment 92 (150≤ZIPINC≤185%)		Medicaid	
	OLS	Fixed-Effect	OLS	Fixed-Effect
FP	0		-0.15***	
	(0.02)		(0.05)	
Public	0.03		0.07	
	(0.03)		(0.06)	
Teaching	-0.02		0.18**	
	(0.03)		(0.07)	
Large_bed	-0.02		-0.06	
	(0.02)		(0.05)	
NICU	0		-0.01	
	(0.03)		(0.05)	
Rat_low	0		0.09**	
	(0.02)		(0.04)	
High_Vol	0.01		0.04	
	(0.03)		(0.06)	
Urban	0.04		-0.1	
	(0.03)		(0.10)	
FP×POST92	0	0	0.11***	0.06**
	(0.01)	(0.01)	(0.03)	(0.03)
Public×POST92	0.02	0	-0.03	-0.04
	(0.02)	(0.01)	(0.03)	(0.03)
Teaching×POST92	0.01	0	-0.05	-0.06**
	(0.01)	(0.01)	(0.03)	(0.03)
largebed×POST92	0.01	0.01	0.02	0
	(0.01)	(0.01)	(0.03)	(0.03)
NICU×POST92	0	0.01	0.03	0.03
	(0.01)	(0.01)	(0.03)	(0.02)
Rat_low×POST92	-0.01	0.01	0	0.01
	(0.01)	(0.01)	(0.02)	(0.02)
High_Vol×POST92	-0.01	-0.01	-0.01	-0.03
	(0.01)	(0.01)	(0.03)	(0.02)
Urban×POST92	-0.04	-0.02	-0.21***	-0.17***
	(0.03)	(0.02)	(0.06)	(0.06)
constant	0.08*	0.15***	0.24	0.19***
	(0.04)	(0.01)	(0.18)	(0.01)
Year F.E.	YES	YES	YES	YES
County F.E.	YES	-	YES	-
Hospital F.E.	-	YES	-	YES
Observations	872	872	872	872
R-square	0.66	0.04	0.55	0.53
F test	352749.3	2.04	42.54	24.21
p value	0	0.02	0	0

In summary, the hospital level analyses show that the treatment group for the 1989 expansion was reallocated to public hospitals, but no statistically significant reallocation effect after the 1992 expansion. These findings provide weak evidence that maternity patients from low-income zip codes switched to different types of hospitals, but I find no evidence to support that the movement is related to better quality of care. However, this aggregate level analysis does not control for distance between hospital and patient, which is one of the important factors in patients' choice of hospitals. Next, I present the results of the individual level analysis, which control for the distance variable.

Table 1.5 and Table 1.6 report the estimated odds ratio of the conditional logit model for the Florida patient sample—Table 1.5 for the 1989 expansion and Table 1.6 for the 1992 expansion. Each of the patient subgroups is further broken down by severity of illness, and the results show that there was not much difference in hospital selection patterns between high-risk and non-high-risk patients, particularly within the control groups. Therefore, I will focus on the discussion of the comparison between the treatment and control groups overall, rather than a comparison between high-risk and non-high-risk patients within each patient subgroup.

For the 1989 expansion, the treatment group consists of those whose zip code income levels were between 100 and 150 percent of the FPL. According to Table 1.5, prior to the 1989 expansion, all patients in the treatment and control groups were less likely to choose distant hospitals (16-18 percent less likely to go to distant hospitals). Maternity patients from low-income zip codes were 6.67 times more likely to deliver at high-volume hospitals than low-volume hospitals, but 15 percent less likely to give birth at public hospitals than hospitals of NFP ownership. Surprisingly, these mothers were 1.12 and 1.73 times more likely to choose hospitals with lower complication rates and NICU hospitals than those with higher complication rates and those without

[Table 1.5] Conditional Logit Model for 1989 Expansion

	100≤ZIPINC≤150% of the FPL (Treatment Group for 1989)			ZIPINC≤100% of the FPL	ZIPINC≥185% of the FPL
	all	high-risk	non-high-risk	All	all
Zipdist	0.84***	0.83***	0.84***	0.84***	0.82***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FP	1.07***	1.21***	1.01	0.70***	0.71***
	(0.03)	(0.05)	(0.03)	(0.04)	(0.01)
Public	0.85***	1.14***	0.72***	0.44***	0.56***
	(0.02)	(0.05)	(0.03)	(0.03)	(0.01)
Teaching	0.83***	0.88***	0.80***	0.96	0.75***
	(0.02)	(0.04)	(0.03)	(0.04)	(0.01)
Large_bed	0.58***	0.60***	0.57***	0.51***	0.65***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)
NICU	1.73***	1.73***	1.73***	1.68***	2.36***
	(0.05)	(0.08)	(0.06)	(0.07)	(0.03)
Rat_low	1.12***	1.01	1.18***	0.68***	0.71***
	(0.02)	(0.03)	(0.03)	(0.02)	(0.01)
High_Vol	6.67***	7.75***	6.26***	4.09***	2.83***
	(0.22)	(0.45)	(0.26)	(0.26)	(0.05)
Urban	0.45***	0.64***	0.37***	3.36***	0.28***
	(0.02)	(0.04)	(0.02)	(0.83)	(0.01)
Zipdist×POST89	1.02***	1.02***	1.02***	1.01***	1.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FP×POST89	0.99	0.81***	1.12***	1.33***	0.93***
	(0.03)	(0.04)	(0.04)	(0.07)	(0.01)
Public×POST89	1.82***	1.35***	2.13***	1.41***	1.37***
	(0.05)	(0.07)	(0.08)	(0.09)	(0.03)
Teaching×POST89	1.35***	1.45***	1.25***	1.15***	1.39***
	(0.04)	(0.07)	(0.05)	(0.05)	(0.02)
largebed×POST89	1.89***	1.94***	1.86***	3.73***	1.42***
	(0.05)	(0.09)	(0.06)	(0.26)	(0.03)
NICU×POST89	0.79***	0.78***	0.80***	1.40***	0.81***
	(0.02)	(0.04)	(0.03)	(0.06)	(0.01)
Rat_low×POST89	1.10***	1.15***	1.09***	1.63***	1.32***
	(0.02)	(0.04)	(0.03)	(0.06)	(0.01)
High_Vol×POST89	0.40***	0.37***	0.40***	0.26***	0.57***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Urban×POST89	2.22***	1.82***	2.41***	1	2.46***
	(0.09)	(0.13)	(0.13)	(0.26)	(0.06)
Observations	1192937	494446	698491	492996	4596160
LR-chi2	188879.41	78360.7	111590.98	56971.27	566720.42
Prob>chi2	0	0	0	0	0
Psuedo R2	0.29	0.29	0.29	0.22	0.26

NICU, respectively. Compared to the control groups, however, the size of the coefficient of NICU is smaller or about the same. Also, these patients were more likely to receive care at rural rather than urban hospitals, non-teaching than teaching hospitals, small-sized than large-sized hospitals. The only difference between high-risk and non-high-risk patients was the use of FP and public hospitals: high-risk mothers before gaining coverage were more likely to choose FP or public hospitals than NFP hospitals.

After the 1989 expansion, the noticeable change for the treatment group, compared to the pre-expansion period, was to have increased access to large, public hospitals. The odd ratio for the distance traveled to hospitals increased up to 1.02, and those in the treatment group were more likely to deliver at public and teaching hospitals relative to NFP and non-teaching hospitals, by 82 and 35 percent respectively. The switch to public hospitals was larger among non-high-risk patients, who also had a higher chance of giving birth at FP hospitals than NFP hospitals by 12 percent. Dependence on high-volume hospitals was significantly reduced, and, in fact, those in the treatment group were 60 percent less likely to choose high-volume hospitals. They also seemed more likely to choose large, urban hospitals than before, 1.89 and 2.22 times, respectively. Although the importance of NICU in the hospital choice decision decreased, it decreased across the other patient subgroups as well. The coefficient of LOW_RAT stayed almost the same, at 1.10, but still larger than one. My findings show that maternity patients from low-income zip codes had increased access to clinically high-performing hospitals as well as safety-net hospitals. Within the treatment group, the reallocation effect was larger for non-high-risk patients. This implies that high-risk patients, even with the coverage gain, may have more constraints on hospital choice, and therefore their health outcomes might not have been improved as much.

Table 1.6 presents the results of the conditional logit model for the 1992 expansion, where the treatment group consists of those whose income ranged between 150 and 185 percent of the FPL. Before obtaining coverage, patients in this income category were more likely to use hospitals with the following attributes: large size, high volume, NICU, high complication rates, teaching, NFP, and urban hospitals. However, after obtaining coverage, they were more likely to give birth at FP and clinically better performing hospitals than NFP and clinically poorly performing hospitals, by 22 and 26 percent, respectively. Again, the switch to FP hospitals occurred more with non-high-risk mothers than high-risk patients. As expected, the changes among the control groups, particularly those from higher income zip codes, were very small: all coefficients have values close to one, while the changes in the always eligible show patterns similar to those for the newly eligible. My results suggest that the 1992 expansion provided those from low-income zip codes with increased access to FP hospitals, hospitals in more private environments, as well as those with better clinical outcomes.

As mentioned in Section V, these conditional logit analyses drop patients who have only one hospital option. Since these patients would have found it difficult to switch between hospitals even if they wanted to, I examine their hospital choice behavior, using binary dependent variable models (Model 3). The number of patients with only one hospital option is 35,475 out of 1,131,395, only 3.14 percent of total discharges: 40 percent are privately insured, 39 percent have Medicaid, and 21 percent are uninsured. They were more likely to be uninsured compared to the average population, and traveled farther to receive hospital care: the average distance to the hospital was 9.15 miles. I do not find statistical evidence about the policy impacts on patient reallocation at the 10 percent level. This implies that the patient reallocation

[Table 1.6] Conditional Logit Model for 1992 Expansion

	150≤ZIPINC≤185% of the FPL (Treatment Group for 1992)			ZIPINC≤150% of the FPL	ZIPINC≥185 % of the FPL
	all	high-risk	non-high-risk	all	all
Zipdist	0.82***	0.83***	0.82***	0.86***	0.82***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FP	0.86***	0.89***	0.84***	0.65***	0.71***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.00)
Public	0.82***	0.98	0.73***	0.91***	0.71***
	(0.01)	(0.03)	(0.02)	(0.02)	(0.01)
Teaching	1.05***	1.28***	0.93***	0.92***	1
	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)
Large_bed	1.07***	1.11***	1.05**	1.05*	0.80***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.01)
NICU	2.21***	2.12***	2.27***	2.38***	2.08***
	(0.03)	(0.06)	(0.04)	(0.05)	(0.02)
Rat_low	0.93***	0.94***	0.92***	0.82***	0.85***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.00)
High_Vol	1.49***	1.49***	1.50***	1.41***	1.91***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.02)
Urban	1.14***	1.58***	0.93*	4.84***	0.40***
	(0.04)	(0.09)	(0.04)	(0.55)	(0.01)
Zipdist×POST92	1.00**	1.01***	1	0.99***	1
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FP×POST92	1.22***	1.13***	1.29***	1.78***	0.91***
	(0.03)	(0.04)	(0.04)	(0.05)	(0.01)
Public×POST92	0.90***	0.76***	1.01	0.43***	1.10***
	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)
Teaching×POST92	0.93***	0.91**	0.90***	1.36***	0.98**
	(0.02)	(0.03)	(0.03)	(0.04)	(0.01)
largebed×POST92	1.33***	1.46***	1.24***	2.18***	1.23***
	(0.03)	(0.05)	(0.04)	(0.08)	(0.01)
NICU×POST92	1.02	1.05	1	0.91***	0.90***
	(0.02)	(0.04)	(0.03)	(0.03)	(0.01)
Rat_low×POST92	1.26***	1.26***	1.27***	1.52***	1.10***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.01)
High_Vol×POST92	0.79***	0.75***	0.82***	0.84***	0.81***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.01)
Urban×POST92	1.12**	0.91	1.27***	0.48***	2.28***
	(0.05)	(0.07)	(0.08)	(0.07)	(0.04)
Observations	946825	385300	561525	492996	4596160
LR-chi2	134695.65	51652.7	83690.68	57530.18	566217.18
Prob>chi2	0	0	0	0	0
Psuedo R2	0.28	0.27	0.3	0.22	0.26

was not occurring with this patient subgroup: those with only one hospital option, without or with coverage, still had constraints on hospital selection[37].

Results from the NIS Data

Now, I extend both hospital and patient level analysis to the national setting. Here, the estimation method for the hospital analysis is the same as the Florida's OLS and hospital fixed-effect model, except for the NICU variable unavailable. For the patient level analysis, I estimate linear probability models instead of the conditional logit model due to lack of patient zip code information. With patients' race information available in the NIS, the national analyses focus on racial disparities in access to different types of hospitals. In doing so, I first categorize patients into four racial subgroups—White, Black, Hispanic, and other race[38]—and then break down each racial group by patients' zip code income levels as in the Florida hospital analysis.

Table 1.7 presents the results of the hospital level analysis. The dependent variable is the proportion of patients whose zip code income ranged between 100 and 185 percent of the FPL. Here, the policy variable (*ELIG*) is the simulated fraction of the Medicaid eligible population among women of child bearing age had they become pregnant. Since this fraction, on average, increased by 0.24 over the years (0.17 in 1988 and 0.41 in 1995), the actual size of the policy impact can be obtained by multiplying 0.24 to the estimates of each covariate.

In response to the increased fraction of the Medicaid eligible population, the proportion of patients in the treatment group, increased at large-size, low-volume, clinically well-performing, teaching, public, rural, FP hospitals relative to the ones

[37] They might have chosen different hospitals after obtaining coverage, but those hospitals would have been more than 30 miles away from home.
[38] Asian or Pacific Islander, Native American, and other

without each of these attributes, respectively. Although the F-test statistic is large enough to reject the null hypothesis such that all of the coefficients are zero, none of the coefficients are statistically significantly different from zero at the 10 percent level, and the actual magnitude of the policy impact is also very small. However, when I break down patients by race and examine the proportion of patients from low-income zip codes within each racial category, there are different patterns in patient reallocation across race. First, this proportion among Whites increased at hospitals by 8 percentage points, except for urban hospitals. For Hispanics and Blacks, these proportions increased by 11 and 9 percentage points respectively, but only at FP hospitals. For other race, the proportion increased at clinically better performing hospitals by 3 percentage points.

[Table 1.7] Hospital Fixed-Effect Model across Race with the NIS data

Proportion of Patient Subgroup	All	White	Black	Hispanic	Other race
	100 ≤ ZIPINC ≤185% of the FPL				
ELIG	-0.02	0.34***	-0.30*	-0.12	-0.13
	(0.07)	(0.12)	(0.17)	(0.14)	(0.12)
ELIG×Public	0.08	-0.13	0.11	0.02	0.08
	(0.08)	(0.11)	(0.16)	(0.13)	(0.12)
ELIG×FP	0.17	0.23	0.74***	0.37*	0.23
	(0.12)	(0.19)	(0.25)	(0.21)	(0.17)
ELIG×Teaching	0.05	-0.05	0.03	0.07	-0.03
	(0.07)	(0.08)	(0.13)	(0.11)	(0.09)
ELIG×Vol_high	-0.02	-0.07	0.07	0.06	0.09
	(0.05)	(0.10)	(0.12)	(0.11)	(0.10)
ELIG×Bed_Large	0.01	-0.03	0.30**	0.07	0.1
	(0.07)	(0.10)	(0.13)	(0.11)	(0.10)
ELIG×Urban	0.01	-0.44***	0.05	-0.09	-0.07
	(0.07)	(0.13)	(0.17)	(0.15)	(0.11)
ELIG×Rat_Low	0.05	0.06	-0.04	0.11	0.14*
	(0.05)	(0.08)	(0.11)	(0.10)	(0.08)
Constant	0.26***	0.07***	0.04***	0.06***	0.05***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	4181	4181	4181	4181	4181
# of Hospitals	1092	1092	1092	1092	1092
R-square	0.02	0.16	0.13	0.09	0.07
F-stat	2.31	12.44	9.42	7.36	7.17
p-value	0	0	0	0	0

[Table 1.7] continued

Proportion of Patient Subgroup	All	White	Black	Hispanic	Other race
	Medicaid Coverage				
ELIG	-0.01	-0.07	-0.44**	-0.14	-0.19
	(0.09)	(0.10)	(0.19)	(0.14)	(0.14)
ELIG×Public	0.23**	0.09	0.30*	0.30**	0.13
	(0.10)	(0.12)	(0.18)	(0.13)	(0.13)
ELIG×FP	0.25**	0.35**	0.80***	0.49***	0.09
	(0.11)	(0.16)	(0.25)	(0.18)	(0.14)
ELIG×Teaching	-0.07	-0.09	-0.04	-0.02	-0.08
	(0.09)	(0.09)	(0.15)	(0.13)	(0.11)
ELIG×Vol_high	-0.13	0.01	0.09	-0.01	0.19*
	(0.08)	(0.09)	(0.13)	(0.11)	(0.11)
ELIG×Bed_Large	0.09	-0.03	0.42***	0.11	0.1
	(0.07)	(0.09)	(0.13)	(0.10)	(0.11)
ELIG×Urban	0.07	0	0.22	0.17	0.13
	(0.08)	(0.11)	(0.17)	(0.13)	(0.13)
ELIG×Rat_Low	0.12*	0.11	-0.07	0.09	0.15*
	(0.07)	(0.07)	(0.12)	(0.10)	(0.09)
Constant	0.17***	0.08***	0.10***	0.02*	0.05***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	4181	4181	4181	4181	4181
# of Hospitals	1092	1092	1092	1092	1092
R-square	0.29	0.25	0.19	0.2	0.13
F-stat	36.33	25.71	16.53	23.03	18.12
p-value	0	0	0	0	0

Next, I compare the proportion of those in the treatment group with that of Medicaid patients within each racial category. As expected, these two proportions move in the same direction, but the size is larger for the Medicaid proportions. The proportion of Medicaid patients in total increased at public and FP hospitals (about 6 percentage points), as well as those with low complication rates (3 percentage points). Except for other race, the proportion of Medicaid mothers among Whites, Blacks, and Hispanics increased at FP hospitals at least by 9 percentage points, with the increase the largest for Hispanics (12 percentage points). While the proportion of Hispanic Medicaid mothers also increased at public hospitals (7.5 percentage points), the proportion of Black Medicaid mothers declined at public and NFP hospitals (11 and 3.5 percentage points). Medicaid mothers of other race moved to higher volume hospitals and clinically better performing ones. My findings suggest that among those from low-income zip codes, patients of color benefited the most from the expansions by switching to FP hospitals and hospitals with lower complication rates. These results imply that the increased coverage might have somewhat reduced racial disparities in access to higher quality of care.

Table 1.8 and Table 1.9 present the results of the patient level analysis in the national setting: Table 1.8 for the four patient subgroups by zip code income levels and Table 1.9 for the three subgroups by coverage type. In the linear probability models, I separately regress each of the binary indicators for hospital attributes (FP, teaching, low complication rate, etc) on the fraction of the Medicaid eligible population (ELIG), as well as patient age and high-risk status. In this way, I test whether a higher fraction of the Medicaid eligible population increased a probability of patients' receiving care at hospitals with one attribute over those without it: e.g. whether those from low-income zip codes are more likely to choose FP hospitals over NFP or public hospitals, or hospitals with low complication rates over those with high complication rates, etc. Additionally, I use four tiers of the clinical outcome measure (Rat_q1, Rat_q2, Rat_q3, and Rat_q4) as the dependent variables.

Table 1.8 reports the coefficients of *ELIG* for the patient subgroups across zip code income levels in the linear probability model: the first row presents the coefficients for patients of all races, and the following four rows report the coefficients when the LPM is separately estimated across the four racial subgroups. The results of these patient level analyses are consistent with the ones in the hospital level analysis. Medicaid expansions enabled those in the treatment group to deliver at teaching and NFP hospitals, as well as hospitals with better clinical performance. In particular, Black mothers among those from low-income zip codes showed the largest reallocation towards such types of hospitals: the coefficient of Rat_low is the largest

[Table 1.8] Linear Probability Model across Income Levels (NIS Data)

Patient Subgroup by X=ZIPINC								
100≤X≤185	**All**		**White**		**Black**		**Hispanic**	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
FP	-0.02***	(0.00)	0.11***	(0.01)	0.07***	(0.01)	-0.06***	(0.01)
Public	-0.01*	(0.01)	0.01	(0.01)	-0.09***	(0.02)	0.43***	(0.02)
Teaching	0.21***	(0.01)	-0.25***	(0.03)	0.06*	(0.03)	-0.33***	(0.04)
Bed_Large	-0.05***	(0.01)	-0.34***	(0.03)	-0.24***	(0.04)	0.34***	(0.03)
Urban	-0.07***	(0.01)	-0.21***	(0.02)	-0.05***	(0.01)	-0.47***	(0.02)
RatQ1	-0.18***	(0.01)	0.05**	(0.02)	-0.01	(0.03)	-0.07**	(0.03)
RatQ2	-0.02**	(0.01)	0.13***	(0.02)	-0.15***	(0.03)	0.43***	(0.03)
RatQ3	0.21***	(0.01)	-0.27***	(0.02)	0.59***	(0.03)	-0.04	(0.03)
RatQ4	-0.02*	(0.01)	0.09***	(0.02)	-0.43***	(0.03)	-0.32***	(0.02)
Rat_Low	0.16***	(0.01)	0.27***	(0.03)	0.50***	(0.04)	0.30***	(0.04)
Vol_high	-0.11***	(0.01)	-0.36***	(0.03)	-0.07***	(0.03)	-0.07**	(0.03)
X<100								
FP	0.03***	(0.01)	0.13***	(0.04)	-0.03	(0.02)	0.01	(0.01)
Public	-0.08***	(0.03)	0.04	(0.08)	-0.67***	(0.06)	0.28***	(0.07)
Teaching	-0.24***	(0.04)	-0.76***	(0.16)	-0.21**	(0.09)	-0.77***	(0.12)
Bed_Large	-0.15***	(0.04)	-0.79***	(0.16)	0.31***	(0.10)	-0.47***	(0.12)
Urban	-0.06***	(0.02)	-0.31***	(0.08)	0	(0.00)	-0.33***	(0.05)
RatQ1	0.30***	(0.03)	0.29**	(0.14)	0.1	(0.08)	0.40***	(0.09)
RatQ2	-0.66***	(0.03)	0.01	(0.13)	-1.71***	(0.07)	-0.21**	(0.09)
RatQ3	0.46***	(0.03)	0.14	(0.16)	0.70***	(0.08)	0.29***	(0.10)
RatQ4	-0.11***	(0.04)	-0.44**	(0.18)	0.91***	(0.09)	-0.48***	(0.08)
Rat_Low	0.85***	(0.03)	0.73***	(0.15)	1.28***	(0.09)	0.65***	(0.12)
Vol_high	-0.10***	(0.02)	-0.16	(0.11)	-0.19**	(0.07)	-0.23**	(0.09)
185<X≤300								
FP	0.03***	(0.00)	0.03***	(0.00)	0.10***	(0.01)	-0.12***	(0.01)
Public	0.06***	(0.00)	0.08***	(0.01)	-0.01	(0.02)	0.34***	(0.01)
Teaching	-0.24***	(0.01)	-0.35***	(0.01)	-0.16***	(0.03)	-0.15***	(0.03)
Bed_Large	0.08***	(0.01)	-0.07***	(0.01)	-0.11***	(0.03)	0.54***	(0.03)
Urban	-0.06***	(0.00)	-0.04***	(0.01)	-0.04***	(0.01)	-0.07***	(0.01)
RatQ1	-0.03***	(0.00)	-0.02*	(0.01)	-0.09***	(0.02)	-0.13***	(0.02)
RatQ2	0.09***	(0.01)	0.07***	(0.01)	-0.24***	(0.02)	0.23***	(0.02)
RatQ3	0.23***	(0.01)	0.32***	(0.01)	0.50***	(0.03)	0.20***	(0.03)
RatQ4	-0.29***	(0.01)	-0.38***	(0.01)	-0.17***	(0.02)	-0.30***	(0.02)
Rat_Low	0.36***	(0.01)	0.40***	(0.01)	0.28***	(0.03)	0.42***	(0.03)
Vol_high	-0.20***	(0.01)	-0.22***	(0.01)	-0.01	(0.02)	0.01	(0.03)

[Table 1.8] continued

X>300	All		White		Black		Hispanic	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
FP	0.07***	(0.00)	-0.03***	(0.00)	0.03*	(0.02)	0.01	(0.01)
Public	0.07***	(0.00)	0.07***	(0.00)	-0.01	(0.03)	0.06***	(0.02)
Teaching	-0.34***	(0.01)	-0.22***	(0.01)	-0.05	(0.04)	-0.28***	(0.05)
Bed_Large	0.51***	(0.01)	0.48***	(0.01)	0.56***	(0.04)	0.46***	(0.04)
Urban	-0.04***	(0.00)	-0.05***	(0.00)	0.01	(0.02)	0.05***	(0.01)
RatQ1	0.01**	(0.00)	0.02**	(0.01)	-0.14***	(0.03)	0.03	(0.04)
RatQ2	0.11***	(0.01)	0.03***	(0.01)	-0.31***	(0.03)	0.32***	(0.03)
RatQ3	-0.39***	(0.01)	-0.08***	(0.01)	-0.36***	(0.04)	0.19***	(0.05)
RatQ4	0.27***	(0.01)	0.03***	(0.01)	0.82***	(0.04)	-0.54***	(0.04)
Rat_Low	0.26***	(0.01)	0.24***	(0.01)	0.56***	(0.03)	0.90***	(0.05)
Vol_high	-0.06***	(0.01)	-0.02***	(0.01)	0.26***	(0.03)	0.05	(0.04)

(0.50), and they moved from the bottom tier to the third tier hospitals in terms of clinical performance. Unlike White or Black patients in the treatment group, Hispanic and other race women in the treatment group were heavily reallocated towards public hospitals. Patients of color from low-income zip codes were able to avoid the clinically worst performing hospitals (Rat_q4), with Blacks benefiting the most, while Whites move up to the top or second tier hospitals (Rat_q1 and Rat_q2). These findings imply that disparities in access to higher quality hospitals between low-income and high-income patients might have lowered when low-income patients obtained Medicaid coverage, but Medicaid patients still had some constraints on access to high-quality hospitals compared to the privately insured.

Table 1.9 reports the coefficients of *ELIG* for patient subgroups across coverage types in each racial subgroup. Similar to the results in Table 1.8, Black and White Medicaid mothers were more likely to choose FP hospitals, while Hispanic or other race women were more likely to select public hospitals. Medicaid patients of all races were able to avoid the clinically worst performing hospitals, Rat_q4. Hispanic Medicaid patients were more likely to deliver at large, teaching, public hospitals, as

[Table 1.9] Linear Probability Model across Insurance Coverage (NIS Data)

Patient Subgroup by Insurance Coverage								
Medicaid	**All**		**White**		**Black**		**Hispanic**	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
FP	-0.02***	(0.00)	0.01**	(0.01)	0.05***	(0.01)	-0.14***	(0.01)
Public	0.12***	(0.01)	0.06***	(0.01)	-0.10***	(0.02)	0.51***	(0.01)
Teaching	0	(0.01)	-0.30***	(0.02)	-0.26***	(0.03)	0.06**	(0.03)
Bed_Large	0.11***	(0.01)	-0.03*	(0.02)	0	(0.03)	0.52***	(0.03)
Urban	-0.02***	(0.01)	-0.05***	(0.01)	-0.03***	(0.01)	-0.20***	(0.01)
RatQ1	-0.11***	(0.01)	-0.07***	(0.02)	-0.01	(0.02)	-0.19***	(0.03)
RatQ2	-0.15***	(0.01)	0.03*	(0.02)	-0.27***	(0.02)	0.07***	(0.02)
RatQ3	0.27***	(0.01)	0.07***	(0.02)	0.39***	(0.03)	0.34***	(0.03)
RatQ4	-0.01	(0.01)	-0.03**	(0.02)	-0.11***	(0.02)	-0.22***	(0.02)
Rat_Low	0.31***	(0.01)	0.38***	(0.02)	0.75***	(0.02)	0.15***	(0.03)
Vol_high	-0.13***	(0.01)	-0.25***	(0.02)	-0.13***	(0.02)	0.03	(0.03)
Private Insurance								
FP	0.05***	(0.00)	0.01***	(0.00)	0.08***	(0.01)	0.03***	(0.01)
Public	0.05***	(0.00)	0.06***	(0.00)	-0.06***	(0.01)	0.10***	(0.01)
Teaching	-0.26***	(0.01)	-0.27***	(0.01)	0.04	(0.03)	-0.68***	(0.03)
Bed_Large	0.22***	(0.01)	0.23***	(0.01)	0.05*	(0.03)	0.24***	(0.03)
Urban	-0.08***	(0.00)	-0.07***	(0.00)	-0.02***	(0.01)	-0.13***	(0.01)
RatQ1	-0.02***	(0.00)	0.01	(0.01)	-0.34***	(0.02)	-0.06*	(0.03)
RatQ2	0.16***	(0.00)	0.11***	(0.01)	-0.24***	(0.02)	0.63***	(0.02)
RatQ3	-0.11***	(0.01)	0.04***	(0.01)	0.28***	(0.03)	-0.04	(0.03)
RatQ4	-0.02***	(0.01)	-0.15***	(0.01)	0.29***	(0.03)	-0.54***	(0.02)
Rat_Low	0.29***	(0.01)	0.30***	(0.01)	0.17***	(0.03)	0.76***	(0.03)
Vol_high	-0.12***	(0.00)	-0.11***	(0.01)	0.20***	(0.02)	-0.01	(0.03)
Self-pay								
FP	-0.01	(0.01)	-0.01	(0.01)	0.06**	(0.03)	-0.16***	(0.02)
Public	-0.08***	(0.01)	0.16***	(0.02)	0.07	(0.06)	-0.06**	(0.03)
Teaching	-0.49***	(0.02)	-0.46***	(0.03)	-0.05	(0.08)	-0.47***	(0.06)
Bed_Large	0.03	(0.02)	-0.04	(0.03)	-0.31***	(0.09)	0.39***	(0.06)
Urban	-0.09***	(0.01)	-0.12***	(0.02)	-0.03	(0.03)	-0.07***	(0.02)
RatQ1	-0.05***	(0.02)	-0.04	(0.03)	0.19***	(0.07)	0.04	(0.06)
RatQ2	0.14***	(0.02)	0.25***	(0.03)	-0.28***	(0.07)	0.26***	(0.04)
RatQ3	0.12***	(0.02)	0	(0.04)	0.09	(0.09)	0.08	(0.06)
RatQ4	-0.21***	(0.02)	-0.22***	(0.03)	0	(0.07)	-0.39***	(0.04)
Rat_Low	0.53***	(0.02)	0.54***	(0.03)	0.31***	(0.08)	0.94***	(0.06)
Vol_high	-0.22***	(0.02)	-0.19***	(0.03)	-0.19***	(0.07)	-0.27***	(0.06)

well as facilities with better clinical outcomes, while other race Medicaid patients moved to lower volume, public, and urban hospitals. The heterogeneous policy effects by patient race suggest that Medicaid expansion might have reduced racial disparities in access to higher quality of care.

VII. Discussion and Conclusion

In the main analysis, I showed that Medicaid expansions reallocated maternity patients from low-income zip codes across hospitals, mostly towards higher quality institutions. However, there may be other factors that might have led Medicaid mothers to switch to higher quality hospitals. In this section, I address potential confounding factors, especially payment changes that could have provided incentives for hospitals to admit more low-income mothers. Then I discuss other issues and conclude this paper.

Medicaid DSH

As shown in Aizer *et al* (2004) and Duggan (2000), the Medicaid DSH program, making extra payments to hospitals which serve a large number of low-income patients, is likely to provide a strong incentive for some hospitals to accept more low-income patients. In order to examine whether the DSH payment is the main reason for those from low-income zip codes being admitted to higher quality hospitals, ideally I would like to control for the amount of DSH payments at the hospital level. With such data unavailable, however, I conduct a counterfactual analysis, comparing maternity patients from low-income zip codes, who were more likely to be influenced by both coverage expansion and the DSH program, with a control group who were influenced by only one of these two policies. The assumption behind this analysis is that if high quality hospitals admitted more maternity patients from low-income zip codes in order to receive Medicaid DSH payments, these hospitals would also increase admissions for patients with other diseases from those poor zip codes.

As for the control group, I study pneumonia patients[39] aged between 20 and 64. Pneumonia was one of the top five causes of hospitalization among the uninsured, along with childbirth, heart disease, mental illness, and alcohol abuse (HCUP, 2006). Therefore, hospitals' potential uncompensated care burden would have reduced if low-income pneumonia patients had come with a reliable payer source. Without a change in the eligibility rules for non-pregnant adults, however, profitability for low-income pneumonia patients would have changed only if Medicaid DSH payments changed.

Table 1.10 presents the results of the hospital fixed-effect model for pneumonia patients in the NIS. Here, the hospital sample and hospital variables are the same as those in the maternity patient analysis. If the proportion of pneumonia patients from low-income zip codes increases at higher quality hospitals, I can infer that the DSH program was part of the reason for maternity patients from low-income zip codes moving to higher quality hospitals. However, I do not find such pattern for pneumonia patients. Nor do I find any statistically significant impact on reallocation of Medicaid pneumonia patients, while the proportion of selfpay patients with pneumonia increased at FP and public hospitals.

In Florida, the Medicaid DSH program was established on July 1, 1988, and the DSH formula did not change during my study period, although the distribution of

[39] I choose pneumonia patients for the following reasons: a) there is a large enough sample of pneumonia patients at each hospital; b) most states have run a separate DSH program for mental institutions; c) heart disease patients usually require immediate medical attention so that their choice of hospitals would be mainly determined by distance to hospital, rather than other hospital attributes; and d) pneumonia patients are considered to have discretion over the hospital choice because a delay of as much as one hour would not directly affect the patient's prognosis (Gowrisankaran and Town, 2003). The principle diagnosis code (ICD-9 code: 480-486) determines pneumonia patients. Those with childbirth DRG codes (370-375), as well as children and the elderly, i.e., those who could have had coverage other than Medicaid, are dropped.

[Table 1.10] Hospital Fixed-Effect Model for Pneumonia Patients (NIS Data)

Fixed effects (X=ZIPINC)	100≤X ≤185	X<100	185<X ≤300	X>300	Medicaid	Privately Insured	Self-pay
ELIG	0.13	-0.01	-0.20*	0.1	0.08	0.22	-0.13**
	(0.09)	(0.02)	(0.11)	(0.08)	(0.10)	(0.16)	(0.06)
ELIG×Public	-0.06	0.01	0.14	-0.09	-0.09	-0.08	0.21***
	(0.10)	(0.02)	(0.10)	(0.10)	(0.11)	(0.14)	(0.07)
ELIG×FP	0.11	-0.03	0.09	-0.17	0.02	0.03	0.16**
	(0.13)	(0.02)	(0.12)	(0.15)	(0.09)	(0.19)	(0.06)
ELIG×Teaching	0.03	-0.01	-0.04	0.03	0.06	0.04	0.01
	(0.08)	(0.02)	(0.09)	(0.08)	(0.07)	(0.13)	(0.05)
ELIG×Vol_high	-0.04	0	0	0.01	-0.07	0.08	0
	(0.07)	(0.02)	(0.07)	(0.07)	(0.07)	(0.11)	(0.04)
ELIG×Bed_Large	0	-0.02	-0.05	0.08	-0.05	0.1	0.04
	(0.08)	(0.02)	(0.07)	(0.09)	(0.06)	(0.10)	(0.04)
ELIG×Urban	-0.12	0.02	0.16*	-0.07	-0.11	-0.1	0.05
	(0.09)	(0.02)	(0.09)	(0.10)	(0.08)	(0.14)	(0.05)
ELIG×Rat_Low	-0.09	0	0.13*	-0.04	0.05	-0.12	0.04
	(0.06)	(0.01)	(0.07)	(0.06)	(0.06)	(0.10)	(0.04)
Constant	0.29***	0.02***	0.39***	0.25***	0.10***	0.61***	0.04***
	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	4097						
# of Hospitals	1084						
F-stat	0.64	0.8	1.33	1.08	3.92	4.03	3.22
p-value	0.85	0.67	0.18	0.37	0	0	0

DSH payments across hospitals or hospitals' response to the DSH program might have changed over time. Without detailed data for hospital DSH payments, I also conduct the same counterfactual analysis on pneumonia patients. Again, I do not find any reallocation effect among pneumonia patients from low-income zip codes at the statistically significant level.

Physician Fee Increases

The other possible factor which could affect patient reallocation is physician fee changes. The Omnibus Budget Reconciliation Act (OBRA) in 1989 encouraged states to raise Medicaid physician fees for pregnant women and children. Higher physician fees for Medicaid mothers may have influenced hospital admissions for low-income mothers through two channels: better access to physicians and a change in the available physician pool through Medicaid. First, the increase in physician care for low-income mothers can prevent development of high-risk pregnancies, and more interactions with physicians may improve physicians' understanding about patients' health and preferences, which can lead them to better and preferred hospitals. Moreover, the increased fees may have motivated physicians to join the Medicaid program. If those new physicians had different referral patterns or admitting privileges with higher quality hospitals, Medicaid mothers could have been reallocated, even without a coverage expansion.

In order to control for the effect of the physician fee increase on hospital admission patterns, I add the ratio of Medicaid to private payer physician fees for obstetric care[40], as well as the interaction terms between this fee ratio[41] and each of the hospital attributes, to the original fixed-effect model (Baker and Royalty, 2000). The results in Table 1.11 show that the increased physician fees did have some effects on Medicaid patients in total, but the reallocation effect on maternity patients from low-income zip codes was still dominated by the eligibility expansion policy. For example, the proportions of White and Black mothers from low-income zip codes increased by 23 and 20 percentage points[42] at FP hospitals, all of which were due to the eligibility expansions. For Hispanic and other race mothers from low-income zip codes, however, the reallocation towards FP hospitals was attributed to the physician fee increases rather than the coverage expansions. Finally, the expansion of Medicaid

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[40] The data for the Medicaid physician fees from 1987 to 1993 come from various sources (see Currie *et al*, 1994). As in Currie *et al* (1995), I estimate private physician fees based on the 1989 data in Schwartz (1991) and state-specific, hospital cost inflation (hospital expenses per inpatient days) from Hospital Statistics (AHA, 1987-1995).

[41] According to Schwartz (1991), this ratio in 1989 was as low as 0.18 in New Jersey, and as high as 1 in South Carolina. On average, the ratio increased by 10 percentage points during the sample period, from 0.41 in 1988 to 0.51 in 1991.

[42] On average, the fraction of eligible population increased by 0.25, while the ratio of Medicaid to private payer physician fees increased by 0.1. Therefore, the change in the proportion of low-income White mothers at FP hospitals is calculated by (0.94)/4+(-0.45+0.40)/10.

[Table 1.11] Hospital Fixed-Effect Model with Physician Fees (NIS Data)

Proportion of Patient Subgroup	100 ≤ ZIPINC ≤ 185% of the FPL				
	All	White	Black	Hispanic	Other Race
ELIG	-0.07	0.94***	-0.34	-0.19	0
	(0.06)	(0.23)	(0.25)	(0.22)	(0.26)
ELIG×Public	-0.02	-0.36**	-0.09	0.06	0.2
	(0.06)	(0.16)	(0.20)	(0.14)	(0.18)
ELIG×FP	0.1	0.03	0.80**	0.01	-0.2
	(0.07)	(0.18)	(0.35)	(0.12)	(0.12)
ELIG×Teaching	0.01	-0.24***	0.01	-0.07	-0.14*
	(0.03)	(0.07)	(0.11)	(0.09)	(0.08)
ELIG×Vol_high	0	0.14	0.08	0.18*	0.31***
	(0.04)	(0.10)	(0.10)	(0.10)	(0.09)
ELIG×Bed_Large	0.03	-0.26***	0.1	-0.07	-0.11
	(0.04)	(0.09)	(0.09)	(0.11)	(0.08)
ELIG×Urban	0.04	-1.02***	0.07	-0.08	-0.29
	(0.06)	(0.22)	(0.23)	(0.19)	(0.20)
ELIG×Rat_Low	0.01	0.1	-0.07	0.08	0.22**
	(0.03)	(0.10)	(0.12)	(0.10)	(0.10)
FEE	0.06	-0.45***	0.04	0.06	-0.12
	(0.05)	(0.12)	(0.12)	(0.11)	(0.12)
FEE×Public	0.18**	0.27***	0.37***	0.16	0.08
	(0.08)	(0.10)	(0.13)	(0.10)	(0.11)
FEE×FP	0.17	0.40**	0.29	0.44***	0.53***
	(0.13)	(0.16)	(0.20)	(0.15)	(0.15)
FEE×Teaching	0.03	0.09	-0.12	0.02	0.06
	(0.06)	(0.08)	(0.11)	(0.10)	(0.09)
FEE×Vol_high	-0.07	-0.07	-0.01	-0.03	-0.09
	(0.05)	(0.09)	(0.11)	(0.11)	(0.10)
FEE×Bed_Large	0.04	0.17**	0.15	0.07	0.18**
	(0.05)	(0.07)	(0.09)	(0.09)	(0.08)
FEE×Urban	-0.05	0.43***	0.15	0.05	0.21*
	(0.06)	(0.12)	(0.13)	(0.12)	(0.11)
FEE×Rat_Low	0.01	0.01	0.05	-0.03	-0.07
	(0.04)	(0.07)	(0.09)	(0.08)	(0.08)
Constant	0.25***	0.07***	-0.02	0.04**	0.04**
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	3466				
# of Hospitals	943				
R-square	0.03	0.19	0.17	0.1	0.09
F-stat	1.38	7.77	7.95	5.04	5.89
p-value	0.11	0	0	0	0

[Table 1.11] continued

Proportion of Patient Subgroup	Medicaid				
	All	White	Black	Hispanic	Other race
ELIG	0.14	0.22*	-0.48*	-0.13	-0.07
	(0.10)	(0.12)	(0.29)	(0.20)	(0.26)
ELIG×Public	0.09	-0.11	-0.03	0.39**	0.29
	(0.12)	(0.12)	(0.23)	(0.19)	(0.19)
ELIG×FP	0.01	0.04	0.59*	0.13	-0.22
	(0.15)	(0.17)	(0.35)	(0.21)	(0.15)
ELIG×Teaching	-0.11	-0.24***	-0.03	-0.11	-0.23*
	(0.09)	(0.08)	(0.15)	(0.15)	(0.14)
ELIG×Vol_high	-0.11	0.13	0.09	0.06	0.26*
	(0.10)	(0.10)	(0.15)	(0.14)	(0.15)
ELIG×Bed_Large	-0.01	-0.20**	0.2	-0.11	0.01
	(0.09)	(0.09)	(0.14)	(0.12)	(0.15)
ELIG×Urban	0	-0.26**	0.23	0.14	0.03
	(0.12)	(0.13)	(0.25)	(0.19)	(0.23)
ELIG×Rat_Low	0.11	0.1	-0.06	0.15	0.18
	(0.07)	(0.07)	(0.15)	(0.13)	(0.13)
FEE	-0.04	-0.31***	-0.21*	-0.24**	-0.24*
	(0.06)	(0.08)	(0.13)	(0.10)	(0.12)
FEE×Public	0.23***	0.38***	0.62***	0.15	0.16
	(0.08)	(0.09)	(0.14)	(0.11)	(0.11)
FEE×FP	0.15	0.50***	0.52***	0.38**	0.52***
	(0.10)	(0.14)	(0.20)	(0.15)	(0.13)
FEE×Teaching	-0.06	0.11	0.05	0.09	0.11
	(0.07)	(0.09)	(0.14)	(0.11)	(0.10)
FEE×Vol_high	-0.03	0.01	0.01	0.05	0.04
	(0.07)	(0.08)	(0.12)	(0.10)	(0.10)
FEE×Bed_Large	0.06	0.12*	0.19*	0.16*	0.04
	(0.06)	(0.07)	(0.10)	(0.08)	(0.09)
FEE×Urban	0	0.23***	0.29**	0.09	0.1
	(0.07)	(0.09)	(0.15)	(0.12)	(0.12)
FEE×Rat_Low	-0.02	0.05	0.02	-0.07	-0.08
	(0.05)	(0.06)	(0.10)	(0.08)	(0.08)
Constant	0.16***	0.08***	0.07***	0.07***	0.09***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
Observations	3466	3466	3466	3466	3466
# of Hospitals	943	943	943	943	943
R-square	0.32	0.28	0.21	0.2	0.15
F-stat	24.71	15.58	13.96	13.84	12.33
p-value	0	0	0	0	0

coverage helped other race mothers from low-income zip codes to receive care at clinically better performing hospitals; the proportion increased by 5 percentage points at hospitals with low complication rates. My findings suggest that the increased physician fees seemed to reinforce the reallocation effects towards FP hospitals for Medicaid patients. These results are consistent with those in Baker and Royalty (2000), which showed that increased physician fees reallocated low-income mothers to private physicians.

Payment Differentials

Lastly, I examine whether the impact of Medicaid expansion varied with hospital reimbursement generosity across states. As Currie and Gruber (2001) noted, the lower the Medicaid hospital payments are relative to private payer reimbursements, the smaller increase in expected payments for hospitals for treating low-income mothers who obtained Medicaid coverage. Therefore, the impact of Medicaid expansions on patient reallocation may be small in states where Medicaid hospital payments are significantly lower than private payer reimbursements, as opposed to states where Medicaid hospital payments are close to the private payers'.

Due to the lack of hospital payment data, however, I use physician fee differentials as a proxy, assuming that states with higher physician fees would also provide higher payments to hospitals. The payment differential is defined as the ratio of private to Medicaid global physician fees for vaginal delivery, the inverse of the fee ratio used in the previous section. To capture the role of the relative payment generosity across hospitals, I add the interaction terms between the differentials and the hospital covariates (*FEE* and *FEE*×X) to the original fixed-effect models.

Table 1.12 presents the results of this hospital fixed-effect model with the NIS data, and supports my hypothesis that the impact of Medicaid expansion was smaller

[Table 1.12] Hospital Fixed-Effect Model with Payment Differentials (NIS Data)

Proportion of Patient Subgroup	100 ≤ ZIPINC ≤ 185% of the FPL				
	All	**White**	**Black**	**Hispanic**	**Other race**
ELIG	0.06	0.80***	0.2	0.31*	0.12
	(0.10)	(0.15)	(0.19)	(0.18)	(0.15)
ELIG×Public	0.16	-0.26*	0.12	0.02	0.05
	(0.10)	(0.15)	(0.18)	(0.17)	(0.16)
ELIG×FP	0.23	0.21	0.73***	0.45*	0.28
	(0.17)	(0.23)	(0.28)	(0.24)	(0.21)
ELIG×Teaching	0.1	-0.06	0.06	0.14	0.01
	(0.10)	(0.14)	(0.17)	(0.16)	(0.15)
ELIG×Vol_high	-0.08	-0.2	0.01	0.06	0.06
	(0.08)	(0.15)	(0.19)	(0.17)	(0.16)
ELIG×Bed_Large	0.02	-0.08	0.29*	0.03	0.1
	(0.09)	(0.14)	(0.16)	(0.15)	(0.14)
ELIG×Urban	-0.07	-0.49***	0.11	-0.2	-0.04
	(0.12)	(0.18)	(0.22)	(0.19)	(0.17)
ELIG×Rat_Low	0.04	0.13	0.02	0.09	0.20*
	(0.06)	(0.12)	(0.15)	(0.14)	(0.11)
ELIG×DIFF	-0.07*	-0.17***	-0.21***	-0.21***	-0.09*
	(0.04)	(0.05)	(0.08)	(0.06)	(0.05)
ELIG×DIFF×Public	-0.07	-0.01	-0.12**	-0.05	-0.04
	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
ELIG×DIFF×FP	-0.06	-0.08*	-0.11	-0.11**	-0.10**
	(0.04)	(0.05)	(0.07)	(0.05)	(0.05)
ELIG×DIFF×Teaching	-0.01	0.02	0.05	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)
ELIG×DIFF×Vol_high	0.01	0.02	-0.05	-0.04	-0.02
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
ELIG×DIFF×Bed_Large	0	0.02	0.03	0.02	0.01
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
ELIG×DIFF×Urban	0.07*	0.08	0.09	0.14**	0.04
	(0.04)	(0.05)	(0.08)	(0.06)	(0.05)
ELIG×DIFF×Rat_Low	-0.01	-0.02	-0.04	-0.01	-0.03
	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
Constant	0.28***	0.08***	0.08***	0.09***	0.07***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Observations	4086				
# of Hospitals	1068				
R-square	0.04	0.2	0.2	0.13	0.09
F-stat	1.55	10.29	10.19	6.95	6.37
p-value	0.05	0	0	0	0

[Table 1.12] continued

Proportion of Patient Subgroup	Medicaid				
	All	**White**	**Black**	**Hispanic**	**Other race**
ELIG	0.08	0.12	-0.15	-0.07	-0.21
	(0.11)	(0.13)	(0.18)	(0.18)	(0.16)
ELIG×Public	0.27**	0.17	0.49***	0.36**	0.34**
	(0.11)	(0.13)	(0.16)	(0.16)	(0.16)
ELIG×FP	0.2	0.46***	0.89***	0.60***	0.35**
	(0.13)	(0.16)	(0.23)	(0.19)	(0.15)
ELIG×Teaching	-0.15	-0.01	0.1	0.1	-0.03
	(0.10)	(0.16)	(0.20)	(0.17)	(0.18)
ELIG×Vol_high	-0.19*	0.01	0.17	0.04	0.37***
	(0.10)	(0.12)	(0.16)	(0.15)	(0.14)
ELIG×Bed_Large	0.06	0	0.50***	0.2	0.02
	(0.08)	(0.11)	(0.14)	(0.13)	(0.12)
ELIG×Urban	0.11	0.01	0.37**	0.32*	0.1
	(0.10)	(0.14)	(0.19)	(0.18)	(0.16)
ELIG×Rat_Low	0.11	0.22**	-0.04	0.01	0.08
	(0.08)	(0.10)	(0.14)	(0.13)	(0.11)
ELIG×DIFF	-0.03	-0.04	-0.09	0	0
	(0.04)	(0.04)	(0.07)	(0.06)	(0.05)
ELIG×DIFF×Public	-0.08*	-0.12***	-0.21***	-0.05	-0.10**
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)
ELIG×DIFF×FP	0.02	-0.12**	-0.14*	-0.04	-0.11**
	(0.04)	(0.05)	(0.08)	(0.05)	(0.04)
ELIG×DIFF×Teaching	0.02	0	0.04	-0.01	0
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)
ELIG×DIFF×Vol_high	0	-0.02	-0.10***	-0.05	-0.07**
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
ELIG×DIFF×Bed_Large	0.01	-0.01	0	-0.02	0.03
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
ELIG×DIFF×Urban	0	0.02	0.01	-0.04	0.01
	(0.03)	(0.04)	(0.07)	(0.06)	(0.05)
ELIG×DIFF×Rat_Low	0	-0.04*	-0.05	0.01	0.01
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Constant	0.17***	0.10***	0.14***	0.03**	0.07***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
Observations	4086				
# of Hospitals	1068				
R-square	0.29	0.29	0.24	0.21	0.14
F-stat	24.05	20.78	21.65	17.62	12.96
p-value	0	0	0	0	0

in states where Medicaid hospital payments were less generous than private payers'. For example, the proportion of Hispanic mothers from low-income zip codes would have increased at FP hospitals by 11 percentage points ((0.31+0.45-0.21-0.11)/4) if there were no payment differentials between private payers and Medicaid. However, if state governments paid hospitals less than private payer reimbursements, the increase in the proportion would be smaller.

Patients Admitted through Emergency Room

In the main analysis, I did not include patients who were admitted through emergency rooms. In the Florida discharge data sets, about 10 percent of childbirth patients (6-16 percent in each year) were admitted through emergency rooms, while in the NIS, 7 percent of the discharges were recorded as emergency room admissions. Not surprisingly, emergency room admissions in Florida had 8 percentage point lower c-section rates and 6 percentage point higher weekend admissions than non-emergency admissions. They were younger, residing in lower income zip codes, staying longer, and making shorter trips to hospitals than routine admissions. The most striking difference lies in the distribution of payer sources. Emergency rooms are heavily used by not only uninsured patients but also Medicaid patients, with these two groups accounting for about 80 percent of ER admissions. It is surprising to see such a large number of Medicaid patients admitted through emergency rooms, even after they obtain a guaranteed payer source. The increase in ER admissions for Medicaid patients after 1989 and 1992 implies that some of new Medicaid-eligible mothers might not have been aware of their eligibility until their admissions to hospitals to deliver babies.

Table 1.13 reports the results of the conditional logit model for the Florida data. Prior to the expansions, maternity patients from low-income zip codes were heavily dependent on emergency departments at public, teaching, and urban hospitals.

[Table 1.13] Conditional Logit Model for Emergency Room Admissions (Florida)

X=ZIPINC as % of the FPL	100≤X ≤150	X≤100	X>300	150≤X ≤185	X≤150	X>300
Zipdist	0.77***	0.66***	0.81***	0.78***	0.60***	0.87
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
FP	0.56***	0.10***	0.35***	0.28***	0.73***	0.64
	(0.05)	(0.01)	(0.03)	(0.02)	(0.09)	(0.02)
Public	22.21***	6.11***	4.86***	3.13***	2.08***	7.87
	(1.27)	(0.59)	(0.29)	(0.13)	(0.18)	0.17
Teaching	5.46***	90.93***	0.56***	3.00***	2.81***	1.46
	(0.47)	(17.41)	(0.04)	(0.15)	(0.25)	4
Large_bed	1.55***	2.12***	1.21	1.69***	4.71***	2.66
	(0.17)	(0.27)	(0.18)	(0.12)	(0.57)	0.12
NICU	0.54***	0.28***	1.54***	1.75***	11.88***	1.2
	(0.05)	(0.05)	(0.14)	(0.11)	(1.69)	0.04
Rat_low	0.97	1.26***	1.47***	1.24***	0.88*	0.82
	(0.05)	(0.11)	(0.09)	(0.04)	(0.06)	0.01
High_Vol	11.99***	1.64***	8.00***	1.38***	0.28***	7.41
	(0.90)	(0.22)	(0.83)	(0.09)	(0.04)	0.21
Urban	21.63***	27.00***	35.69***	66.95***	3.75**	49.8
	(2.58)	(6.45)	(7.53)	(12.06)	(2.40)	5.09
Zipdist×POST	1.13***	1.04***	1.01*	1.05***	0.97**	0.99
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	0
FP×POST	1.67***	3.25***	1.32***	2.42***	3.45***	1.44
	(0.15)	(0.52)	(0.12)	(0.22)	(0.64)	0.07
Public×POST	0.32***	0.80**	0.38***	1.28***	1.49***	0.84
	(0.02)	(0.08)	(0.03)	(0.09)	(0.23)	0.03
Teaching×POST	0.45***	0.26***	4.39***	1.48***	1.41**	1.46
	(0.04)	(0.05)	(0.36)	(0.13)	(0.23)	0.07
largebed×POST	1.61***	0.64***	0.94	1.39***	0.04***	0.68
	(0.18)	(0.09)	(0.15)	(0.14)	(0.01)	0.04
NICU×POST	2.09***	2.59***	0.83*	0.76***	0.21***	0.9
	(0.22)	(0.50)	(0.08)	(0.07)	(0.04)	0.05
Rat_low×POST	0.71***	0.96	0.84***	0.81***	0.82*	0.95
	(0.04)	(0.09)	(0.06)	(0.05)	(0.09)	0.03
High_Vol×POST	0.29***	1.29*	0.37***	0.94	7.26***	0.43
	(0.02)	(0.19)	(0.04)	(0.10)	(1.69)	0.02
Urban×POST	0.96	0.74	0.36***	0.17***	1.06	0.35
	(0.15)	(0.19)	(0.09)	(0.04)	(1.28)	0.05
Observations	252390	222580	128782	113298	108934	356995
LR-chi2	49868.53	78411.78	23733.43	23585.8	39459.96	63873.58
Prob>chi2	0	0	0	0	0	0
Psuedo R2	0.38	0.64	0.37	0.43	0.63	0.35

After the coverage expansions, their access to FP hospitals was greatly improved, while dependence on safety-net hospitals decreased. This indicates that the policy effect on patient reallocation is different between maternity patients admitted through an emergency room and those admitted with a referral: the finding that ER admissions are more likely to give birth at FP hospitals, which referred low-income mothers still had difficulty in accessing, implies that FP hospitals had no choice but to provide care for those who showed up at their emergency rooms.

Other Discussions

The conditional logit model, focusing on the effect of hospital attributes on patient choice, is based on the strong assumption such that the probability ratio of patients choosing between two hospitals does not depend on the availability or attributes of other hospital options, i.e., the error terms are independent across alternatives. This restrictive assumption, called independence from irrelevant alternatives (IIA), raises some concerns because the violation of the IIA could produce inconsistent estimates (Tai, 2004). There are alternative discrete choice models, such as nested logit, multinomial probit and mixed logit models, that partially or fully relax the IIA assumption[43]. However, the task of relaxing the IIA assumption accompanies significant time and computational costs, while the results of the conditional logit model and other models with the relaxed IIA assumption produced qualitatively similar results (Christiadi and Cushing, 2007). Since my goal was to examine patients' average preference on hospital attributes, not to predict the substitution patterns among hospital options, the conditional logit model would suffice to address my questions[44].

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[43] Borah (2006) and Pope (2007) used the mixed-logit model to investigate hospital choice decisions in India and for American Medicare patients, respectively.
[44] Moreover, I applied the conditional logit model to the various patient subgroups as an attempt to take into account taste variations among patients, which mixed logit or multinomial probit models aim to capture. This further breakdown of my sample across patient characteristics (income, coverage type, and risk-level) would minimize the potential bias (Train, 2003).

Conclusion

The original goal of the Medicaid program was to provide low-income people with health insurance coverage so that they would not be at a disadvantage in receiving necessary medical services due to inability to pay. Past studies have provided ample evidence that the expansion of the Medicaid program increased utilization of medical services and thereby improved health outcomes for low-income individuals. However, this paper shows that these improved health outcomes could actually have been the product of not only increased access to care but also accessibility to higher quality providers. If increased access to high-quality care is as important a factor in improved health outcomes as increased quantity of care received, without considering this quality channel, previous studies may not have fully understood the mechanisms for improved health outcomes as a result of the Medicaid expansion policy.

In this paper, I show that types of hospitals utilized by maternity patients differ by zip code income level, coverage type, and severity of illness. Traditionally, uninsured low-income patients have relied on safety-net hospitals such as major teaching or public hospitals. However, increased public insurance coverage makes those who were previously uninsured but obtained Medicaid coverage more profitable and thereby can steer them toward higher quality hospitals. Without patient income information, I study how Medicaid expansions reallocated maternity patients from low-income zip codes across hospitals. Overall, my findings confirm that those from low-income zip codes, who were more likely to obtain Medicaid coverage after the expansion policy, had a higher probability of being guided to better hospitals after the expansions. In Florida, the two eligibility expansions in 1989 and 1992 increased access to higher quality hospitals to different extents. While the 1989 expansion reallocated those from low-income zip codes to safety-net hospitals, hospitals with

NICU, and those with low complication rates, the 1992 expansion sent them to non-safety-net hospitals, i.e., private FP or NFP hospitals, and those with better clinical outcomes. The physician fee increase in 1992 seemed to solidify the reallocation effects, but was not entirely responsible for this change in site of hospital care. Nor did the high-risk status among maternity patients from low-income zip codes lead them to higher quality hospitals. At the national level, the impacts of Medicaid expansion on patient reallocation were similar to those of the 1989 expansion in Florida, but somewhat smaller than the effects found in the Florida analysis. However, my findings from the NIS consistently support my hypothesis that those from low-income zip codes were more likely to receive care at higher quality hospitals such as institutions with low postnatal complication rates. I also find that the increased public insurance coverage somewhat reduced racial disparities in access to higher quality hospitals.

This paper suggests two future research directions. First, there has been an ongoing discussion concerning the measurement of hospital quality, dissemination of quality information, and incentives for hospital quality improvement. More research should be done with regard to how this increasing attention to quality improvement can benefit the vulnerable, low-income population. Second, in order to have a better understanding of hospital admission and selection processes, more studies concerning the role of physicians in patients' choice of hospitals, as well as the dynamics between hospitals and physicians, are necessary.

Nonetheless, my findings provide two important implications for policy makers. First, this paper shows that expansion of the public insurance program results not only in increased access to care but also in access to better care, which may lead to improved health outcomes. Therefore, policy makers should pay attention to the quality of providers accessible to low-income individuals, in addition to the increase in public insurance coverage. Second, my findings suggest that higher payments to providers reinforce the reallocation effect toward better care. Therefore, increased coverage combined with direct financial support to providers such as increases in hospital payments or physician fees may be more effective in providing a better health care safety net for low-income people.

REFERENCES

American Academy of Pediatrics, American College of Obstetricians and Gynecologists, *Guidelines for Perinatal Care*, 2nd ed. Elk Grove, IL, American Academy of Pediatrics, 1988.

Adams, Kathleen, Frank Porell, and James Robbins, "Estimating the Utilization Impacts of Hospital Closures Through Hospital Choice Models: a Comparison of Disaggregate and Aggregate Models," *Socio-Economic Planning Services*, Vol. 30, No. 2, June 1996.

Aizer, Anna, Adriana Lleras-Muney, and Mark Stabile, "Access to Care, Provider Choice and Racial Disparities," *American Economics Review*, Vol. 95, Issue 2, May 2005: pp. 248-252.

Baicker, Katherine and Douglas Staiger, "Fiscal Shenanigans, Targeted Federal Health Care Funds, and Patient Mortality," *Quarterly Journal of Economics*, 120 (1), February 2005: pp. 345-386.

Baker, Laurence, and Ann Beeson Royalty, "Medicaid Policy, Physician Behavior, and Health Care for the Low-income Population," *Journal of Human Resources* 35 (3), summer 2000: pp. 480-502.

Bazzoli, Gloria J. Linda R. Brewster, Gigi Liu, and Sylvia Kuo, "Does U.S. Hospital Capacity Need to Be Expanded?" *Health Affair*, Vol. 22, No. 6, Nov/Dec. 2003.

Borah, Bijan, J., "A Mixed Logit Model of Health Care Provider Choice: Analysis of NSS Data for Rural India," *Health Economics*, Vol. 15, Issue 9, Aug 2006.

Burns, Lawton, and Douglas Wholey, "The Impact of Physician Characteristics in Conditional Choice Models for Hospital Care," *Journal of Health Economics*, Volume 11, Issue 1 , May 1992: pp. 43-62.

Chernew, Michael, Dennis Scanlon, and Rod Hayward, "Insurance Type and Choice of Hospital for Coronary Artery Bypass Graft Surgery," *Health Service Research*, 33(1), 1998: pp. 447-66.

Chiswick, Barry R. “Regional Variations in Hospital Occupancy Rates,” *Journal of Urban Economics*, Volume 3, Issue 2, April 1976: pp. 113-126.

Christiadi and Brian Cushing, “Conditional Logit, IIA, and Alternatives for Estimating Models of Interstate Migration,” West Virginia University Working Paper, 2007.

Cohen Joel W., and Peter J. Cunningham, “Medicaid Physician Fee Levels and Children’s Access to Care,” *Health Affairs*, 14 (1), Spring 1995: pp. 255-262.

Coughlin, Teresa and David Liska, “Changing State And Federal Payment Policies For Medicaid Disproportionate-Share Hospitals,” *Health Affairs* Vol. 17, No.3, 1998.

Coughlin Teresa, Brian K. Bruen, and Jennifer King, “States' Use of Medicaid UPL and DSH Financing Mechanisms,” *Health Affairs* 23 (2): 245-257 MAR-APR 2004.

Cunningham, Peter, and Len Nicholas, “The Effects of Medicaid Reimbursement on the Access to Care of Medicaid Enrollees: A Community Perspective,” *Medical Care Research and Review*, Vol. 62, No. 6, December 2005.

Currie, Janet, and John Fahr, “Medicaid Managed Care: Effects on Children's Medicaid Coverage and Utilization,” *Journal of Public Economics*, Vol. 89, No. 1, Special Issue Jan. 2005.

Currie, Janet, and Jonathan Gruber, “Saving Babies: The Efficacy and Cost of Recent Expansions of Medicaid Eligibility for Pregnant Women,” *Journal of Political Economy* 104 (6), Dec.1996: pp.1263-1296.

Currie, Janet, and Jonathan Gruber, “Public Health Insurance and Medical Treatment: the Equalizing Impact of the Medicaid Expansions,” *Journal of Public Economics*, Vol. 82, Issue 1, October 2001: pp. 63-89.

Currie, Janet, Jonathan Gruber, and Michael Fischer, “Physician Payments and Infant Mortality: Evidence from Medicaid Fee Policy,” *American Economic Review*, Vol. 85, No. 2, May 1995: pp. 106-111.

Currie, Janet, and Duncan Thomas, “Medicaid and Medical Care for Children,” *Journal of Human Resources*, Vol. 30, No. 1, Winter 1995: pp. 135-162.

Dafny, Leemore, and Jonathan Gruber, "Public Insurance and Child Hospitalizations: Access and Efficiency Effects," *Journal of Public Economics*, Vol. 89, No. 1, Special Issue Jan. 2005: pp. 109-129.

Decker, Sandra L., "Medicaid Physician Fees and the Quality of Medical Care of Medicaid Patients in the USA," *Review of Economics of the Household*, Vol. 5, No. 1, March, 2007.

DeLeire, Thomas, Leonard M. Lopoo, and Kosali I. Simon, "Medicaid Expansions and Fertility in the United States," NBER Working Paper, No. 12907, February 2007.

Dranove, David, and William D. White, "Medicaid-dependent Hospitals and Their Patients: How Have They Fared?" *Health Services Research* 33 (2), June 1998.

Duggan, M., "Hospital Ownership and Public Medical Spending" *Quarterly Journal of Economics* 115 (4), November 2000: pp. 1343-1373.

Eggleston, Karen, Yu-Chu Shen, Joseph Lau, Christopher H. Schmid, and Jia Chan, "Hospital Ownership and Quality of Care: What Explains the Different Results?" NBER Working Paper, No. 12241, May 2006.

Elixhauser, Anne, Claudia Steiner, Robert Harris, and Rosanna Coffey, "Comorbidity Measures for Use with Administrative Data," *Medical Care*, 36(1), Jan. 1998: 8-27.

Epstein, Arnold, and Joseph Newhouse, "Impact of Medicaid Expansion on Early Prenatal Care and Health Outcomes," *Health Care Financing Review*, Volume 19, Number 4, Summer 1998.

Epstein, Andrew, Jonathan Ketcham, and Sean Nicholson, "Professional Partnerships and Matching in Obstetrics," NBER Working Paper, No. 14070, June 2008.

Finkelstein, Beth, Jagdip Singh, J. B. Silvers, Duncan Neuhauser, and Gary E. Rosenthal, "Patient and Hospital Characteristics Associated With Patient Assessments of Hospital Obstetrical Care," *Medical Care*, Vol. 36, No. 8, Aug. 1998: AS68-AS78.

Forthman, Thane, Susan DesHarnais, Robert Gold, Kirk Phillips, and Richard Henderson, "Measuring the Quality of Inpatient Care: Risk-Adjusted Indexes for

Comparing Rates of Mortality, Complications, and Readmissions," White Paper, The Delta Group, Inc. Greenville, South Carolina, 2005.

Gaskin, Darrell J., Jack Hadley, and Victor G. Freeman, "Are Urban Safety-Net Hospitals Losing Low-Risk Medicaid Maternity Patients?" *Health Services Research* 36 (1): 25-51 Part 1, April 2001.

Geronimus, Arline, John Bound, and Lisa Neider "On the Validity of Using Census Geocode Characteristics to Proxy Individual Socioeconomic Characteristics," *Journal of the American Statistical Association*, Vol. 91, No. 434, June 1996: pp. 529-537

Gray, Bradley, "Do Medicaid Physician Fees for Prenatal Services Affect Birth Outcomes?" *Journal of Health Economics* 20 (4), July 2001: pp. 571-590.

Gregory, Kimberly, Lisa Korst, Jeffrey Gornbein, Lawrence Platt, "Using Administrative Data to Identify Indications for Elective Primary Cesarean Delivery," *Health Services Research* 37 (5), (2002), pp. 1387–1401.

Gruber, Jon, John Kim, and Dina Mayzlin, "Physician Fees and Procedure Intensity: the Case of Cesarean Delivery," *Journal of Health Economics*, Vol. 18, no. 4, 1999.

Healthcare Cost and Utilization Project (HCUP)**, "**Circumcisions Performed in U.S. Community Hospitals," Statistical Brief #45, January 2008

Healthcare Cost and Utilization Project (HCUP), "Conditions Related to Uninsured Hospitalizations, 2003," Statistical Brief #8, May 2006.

HealthGrade, "The Health Grade Maternity Report," June 2007.

Hill, Ian, Beth Zimmerman, Renee Schwalberg, and Arik Ben-Avi, "Frorida's Ongoing Efforts to Improve Systems of Care for Pregnant Women: A Qualitative Analysis of Medicaid Expansions and Other Policies Implemented From 1992 to 1995," *Health Systems Research*, Inc., Washington D.C., September 1998.

Hodgkin, Dominic, "Specialized Service Offerings and Patients' Choice of Hospital: The Case of Cardiac Catheterization," *Journal of Health Economics*, Vol. 15, 1996.

Howard, David, “Quality and Consumer Choice in Healthcare: Evidence from Kidney Transplantation,” Topics in Economic Analysis & Policy, Vol. 5, Issue 1, 2005.

Jha, Ashish K., Zhonghe Li, E. John Orav, and Arnold M. Epstein, “Care in U.S. Hospitals — The Hospital Quality Alliance Program,” *The New England Journal of Medicine*, Vol. 353, No. 3, 2005: pp. 265-274.

Kaestner, Robert, Theodore Joyce, and Andrew Racine, “Does Publicly Provided Health Insurance Improve the Health of Low-Income Children in the United States,” NBER Working Papers, No. 6887, January 1999.

Kupersmith, Joel, “Quality of Care in Teaching Hospitals: A Literature Review,” *Academic Medicine: Journal of the Association of American Medical Colleges*, 80(5), May 2005: pp. 458-66.

Lewin Group, “The Foundation, History and Implications of the Cost-Shift Hydraulic,” Conference on the Future of Hospital Payments, Washington, DC, 2005.

Long, Stephen and Susan Marquis, “The Effects of Florida's Medicaid Eligibility Expansion for Pregnant Women,” *American Journal of Public Health*, Vol. 88, Issue 3, MAR 1998: pp. 371–376.

Long, Sharon, Teresa Coughlin, and Jennifer King, “How Well Does Medicaid Work in Improving Access to Care?” *Health Services Research*, Vol. 40, Issue 1, 2005.

Luft, Harold, Deborah Garnick, David Mark, Deborah Peltzman, Ciaran Phibbs, and Erik Lichtenberg, “Does Quality Influence Choice of Hospital?” *JAMA*, Vol. 263, No. 21, June 1990: pp. 2899-2906.

Marquis, Susan, and Stephen Long, “Medicaid Eligibility Expansion in Florida: Effects On Maternity Care Financing and the Delivery System,” *Family Planning Perspectives*, 1999, 31(3): 112-116 & 121.

Marquis, Susan, and Stephen Long, “The Role of Public Insurance and the Public Delivery System in Improving Birth Outcomes for Low-Income Pregnant Women,” *Medical Care*, Vol. 40, No. 11, 2002: pp. 1048-1059.

McClellan, Mark, and Douglas Staiger, "The Quality of Health Care Providers," NBER WP 7327, Aug 1999.

McGuirk, M.A., and Frank W. Porell, "Spatial Patterns of Hospital Utilization: The Impact of Distance and Time," *Inquiry* 21(2), 1984: pp. 84-95.

Mukamel, Dana, Jack Zwanziger, and Kenneth Tomaszewski, "HMO Penetration, Competition, and Risk-adjusted Hospital Mortality," *Health Services Research* 36, 2001: pp. 1019-1035.

Nichols, Donald, "Racial Differences in the Decision Choice Models of the Hospital Assignment Process," University of Washington Working Paper, 2005.

Norton, Edward, Steven Garfinkel, Lisa McQuay, et al, "The Effect of Hospital Volume on the In-Hospital Complication Rate in Knee Replacement Patients," *Health Services Research*, 33, 1998: pp. 1191-1210.

Phibbs Ciaran S., David H. Mark, Harold S. Luft, Deborah J. Peltzman-Rennie, Deborah W. Garnick, Erik Lichtenberg, and Stephen J. McPhee, "Choice of Hospital for Delivery – A Comparison of High-risk and Low-risk Women," *Health Services Research* 28 (2), June 1993: pp. 201-222.

Pope, Devin, "Reacting to Rankings: Evidence from America's Best Hospitals," The Wharton School University of Pennsylvania, Working Paper, 2008.

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

Rogowski, Jeannette A., Jeffrey Horbar, Douglas Staiger, et al., "Indirect vs. Direct Hospital Quality Indicators for Very Low-Birth-Weight Infants," *JAMA* 291, 2004.

Romano, Patrick, Shagufta Yasmeen, Michael E. Schembri, Janet M. Keyzer, and William M. Gilbert, "Coding of Perineal Lacerations and Other Complications of Obstetric Care in Hospital Discharge Data," *American College of Obstetricians and Gynecologists,* Vol. 106, No. 4, October 2005.

Sarrazin, Mary Vaughan, Mary Campbell, and Gary E. Rosenthal, “Racial Differences in Hospital Use After Acute Myocardial Infarction: Does Residential Segregation Play a Role?” *Health Affairs* 28(2), March/April 2009: pp. 368-378.

Schwartz, Anne, David C. Colby, and Anne Lenhard Reisinger, “Variation in Medicaid Physician Fees,” *Health Affairs*, Spring 1991.

Shen, Yu-Chu, “The Effect of Hospital Ownership Choice on Patient Outcomes After Treatment for Acute Myocardial Infarction,” *Journal of Health Economics*, 21, 2002.

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

Smith, David B. “The Racial Segregation of Hospital Care Revisited: Medicare Discharge Patterns and Their Implications,” *American Journal of Public Health*, Vol. 88, No. 3, 1998: pp. 461–463.

Soobader, Mah-jabeen, Felicia LeClere, Wilbur Hadden, and Brooke Maury, “Using Aggregate Geographic Data to Proxy Individual Socioeconomic Status: Does Size Matter?” *American Journal of Public Health*, Vol. 91, Issue 4, 2001, pp. 632-636.

Tai, Wan-Tzu Connie, Frank W. Porell, and E. Kathleen Adams, “Hospital Choice of Rural Medicare Beneficiaries: Patient, Hospital Attributes, and the Patient-Physician Relationship,” *Health Services Research* 39 (6): 1903-1922, Part 1, December 2004.

Tay, Abigail, “Assessing Competition in Hospital Care Markets: The Importance of Accounting for Quality Differentiation,” *The RAND Journal of Economics*, Vol. 34, No. 4, Winter, 2003: pp. 786-814.

Taylor, Donald, David Whellan, and Frank Sloan, “Effects of Admission to a Teaching Hospital on the Cost and Quality of Care for Medicare Beneficiaries,” *New England Journal of Medicine*, 340, 1999: pp. 293-299.

Train, Kenneth, *Discrete Choice Method with Simulation*, Cambridge, MA: Cambridge University Press, 2003.

Wolinksy, Fredric D. and Richard S. Kurz, “How the Public Chooses and Views Hospitals,” *Hospital and Health Services Administration* 29(6), 1984: pp. 58-67.

CHAPTER 2

The Impact of Health Policy and Market Structure on Hospital Indigent Care

I. Introduction

Nearly 46 million Americans, or 18 percent of the population under age 65, do not have health insurance, among whom 64 percent have incomes below 200 percent of the federal poverty line (CPS, 2007). Although physicians provide some indigent care, hospitals have been a primary source of care for this uninsured low-income population[45] (Hadley and Holahan, 2004). According to the most recent national study (HCUP, 2009), uninsured hospitalizations have increased by 34 percent, from 1.7 million in 1997 to 2.2 million in 2006[46], and account for 4.8 and 5.7 percent, respectively, of total hospitalizations. This increasing trend in uninsured hospitalizations implies that hospital indigent care has been in high demand.

At the same time, hospitals have experienced considerable financial strain since the 1990s due to low payments from both private and government payers (Figure 2.1). In the private sector, growth of managed care organizations has increased price competition, making it difficult for hospitals to cross-subsidize the uninsured and the underinsured (Thorpe *et al*, 2001; Weissman, 2003; McKay and Meng, 2007). Meanwhile, low government reimbursements have been a perennial problem for safety-net hospitals, i.e., those whose payer mix consists mainly of Medicaid and self-pay. Hospitals' financial distress deepened in 1997 when the Balanced Budget Act

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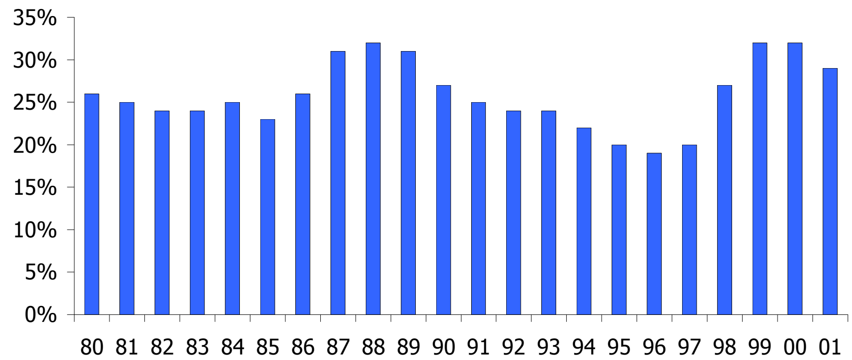
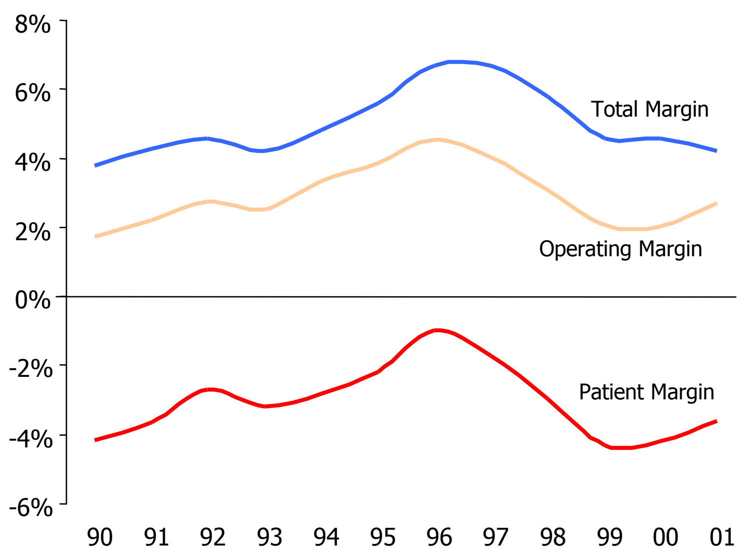
[45] Sixty three percent of indigent care is provided by hospitals, whereas physicians and clinics/direct care programs provide about 20 percent of indigent care.

[46] Over those ten years, privately insured hospitalizations did not change; the increase in Medicare hospitalizations was much smaller, 17%, while Medicaid hospitalizations increased the most, by 36%.

(a) Percentage of Hospitals with Negative Total Margins 1980-2001



(b) Hospital Margins: 1990 – 2001



Source: AHA Trend Watch Chartbook, 2003: p. 45

[Figure 2.1] Hospital Financial Distress: 1980-2001

further reduced Medicare and Medicaid hospital payments (Zuckerman *et al*, 2001; Bazzoli *et al*, 2004).

Concern about increased demand for indigent care, along with hospitals' decreased ability to finance it, triggered implementation of several health policies that aimed to ease the financial burden for both hospitals and indigent patients. For example, the federal and state governments have run financial support programs—the Disproportionate Share Hospital (DSH) program, Indirect Medical Education (IME), and uncompensated care pool—for indigent care providers, directly injecting extra funds into hospitals that disproportionately serve the poor. At the same time, expansions of public insurance coverage through Medicaid and other state-run insurance programs are designed to lower the financial burden of indigent patients, which will ultimately reduce disparities in access to care and in health outcomes. Indirectly, however, this increased coverage may also benefit hospitals by decreasing demand for indigent care, as well as offering some payments to them for treating low-income patients.

The objective of this study is to examine hospitals' provision of indigent care in response to two U.S. health policies: expansions of the Medicaid program for pregnant women and infants in 1992 and the Balanced Budget Act (BBA) in 1997. The BBA, reducing government payments, increased financial pressure on hospitals, thereby giving them a greater incentive to reduce the supply of indigent care. The impact of the Medicaid expansion is rather ambiguous because coverage expansions affect both the demand and supply sides of indigent care. On the demand side, expanded coverage for pregnant women and infants (the target group) is expected to lower demand for indigent care, considering that childbirth has been the most common reason for hospitalization for the uninsured (HCUP, 2009). The equilibrium level of indigent care, however, may fall because of potential effects on demand for and supply of indigent care. On the demand side, if there is large excess demand for indigent care, increased coverage will reduce that excess demand to some degree, but may not completely eliminate it (only a small reduction in unmet indigent care). The other possibility is that if non-maternity and non-infant patients (non-target group) increase demand for indigent care, the total demand will not decrease. On the supply side, despite low Medicaid hospital payments, revenues generated from a larger number of Medicaid mothers and infants may motivate hospitals to provide more indigent care to other low-income uninsured patients (income effects). If hospitals supplement the decreased indigent care for the target group with increased indigent care for those in the non-target group, the expansion policy will not necessarily reduce the observed equilibrium amount of indigent care. Therefore, whether the expansion of Medicaid coverage reduces the equilibrium level of hospital indigent care is an empirical question.

In order to examine the impacts of these two policies on hospitals' provision of indigent care, I study a sample of 1739 hospital-year observations for 1990-2000 from 168 different hospitals in Florida hospitals' financial and discharge data sets[47]. As shown in Table 2.1, I define hospital indigent care in the following three ways: uncompensated care costs in dollars, volume of indigent patients, and amounts of unprofitable services provided. First, uncompensated care (UC) is the sum of charity care and bad debt: both are unpaid care, but charity care is care for which hospitals never expect to be reimbursed, while bad debt arises when hospitals cannot obtain reimbursement for care provided, as opposed to their initial expectation of payment (AHA, 2008). I examine charity care and UC as a percent of operating costs, as well as their log values. Second, I examine number and proportion of indigent admissions. Due to the data limitation, I define indigent patients based on payer source, and examine admissions for uninsured (selfpay) patients. Since not all uninsured patients are indigent, I am aware of the possible biases resulting from studying total uninsured

[47] I choose to study the state of Florida due to not only the availability of the detailed data sets but also interesting features in its health care market. Florida ranks third in the nation in uninsured persons, 20.2% of the state population (Census, 2005); demographically, racial and ethnic minorities are over-represented among the uninsured: Hispanics make up 31.6% of the uninsured, Blacks 19.5%; the Florida hospital market includes a large number of for-profit hospitals (47%) compared to the average hospital market in the nation (10%).

[Table 2.1] Definition of Hospital Indigent Care

<table>
<tr><th colspan="2">Hospital Indigent Care</th><th>Definition</th></tr>
<tr><td rowspan="2">Uncompensated Care</td><td>Charity Care</td><td>Unbilled care that hospitals initially do not expect to be reimbursed for. Hospitals report full charges on their financial statements, but not true costs of providing the care. Active willingness to provide indigent care or hospitals' intention of providing indigent care. Ex-ante concept.</td></tr>
<tr><td>Bad Debt</td><td>Billed but unpaid care that hospitals initially expect to be reimbursed for, but fail to collect payments due to patients' unwillingness or inability to pay. No intention of providing indigent care in the first place. Ex-post concept.</td></tr>
<tr><td colspan="2">Admissions for Indigent patients</td><td>I use indigent, uninsured, and selfpay patients, interchangeably.</td></tr>
<tr><td colspan="2">Provision of Unprofitable Services</td><td>See Table 2.3.</td></tr>
</table>

patients instead of just the indigent segment of uninsured patients. I will discuss this issue in Section V. Admissions for uninsured patients are broken down into non-emergency vs. emergency patients, and for the analysis of the Medicaid expansion, into the target group (maternity and infant patients) vs. the non-target group. Last, I classify hospital services as profitable and unprofitable services based on Horwitz (2005) and consider provision of unprofitable services (such as emergency room and clinic services) as indigent care.

While studying the policy impacts on hospital indigent care, I particularly focus on two factors that could generate heterogeneous policy impacts: hospital ownership type and level of concentration of indigent care burden among hospitals within markets. First, I divide hospitals into three groups by ownership status: private for-profit (FP), private not-for-profit (NFP), and public. The general consensus is that FP hospitals, as profit maximizers, have the least incentive to provide indigent care, while public or NFP hospitals are major indigent care providers by mission, or due to the requirement to provide community benefits in exchange for tax exemptions[48]. Since hospitals' objective functions and constraints differ by ownership type, demand or supply shocks such as Medicaid expansions or the BBA are expected to have a heterogeneous impact on provision of indigent care across hospitals with different ownership types. For example, FP hospitals, concerned with profits, may be more responsive to financial incentive changes than NFP or public hospitals. On the other hand, FP hospitals may not need to be as responsive because these types of policies are likely to have a larger impact on hospitals with high indigent care burdens in the first place, which would not be the case for FP hospitals.

In addition to ownership types, the extent to which hospitals are able to adjust their provision of indigent care may vary across markets, or more precisely, according to markets' levels of concentration of indigent care burden across hospitals. Therefore, I compare hospitals' supply of indigent care across three types of markets: markets with a single hospital; markets with multiple hospitals of which very few disproportionately serve the indigent; markets with multiple hospitals among which the indigent care burden is equally spread out. For markets with multiple hospitals, I measure the concentration level based on distribution of hospitals and indigent patients. If a large public hospital serves a great number of indigent patients because it is located in an area in which indigent patients are largely populated (e.g. Jackson Memorial Hospital in Miami-Dade County), I do not consider this market highly concentrated. However, if indigent patients have to make a long trip to a public hospital because nearby hospitals do not welcome them, this public hospital disproportionately serves the poor, and its market is considered highly concentrated.

[48] As an exception to this, Norton and Staiger (1994) showed that there is no difference in the provision of charity care across hospital ownership types after controlling endogeneity of ownership type and services provided.

Hospital payment cuts such as the BBA are major supply shocks that would give hospitals a greater incentive to reduce indigent care, but probably to different extents across markets. If hospitals are operating as sole providers in markets, it may be difficult for them to reduce indigent care to a large extent, because there is no alternative institution that could provide indigent care in their markets. If there are alternative providers in markets, hospitals may make larger adjustments to indigent care, hoping that other hospitals will meet the indigent care needs of their communities. In particular, hospitals operating in markets where every hospital shares indigent care burden may be able to reduce indigent care to greater extents than those operating in markets where only a few hospitals disproportionately serve the poor. Because indigent care has a public good property (Nicholson *et al*, 2000; Sloan, 2002), I conjecture that hospitals will minimize the provision of indigent care if they can, and prefer to free-ride instead of acting as major indigent care providers. Whether and to what extent hospitals can free-ride depends on other hospitals' supply of indigent care. Here, I use the level of concentration of indigent care burden among hospitals as a measure for how easily hospitals can make adjustments to indigent care or free-ride in terms of indigent care contributions to communities. I compare the supply of indigent care after the policy changes, not only across hospital ownership types but also between markets in which distribution of indigent care burden is different.

Estimating difference-in-difference and triple difference type regression models, I find that policy impacts did differ across ownership status, but do not find a consistent pattern for the relationship between the market conditions and hospitals' provision of indigent care. For the Medicaid expansion, increased coverage lowered provision of charity care, regardless of ownership type or market structure, with the decrease larger at public and NFP hospitals. The policy impact on overall volume of uninsured patients was small and statistically insignificant. However, the composition of uninsured admissions between the target and non-target groups appeared to change: public and NFP hospitals seemed to supplement their decreased indigent care for maternity and infant patients with increased care for non-maternity indigent patients who did not have emergency conditions; however, FP hospitals decreased their uninsured admissions after the expansion unless they were sole providers within markets. I also find that the coverage expansion reallocated provision of maternity and infant care services across hospitals: public and NFP hospitals acting as sole providers or operating in markets with low concentrations of indigent care burden increased NICU days after the expansion; in contrast, in markets with high concentrations of indigent care burden, FP hospitals increased services associated with maternity and pediatric patients, the target groups of the expansion.

For the BBA, hospitals reduced indigent care by admitting fewer uninsured and Medicaid admissions, while amounts of uncompensated care did not change. Policy impacts were large at safety-net hospitals, such as public and NFP hospitals, which were hit hard by the BBA. Although FP hospitals with the least detrimental effects after the BBA made little adjustment to indigent care, they increased provision of profitable services and decreased provision of unprofitable services. After both policy changes, public hospitals remained major indigent care providers.

The structure of this paper is as follows. Section II summarizes the background of the BBA and the Medicaid expansion. Section III provides the conceptual framework: the supply side of indigent care, the demand side of indigent care, three measures for hospital indigent care, and the measure for market level concentration of indigent care burden. I introduce data and empirical strategies in Section V, discuss the empirical results in Section VI, and conduct robustness checks in Section VII. Section VIII concludes this paper.

II. Background of Health Policy

The Balanced Budget Act of 1997

The BBA was widely considered a broad, fundamental change in the whole reimbursement system of health care providers. The BBA reduced hospital reimbursements for Medicare patients, set Medicaid DSH spending limits, refined the physician payment system to more accurately reflect practice expenses, and expanded the Prospective Payment System to outpatient care, home health agencies, rehabilitation hospitals, as well as skilled nursing facilities. Through the reductions of annual inflation updates, Medicare DSH payments, and direct/indirect graduate medical educational payments, Medicare hospital revenues were expected to decrease by $72 billion for 1998-2002 and $119 billion for 1998-2004 (AHA, 2001). With the BBA effective on the first day of 1998, however, larger than anticipated reductions in hospital Medicare revenues convinced the U.S. Congress to enact the Balanced Budget Refinement Act (BBRA) in 1999 and Benefits Improvement and Protection Act (BIPA) in 2000. These two provisions relaxed or delayed some of the original reductions ($8.4 billion under the BBRA and $11.5 billion under the BIPA), lengthened the transition period for reductions in IME adjustments, and limited DSH reductions (AHA, 2001). However, the BBRA and BIPA were considered to be small, temporary relief from the BBA.

The size of the financial shock was measured with a BBA-simulator (Volpp et al, 2005; Seshamani *et al*, 2006; Tamara *et al*, 2005) or Financial Pressure Index (Bazzoli *et al*, 2004; Lindrooth *et al*, 2006). The BBA-simulator, constructed by the American Hospital Association (AHA) based on hospital data from Medicare Cost Reports, estimated Medicare revenues under inflation for post-BBA periods, had the BBA not been implemented. The difference between these estimated and actual revenues indicates the magnitude of the policy impact on hospitals. Table 2.2 presents the simulated results (Seshamani *et al*, 2006): the BBRA and BIPA, the two follow-up policies after the BBA, did not change the size of the financial impact at all, except in 2001, while the magnitude of net impact stayed the same after 2000. This indicates that the BBA was the main driving force that increased hospitals' financial distress in the late 1990s, and that most of the policy impact was absorbed in the short run (1998-2000), during the first three years after the enactment of the BBA. Although this AHA simulator would conveniently extract exogenous policy impacts, without access to the AHA resources, I turn to an alternative measure, the Financial Pressure Index (FPI). The FPI also aims to capture potential losses attributed to the BBA, using hospitals' pre- and post-BBA financial information. The Medicare FPI for hospital h is constructed in the following way:

$$\text{McareFPI}_{h,98} = [(\text{per\_McareCost}_{h,97} - \text{per\_McarePrev}_{h,98}) \times \text{Mcare\_AdjAdm}_{h,97}]/\text{TE}_{h,97}$$

where *per_McareCost* is hospital h's Medicare costs per adjusted admission in 1997; *per_McareRev* is total Medicare revenues per adjusted Medicare admission in 1998; *Mcare_AdjAdm* is an estimate of Medicare adjusted admissions in 1997; *TE* is total hospital expenses in 1997. The adjusted admissions account for both inpatient and outpatient care. The numerator means potential losses attributed to the BBA under the assumption that the trend for cost and revenue structure would have continued had the BBA not been implemented. Similarly, I construct Medicaid FPI, replacing Medicare costs, revenues, and admissions with respective values for Medicaid. These FPI measures are assigned to each hospital, and the values do not vary over time within hospitals.

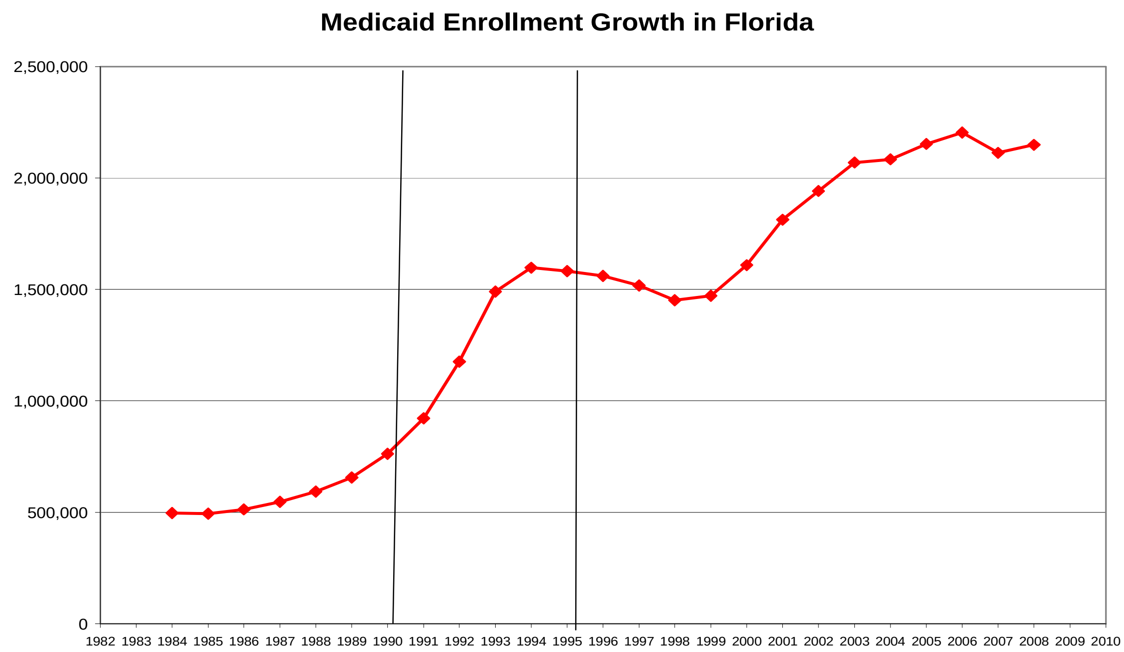
[Table 2.2] Relative Changes in DRG Payments for Sole-Community Hospitals under BBA, BBRA, and BIPA Using a Baseline of FY 1997

	FY 1997	FY 1998	FY 1999	FY 2000	FY 2001
Inflation Alone	1.000	1.027	1.052	1.083	1.114
BBA	1.000	0.999	0.995	1.007	1.024
BBA+BBRA	1.000	0.999	0.995	1.007	1.036
BBA+BBRA+BIPA	1.000	0.999	0.995	1.007	1.038
Net Impact (BBA+BBRA+BIPA-inflation)	0	-0.028	-0.057	-0.076	-0.076

Source: Table 1 in Seshamani *et al* (2006)
Note: DRG, diagnosis-related groups; BBA, Balanced Budget Act; BBRA, Balanced Budget Refinement Act; BIPA, Benefits and Improvement Protection Act.

Medicaid Expansions in 1992

Medicaid is an entitlement program under Title XIX of the Social Security Act, jointly funded by the state and federal governments. Since its establishment in 1965, the Medicaid program has been a major source of health insurance for low-income individuals who otherwise would not be able to afford private health insurance. States have broad discretion to decide eligibility, scope of services and provider reimbursements. Before 1984, Medicaid eligibility was closely tied to the Aid for Families to Dependent Children (AFDC) program, so that only indigent, single mothers were eligible for Medicaid, and its income cutoffs were fairly low (Currie and Gruber, 1997). After states were allowed to delink Medicaid eligibility from the cash welfare assistance program in 1986, Congress required all states to cover pregnant women and children under age six with incomes at or below 133% of the federal poverty line (FPL) by 1990, with the option to cover up to 185% of the FPL. In Florida, there were several eligibility expansions for pregnant women and children from the late 1980s to the early 1990s. In this paper, I study the 1992 expansion, in which the income threshold increased from 150 to 185 percent of the FPL for low-income expectant mothers as well as infants under age 1. Figure 2.2 shows the trend of



Source: Social Services Estimating Conference, various years.
Downloaded at the following website: http://collinsinstitute.fsu.edu/research/table/71

[Figure 2.2] Medicaid Enrollment Growth in Florida (1984-2008)

Medicaid enrollment growth in Florida over time: with a sharp increase in enrollment between 1991 and 1993.

III. Conceptual Framework

A. Supply of Hospital Indigent Care

Motives for Provision of Indigent Care

Provision of indigent care is an unprofitable business in which hospitals generate very little revenues or even incur losses. However, hospitals provide indigent care for several reasons. First of all, the Emergency Medical Treatment and Active Labor Act (EMTALA) of 1986 prohibited hospitals from dumping patients with emergency medical conditions (GAO, 2001). This law virtually calls upon every hospital to provide some amount of indigent care. Besides this emergency care offered to indigent patients, some hospitals have obligations to provide more indigent care, while other hospitals voluntarily provide it, but out of different motivations. The three ownership types define hospitals' objective functions and constraints differently (Frank and Salkever, 1991; Norton and Staiger, 1994; Banks et al, 1997; Gaskin, 1997; Weissman et al, 2003; Rosko, 2004; GAO, 2005), and thus create different incentives to supply indigent care. Public hospitals, which receive government funding, are obliged to provide indigent care by mission, while NFP hospitals are required to provide community benefits in exchange for tax benefits. Although community benefits[49] include indigent care, their magnitude and categories are not clearly specified. Therefore, there is room for NFP hospitals to fulfill their obligations by taking on other, possibly less costly, activities, such as educational and outreach programs, instead of providing indigent care.

Duggan (2000) presents three theoretical models for hospital organization, from which we can infer hospital behavior in response to changes in financial incentives. His first model is based on the assumption that all hospitals, regardless of ownership type, prefer maximizing profits, but different constraints in appropriating profits make them behave differently. For example, for-profit and not-for-profit entities face a different level of easiness of distributing profits to owners: FP hospitals can distribute their profits to owners, while NFP and public hospitals cannot. With the value of profits larger for FP hospitals, FP hospitals are expected to be more responsive to incentive changes, while NFP hospitals may want to increase perquisites. Duggan's second model assumes that non-profit entities have different

[49] Community benefits can range from uncompensated care, Medicaid and Medicare losses, health clinics, as well as other community activities such as health fairs, screening events, educational and outreach programs (health professional education, residency program, support group, and children's literacy promotion), and so on.

preferences—they are more altruistic. Therefore, in response to any incentive changes, NFP and public hospitals are more likely to be concerned about the well-being of indigent patients than FP hospitals. The third model is based on the soft budget constraints of the public entities. Since public hospitals can smooth out financial fluctuations through government subsidies, positive or negative financial shocks may not have a large impact on them[50].

Duggan's three models offer concrete explanations of the motivation for providing indigent care by NFP and public hospitals (altruism and soft budget constraint). However, his models do not explain what motivates FP hospitals to supply indigent care. Hirth (1997) and Banks *et al* (1997) provided theoretical frameworks that may explain FP hospitals' provision of indigent care. Hirth (1997) pointed out that FP and NFP hospitals compete in terms of quality, including charity care, and this rivalry can lead FP hospitals to provide indigent care. Banks *et al* (1997) suggested that FP hospitals view supply of indigent care as part of business costs in the future profit maximizing process, and provide some amount of community benefits in order to avoid the penalty of losing business in the future. In the same context, one can apply the conception of NFP hospitals' strategic behavior in Frank and Salkever (1991) to FP hospitals' supply of indigent care. In other words, FP hospitals provide indigent care to communities in order to build good reputations as caring neighbors, which they hope will increase their future profit opportunities. As for NFP hospitals, which make up of the majority of the U.S. hospital market, there are more theoretical and empirical studies that have tried to provide further explanations of what they maximize and why they provide indigent care (Sloan, 2000): Chang and Jacobson (2008) showed that NFP hospitals behave as a perquisite maximizer, while Duggan

[50] Business cycles, through government budgets, can affect subsidies for public entities. Here, I assume that there is sufficient government funding that could subsidize public hospitals.

(2002) and Horwitz (2007) suggested that NFP hospitals act like FP hopsitals if they operate in markets where FP hospitals' penetration is high.

Rationing of Indigent Care

So far, I have discussed the way in which hospitals' ownership status creates different objective functions (mission) and thus generates different behaviors toward indigent care. Since the scope of a hospital's mission is limited by availability of resources, I now discuss how hospitals' constraints affect provision of indigent care. Here, I conjecture that hospitals with budget or resource constraints ration care based on the following criteria: need for urgent medical intervention, patients' ability to pay, and types of services demanded. First, as discussed in the previous section, the EMTALA rules ensured that care for those in need of urgent medical interventions has priority over any other care. Second, hospitals are likely to prioritize care to those with reliable payer sources, preferably more profitable ones, although the degree of this rationing could vary greatly across ownership types. Lastly, hospitals may prioritize care based on types of services demanded. This rationing could be more significant among indigent patients if hospitals set aside a limited amount of resources for indigent care other than emergency care rendered to the indigent. The idea of prioritizing services has not been formally addressed, although some states seemed to have practiced it (Sasse, 1990; Hadorn, 1991; Rosner et al, 1996): Sasse (1990) discussed an effort in Alameda County in California to prioritize its health care system, while Hadorn (1991) and Rosner et al (1996) studied Oregon's Medicaid rationing plans. In 1993, the state of Oregon dropped very costly procedures, such as bone marrow and organ transplants, from its Medicaid benefit packages in order to expand Medicaid coverage to more low-income persons. In doing so, the state ranked 17 categories of services in order of importance: criteria for setting the priority are based on cost of treatment, probable improvement in patient's quality of life, and expected duration of that improvement (Rosner et al, 1996). According to Hadorn (1991), maternity and pediatric care were among the top five services deemed important: acute care (e.g., appendectomy or repair of open wound on neck) topped the list, but maternity and pediatric care, including disorders of newborns and preventive care for children (e.g., immunization and screening for vision or hearing problems), came in second and fourth, respectively.

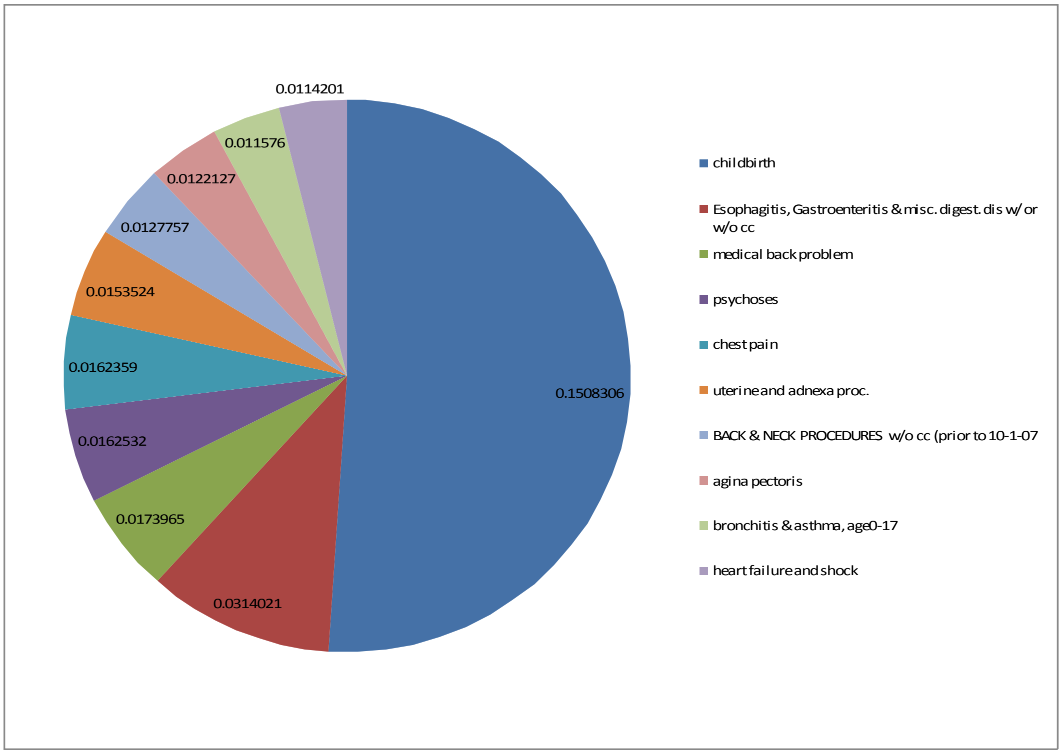
The Medicaid expansion moved some low-income pregnant women and infants from the uninsured to Medicaid group. If hospital indigent care had focused on maternity and infant patients prior to the expansion, the increased coverage would have lowered hospitals' indigent care burden for this group of patients. As a result, hospitals after the expansion may have turned to indigent patients who demanded less priority care, such as those with chronic conditions. In the analysis of the Medicaid expansion, I will offer a formal test of whether hospitals did replace their maternity and infant indigent patients with non-maternity care patients above age one.

B. Demand for Hospital Indigent Care

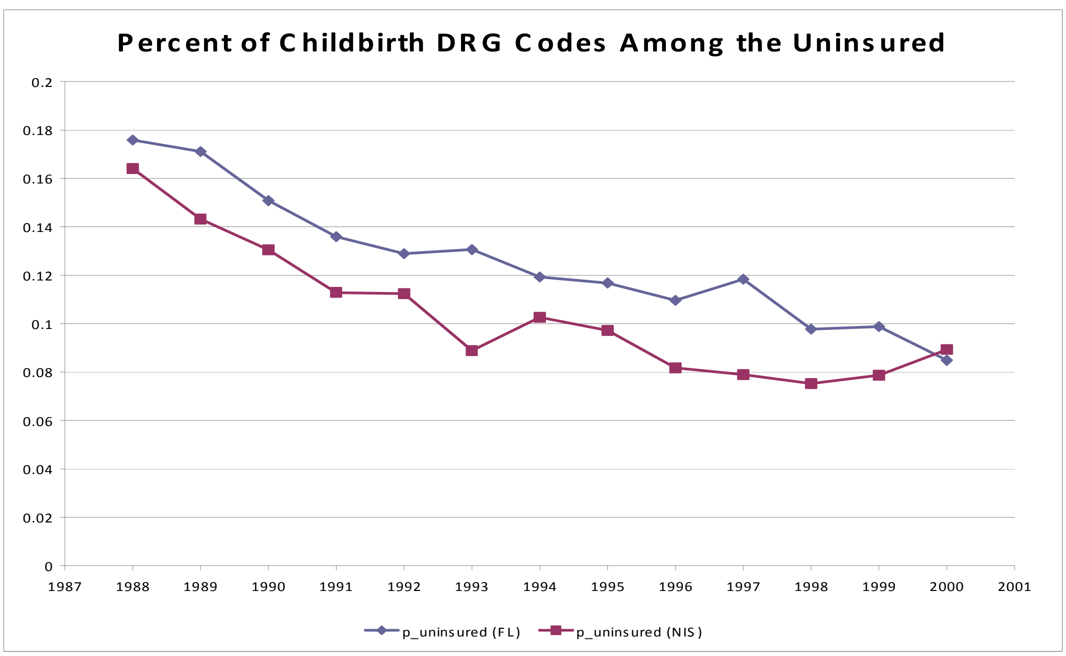
In this section, I discuss the demand side of hospital indigent care, i.e., primary causes of hospitalization among the uninsured. It is important to understand this demand side for the following three reasons: first, expansions of public insurance coverage for pregnant women will be a major force that causes a shift in demand for indigent care, because childbirth has been a primary cause of hospitalization among uninsured patients; second, types of hospital services demanded by the indigent may differ from those demanded by the general population; third, demand for indigent care may be more inelastic than its supply, which means that the demand side is likely to determine the overall amount of indigent care.

According to Saywell *et al* (1989), pregnancy and childbirth accounted for the largest proportion of uncompensated hospital care in Indiana as of 1987, in terms of both cases (19.1%) and expenditure (17.4%). Based on the most recent years of the Nationwide Inpatient Sample (NIS), researchers at HCUP (2009) also found that maternity care still is the first reason for hospital stay among the uninsured (11.2%) at the national level. Using Florida hospital discharge data (1990-2000), I examine numbers of uninsured patients (selfpay and no charge) in each DRG code: Figure 2.3 presents the top ten causes of hospitalizations among uninsured patients in Florida for 1990 and 2000. I can confirm that throughout the 1990s, childbirth has been the primary cause of hospitalization among the uninsured[51], although the share of childbirth patients among uninsured hospitalizations decreased from 17 percent in 1988 to below 10 percent in 2000 (Figure 2.4). This implies that the expansion of Medicaid coverage for pregnant women in the early 1990s would have alleviated a considerable amount of hospitals' indigent care burdens. Although the large part of the financial burden for indigent care is associated with maternity indigent patients, it remains unambiguous whether coverage expansions reduce the total demand for hospital indigent care: for example, there may be always excess demand for indigent care among the target group, so that even though some of these uninsured patients gain coverage and move to the Medicaid group, there may be still a significant number of maternity and pediatric patients who would demand indigent care.

[51] Other leading causes of hospitalization among the uninsured include digestive disorders (esophagitis, gastroenteritis, gastro-intestinal hemorrhage), psychoses, poisoning, alcohol/drug abuse, cardiac problems (chest pain, heart failure, heart shock), pneumonia, and back problems.



[Figure 2.3] Percent of DRG Codes among the Uninsured in Florida as of 1990



[Figure 2.4] Percent of Childbirth DRG Codes among the Uninsured

C. Measure for Hospital Indigent Care

Now, I discuss the concept and measure of hospital indigent care, exploring the following three aspects of hospital indigent care: uncompensated care costs in dollars, volume of the indigent, and quantifies of unprofitable services provided.

Hospital Uncompensated Care

Uncompensated care is the sum of charity care and bad debt, widely used in existing literature (Bazolli *et al*, 2006; Davidoff *et al*, 2000; Lo Sasso *et al*, 2007; Thorpe *et al*, 2001). Charity care is *ex-ante* indigent care that hospitals offer with no intention or expectation of payment from the beginning, while bad debt is *ex-post* indigent care for which hospitals initially anticipated receiving payments but end up unpaid, due to patients' unwillingness or inability to pay[52]. Ideally, I would like to isolate unpaid care offered to low-income uninsured patients from uncompensated care. Charity care, by definition, is such care, but bad debt can include any unpaid care, irrespective of its payer source. Moreover, hospitals have broad discretion to independently develop their own eligibility policies for charity care[53] and determine bad debt. This generates inconsistency in classification of these two items across hospitals, but using the sum of charity care and bad debt alleviates these concerns.

Despite the popularity of the UC measure, this measure can be misleading[54]: for instance, hospitals can report a large amount of uncompensated care, while treating only a few, high-cost indigent patients. Moreover, changes in UC do not provide much insight on how hospitals have altered the supply of indigent care.

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[52] For example, an unpaid portion of deductibles or co-payments from the insured is bad debt, whereas discounts to private payers or underpayments from Medicaid/Medicare are not.

[53] Based on the conversation with a staff from the American Hospital Association, some hospitals classify a patient who could be a charity care case as bad debt if the patient is unconscious when admitted.

[54] Each hospital has a different charging method so that different mark-up rates make it difficult for researchers to compare true costs of care between hospitals. In fact, Gruber and Rodriguez (2007) showed that physician UC significantly decreased if differently measured.

Volume of the Indigent

Possibly, hospitals can manipulate the volume of indigent patients in order to change amounts of indigent care. Here, indigent patients are defined as uninsured patients, those who were recorded as "selfpay" in payer source. Ideally, I would like to examine volume of uninsured low-income patients who cannot pay medical bills (the low-income segment of the uninsured who actually demand hospital indigent care), rather than volume of all uninsured patients. With patients' income information unavailable in hospital discharge data, however, I use uninsured patients as a proxy for the indigent, and thus overestimate the actual volume of indigent patients.

Although I acknowledge possible biases resulting from using the whole uninsured population instead of its low-income subgroup, this will be an attenuation bias. Moreover, there is some evidence that the magnitude of the bias may not be large. One way to directly measure the size of this bias is to examine hospitals' collections of medical bills for the uninsured. If all uninsured patients are homogeneously indigent and thus cannot afford medical care, hospitals will collect nothing from the uninsured. Based on a case study conducted by University of Central Florida in 2000, collection from self-pay patients among those admitted to emergency departments at Florida Hospital Orlando and East Orlando was only 11.3 cents on the dollar[55]. Lewin Group (2005) also provided evidence that hospitals recover only 14% of uncompensated care costs.

The other way to indirectly prove that this bias is not too large is to show that the majority of uninsured patients who use hospital care actually belong to low-income households, and thus cannot afford medical care. Using CPS March data of 2004, Lynk and Alcain (2008) studied distribution of family income among non-

[55] The uninsured were frequent visitors to the emergency department for non-emergency conditions, for which 79% did not pay. On average, only $49 was collected among $1,431 charges from selfpay patients: downloaded at http://flhosp.net/govpubaffairs/pubs/healthissues/healthbrf_edstudy.htm

elderly uninsured individuals (18-64 year old adults) in 2003. Their findings provide evidence that the majority of uninsured persons did come from low-income households: the uninsured population, on average, earned only half as much as the annual income of the general population ($39,250 vs. $79,209 for a household of three), and that their income distribution was extremely right-skewed compared to that of the insured (see Panel A in Figure 2.5). A limitation of this study is that it looked at the income distribution of the nation's uninsured population as a whole, not restricting its scope to uninsured patients who actually used hospital care. Therefore, its results may have over- or under- estimated the true income distribution of uninsured patients who received care at hospitals.

Using the Medical Expenditure Panel Survey (MEPS) of 2003, I am able to examine the income distribution of only those who were uninsured and used hospital care (inpatient, outpatient, or emergency room)[56]. Panel B in Figure 2.5 shows the income distribution of uninsured and insured patients who used hospital care to be similar to that in Panel A. Those who actually used hospital care in the MEPS appeared to be poorer than the general population in the CPS, but the pattern of income distribution among those who used hospital care looks similar to that for the whole uninsured population in the CPS. Based on the MEPS, I find that a very high proportion of the uninsured population with hospital costs (66.9%) reported income of less than 200% of the FPL, the income range that is generally considered to be eligible for charity care, and 90% reported income of less than 400% of the FPL. However, only 37.8% of the insured reported to earn income less than 200% of the FPL, and 67% earned income less than 400% of the FPL. However, this also means that a third (31.1%) of the uninsured earned income more than twice the poverty level and would

[56] To be consistent with Lynk and Alcain (2008), I restrict the sample to the non-elderly adult population in the MEPS who received care at hospitals in 2003 and distribution of income greater than $250,000 is not shown.

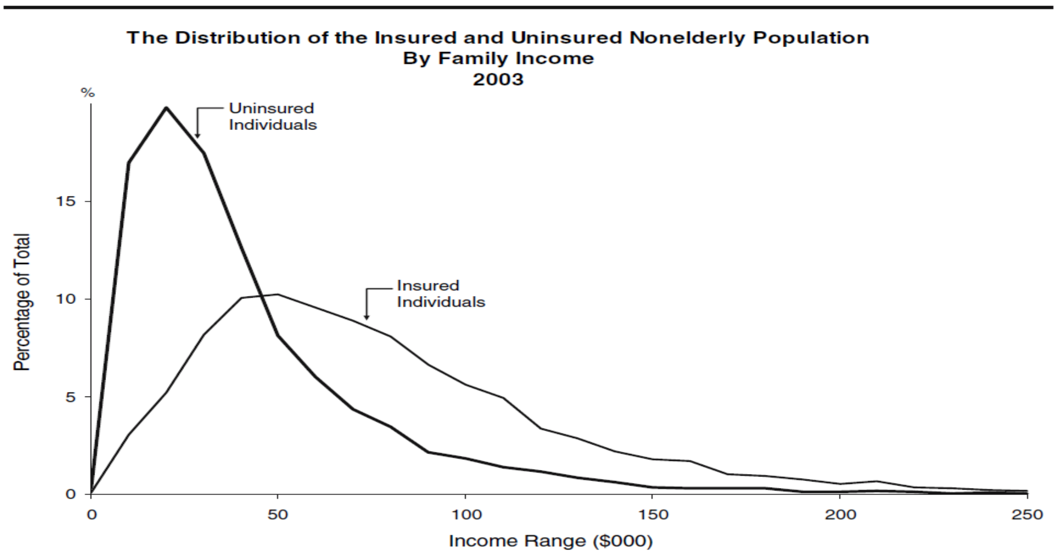
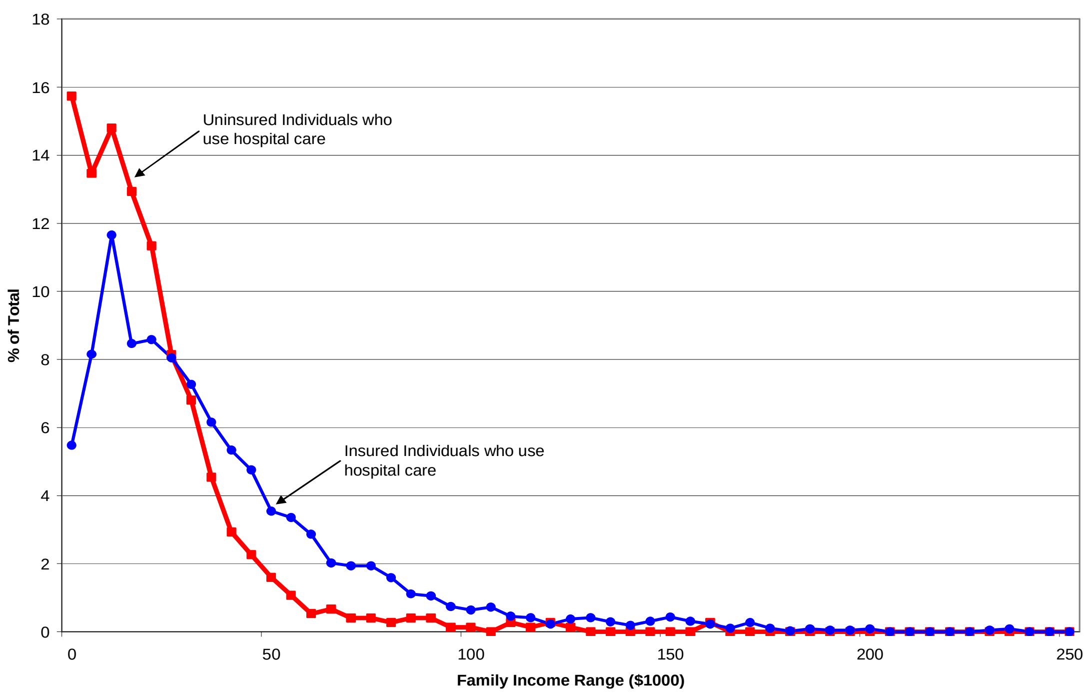


Fig. 1 The distribution of the insured and uninsured nonelderly population by family income 2003. *Source:* See Table 1. *Note:* Family income bracket size is $10,000; distribution > $250,000 not shown

A. The Non-Elderly Adult Population (18-64 year old) in the CPS: Lynk and Alcain (2008), Figure 1, p. 58.



B. The Non-Elderly Adult Population that Use Hospital Care in the MEPS (2003)

[Figure 2.5] The Distribution of the Uninsured and Insured Population in 2003

not have qualified for charity care. With this possible bias in mind, I separate uninsured admissions into emergency and non-emergency patients because hospitals, abiding by the EMTALA regulations, have discretion over admissions for only those with non-emergency conditions.

In order to distinguish non-emergency conditions from emergency conditions, I use two approaches: first, I use admission type information (emergency, urgent, and elective); second, I use principle diagnosis codes of privately insured patients, combined with admission source (physician referral, HMO referral, emergency room, etc). Admission type is determined based on how urgently patients need to be accommodated and receive medical interventions[57]. Here, I group patients by their DRG codes and calculate, for each DRG code, a percentage of patients who are categorized as “emergency” by admission type. If this percentage is greater than 0.50 for 90% of the time during 1990-2000, I define that DRG code as an emergency condition. The rest of the DRG codes are defined as non-emergency conditions. Among the 503 DRG codes, 146 codes (29%) are defined as emergency conditions. Examples of emergency conditions are heart attack, stroke, pneumonia, acute appendicitis, poisoning, burn care, head or neck injuries, and transplants, while examples of non-emergency conditions are child delivery, diabetes, benign tumors, various types of cancer, mental disease, and metabolic and immunity disorders.

The second approach follows the novel method in Nakamura (2007), which restricted the sample to privately insured patients under age 65 and examined the first three digits (DX3) of their principle diagnosis codes (ICD-9 code) along with admission source information. In the Florida discharge records of 1990-2000, I look at

[57] The admission type is recorded as “emergency” if they require immediate medical intervention because of severe, life-threatening, or potentially disabling medical conditions, “urgent” if patients’ conditions are not life-threatening but need reasonably urgent medical intervention, and “elective” if the patient’s condition permits adequate time to schedule the availability of a suitable accommodation.

how many of the privately insured[58] in each DX3 were admitted through emergency rooms in each year. I define a DX3 as an emergency condition if more than 50 percent of privately insured patients with that DX3 are admitted to emergency rooms in all years from 1990 to 2000; otherwise, DX3's are defined as non-emergency conditions. Note that I do not regard all emergency room admissions as emergency conditions, and use the principle diagnosis code information, which denotes the condition that is chiefly responsible for the admission. Due to a lack of a regular source of care, the uninsured are more likely to be admitted through emergency departments, no matter how urgent their actual need for medical attention; as such, studying diagnosis codes of privately insured patients, combined with whether they were admitted through the emergency room, gives a better idea of severity of illness for each disease type.

By this second approach, I categorize 150 DX3 (28%) as emergency conditions and 383 (72%) as non-emergency conditions. The assignment of principle diagnosis codes may differ across hospitals or vary over time. However, the first three digits define a general category of the disease, so are unlikely to vary across hospitals or over time. Moreover, DX3 categorization is not sensitive to upcoding practices because hospitals' manipulation, if any, occurred in changing the fourth and fifth digits of the ICD-9 codes (Silverman and Skinner, 2004), or by adding secondary diagnoses (Dafny, 2005).

Finally, I compare these two approaches. For more than 90% of patients, the classification into emergency vs. non-emergency conditions by the first approach is matched with that by the second approach. In this paper, I choose the first approach to distinguish between emergency and non-emergency conditions.

[58] Transferred patients and those with unknown admission sources are dropped. The DX3's assigned to less than ten patients in a year, as well as the DX3's that were dropped or newly introduced during 1990-2000, are excluded.

Provision of Profitable vs. Unprofitable Services

In the longer term, hospitals can change types of services provided as a means of manipulating indigent caseload. They may cut back or eliminate unprofitable services, while increasing or opening profitable services. I identify unprofitable and profitable services based on the classification in Horwitz (2005). Horwitz[59] (2005) categorized hospital services into three groups: relatively profitable, relatively unprofitable, and variably profitable services. Among the total of 17 profitable and 10 unprofitable services[60] listed in Horwitz (2005), the Florida hospital data sets include information for 10 profitable and 5 unprofitable services. Adding (free-standing) clinic visits to the list of unprofitable services, I am able to examine the provision of 10 profitable services and 6 unprofitable services for my Florida hospital sample. Table 2.3 presents the classifications in Horwitz (2005), the list of services available in the Florida data sets, and units of services measured. Profitable services include cardiac care (angioplasty, cardiac catheterization, and open-heart surgery), orthopedic services, Extracorporeal Shock-Wave (ESW) Lithotripter, diagnostic tests (Magnetic Resonance Imaging (MRI), Computed Tomography scanner (CT), and radioisotope facility), and some intensive care (neonatal and pediatric intensive care). Unprofitable services include burn care, emergency room visits, free standing clinic services, psychiatric care, substance abuse (alcohol and drugs) treatment, and labor/delivery procedures. These are total amounts of services rendered to patients regardless of their payer source.

[59] Their classifications were based on various sources from academic literature (peer-reviewed medical, business, finance, statistics, sociology, and public policy literatures) to policy reports (Medicare Payment Advisory Commission and Prospective Payment Assessment Commission reports to Congress), press articles (trade publications, business magazines, and newspaper reports), and interviews with relevant experts (hospital administrators and doctors). Although she did not take a systematic approach, Horwitz (2005) noted that these various methods of characterizing services yielded remarkably consistent results, and provided a detailed research note[59].

[60] Horwitz (2005) listed 14 unprofitable services in Exhibit 1 (p. 792), out of which two are outpatient services (AIDS and Alcohol/drugs). With the remaining 12 unprofitable inpatient services, I combine AIDS unit and AIDS services into one service, and obstetric (beds) and obstetric (birth) into another.

[Table 2.3] Profitable vs. Non-Profitable Services

Services	Relatively profitable	Availability in FL data	Notes (Units)
AIDS services/units	NO	-	
Alcohol beds	NO	Available	Substance Abuse Acute Care (Inpatient Days)
Angioplasty	YES	Available	Coronary Care Unit (Days)
Birthing room	YES	-	
Burn Treatment	NO	Available	Burn Intensive Care Unit (Days)
Cardiac Catheterization Lab	YES	Available	Cardiac Catheterization Lab (Procedure)
Computed tomography (CT) Scanner	YES	Available	CT (Procedure)
Child Psychiatric Services	NO	-	
Diagnostic Radioisotope Facility	YES	Available	Radiology/Diagnostic (Procedure)
Emergency Room	NO	Available	Emergency Services: 24-hour/Inhouse M.D.+ 24-hour/M.D. on-call (Visits)
Clinic Services (incl. Free Standing Clinic)	NO	Available	Clinic Services + Free Standing Clinic Services (Visits)
Extracorporeal Shock-Wave (ESW) Lithotripter	YES	Available	ESW (Procedures)
Fitness center	YES	-	
HIV test	NO	-	
Magnetic resonance imaging (MRI)	YES	Available	MRI (Procedures)
Neonatal Intensive Care	YES	Available	Neonatal Intensive Care Unit (Days)
Obstetrics (beds or births)	NO	Available	Labor and Delivery Services (Procedures)
Open Heart Surgery	YES	Available	Open Heart Surgery (minutes)
Orthopedic Surgery	YES	Available	Number of Staff (Persons)
Pediatric Intensive Care Unit	YES	Available	Pediatric Intensive Care (Inpatient Days)
Positron Emission Tomography	YES	-	
Psychiatric	NO	Available	Psychiatric Acute Care (Days)
Psychiatric Emergency Services	NO	-	
Single Photon Emission CT	YES	-	
Sports Medicine	YES	-	
Trauma Center	NO	-	
Ultrasound	YES	-	
Women's center	YES	-	
Number of Profitable Services/Total	17/29	10/16	

Source: Horwitz (2005)

D. Concentration of Indigent Care Burden among Hospitals across Markets

Market Concentration

A large volume of health care literature has studied market concentration or competition, particularly related to the introduction and growth of managed care organizations in the 1990s (Shen *et al*, 2008; Dranove *et al*, 2008). This increased market competition put pressure on hospitals to reduce prices and costs, as well as make adjustments in types of services provided, intensity or quality of care, and supply of indigent care. In extreme cases, higher market competition forced some hospitals to convert, merge or close, which consequently changed the landscape of the whole hospital market.

In order to test my hypothesis regarding the level of market concentration of indigent care burden, I need to isolate market concentration for indigent patients and determine, for each market, whether or not the indigent care burden is highly concentrated across hospitals. In doing so, I categorize hospital markets into three groups according to number of hospitals, as well as the degree of indigent care concentration across hospitals if the market consists of multiple hospitals. The three types of hospital markets are as follows: markets with a single hospital, markets with multiple hospitals among which the indigent care burden is equally spread out (low concentration of indigent care burden), and markets with multiple hospitals among which only a few hospitals disproportionately serve the indigent (high concentration of indigent care burden). For markets with multiple hospitals, to what extent the indigent care burden is highly concentrated is determined by the median value of Herfindahl-Hirschman Index (HHI) for indigent patients.

The HHI is the most commonly used index for market concentration in the economics literature. In general, the HHI[61] is calculated by the sum of squared shares of beds, admissions, or discharges in the market. Although hospitals compete for patients, my conjecture is that they would compete only for paying patients, not for uninsured, indigent patients. Therefore, I decompose the traditional market concentration measure (HHI) into two parts: concentration of paying patients and concentration of indigent care burden. The former is calculated by summing the squared market shares of hospital admissions for paying patients—privately insured, Medicare, Medicaid, and other payer sponsored patients—while the latter, the variable of my interest, is measured as explained below.

<u>Measure for Concentration of Indigent Care Burden across Hospitals</u>

In order to measure market concentration of indigent care burden, I first define hospital market based on counties[62], measure individual hospitals' indigent care burden, and create a market level index for the level of concentration of indigent care burden. The simplest method to measure market concentration is to construct a traditional HHI associated with uninsured patients, i.e., the sum of hospitals' squared shares of uninsured admissions in a given county. Here, I consider patients' types of illness and dispersion of the indigent within counties. A patient's choice of hospital, regardless of her payer source, depends on whether the hospital provides services that she need, and whether the hospital is close to her residence. For example, the indigent with cardiac problems may choose hospital B over A because hospital A does not provide cardiac care, or simply because hospital B is closer than A if both provide cardiac care.

[61] The HHI can have a value from 1/n (n=the number of hospitals in the market) to 1. Higher HHI values mean higher market concentration, i.e., lower market competition.
[62] "The Florida state statute delegates responsibility for caring for the uninsured to the counties, and consequently it is flexible regarding how counties provide this care." (Jackson and Beatty, 2003)

In order to take into account these two factors, I break down uninsured patients by DRG group and zip code, using Florida discharge data sets. Patients are grouped into one of the eleven DRG groups: pediatrics, maternity, transplant, tumor (benign and malign), cardiac care, burn and trauma, orthopedics, psychiatrics, HIV, other medical care, and other surgical care. For hospital h in county c, I calculate a share of uninsured patients in disease group d from zip code z for all disease groups and all zip codes that the hospital serves within the county. Once a hospital-level concentration measure is created by summing the squared shares over the disease groups and zip codes, I add this hospital-level measure for all hospitals in county c, which creates the concentration measure at the market level.

For example, let's suppose that Hospital A served 20 and 10 uninsured patients who were hospitalized for cardiac care and resided in zip code 32008 and 32009, respectively. If zip code 32008 had a total of 50 uninsured patients with cardiac diseases and zip code 32009 had 100 uninsured, cardiac patients, Hospital A's share of indigent patients with cardiac disease is 20/50=0.4 for zip code 32008 and 10/100=0.1 for zip code 32009. Their squared values are 0.16 and 0.01, respectively, which sum up to 0.17 for the hospital's HHI for indigent patients with cardiac diseases. I repeat the same exercise for all other disease groups and aggregate the obtained HHI values in each disease group to create the hospital level HHI for indigent patients. If the county in which this hospital is located contains two other hospitals whose HHI values are 0.13 and 0.20, respectively, the market level HHI is the sum of these three hospitals' HHI values: 0.17+0.13+0.20=0.50.

For this HHI measure, there may be endogeneity concerns. Since the market level HHI is a function of hospitals' actual admissions, this concentration measure and individual hospitals' provision of indigent care are simultaneously determined. Moreover, some unobserved factors such as hospital quality may affect both the market concentration level and hospitals' supply of indigent care. For example, hospitals of certain types which attract a large number of privately insured patients (such as high-quality hospitals or FP hospitals) may be less able or willing to supply indigent care, given limited bed capacities (their opportunity costs of treating the indigent are much higher than those of low-quality or non-FP hospitals). In such cases, other hospitals without those attributes would have to serve a disproportionately large number of indigent patients, which would result in inequitable distribution of indigent care burdens across hospitals. In other words, quality or ownership mix within markets may be correlated with a hospital's provision of indigent care and the distribution of the indigent care burden within markets.

There are two approaches to address this endogeneity problem. The first is to construct the HHI based on years prior to any policy changes and use this baseline level for the entire hospital sample. The second approach is to instrument actual admissions with expected patient flow (Kessler and McClellan, 2000; Gorinsakaran and Town, 2003; Dranove *et al*, 2008) and construct the HHI based on predicted numbers of indigent admissions. Here, I select the second approach in which I estimate hospital choice models for the uninsured in each year and in each disease group (11 years×11 disease groups). All patients in the same disease group are expected to have the same set of hospital options if they reside in the same zip codes. Hospitals are dropped if they are more than 75 miles away from patients' home. I use zip code level grouped logit models in which distance to hospital, an indicator for whether a hospital is within 10 miles, and patients' zip code median income levels (in log form) are included. Then I obtain the predicted number of uninsured admissions for each hospital: this number is calculated by aggregating the predicted probabilities of an uninsured patient being admitted to the hospital. Finally, I use these expected numbers of uninsured admissions to calculate the concentration level for the indigent.

IV. Literature Review

In this section, I review empirical literature related to hospital indigent care. I categorize previous literature into three groups, depending on which health policy or market structure they studied: expansions of public insurance coverage, changes in government hospital payments, and changes in other market conditions. Davidoff et al (2000) and Lo Sasso and Seamster (2007) are two studies that comprehensively analyzed the impact of the federal and state policies on hospital indigent care. Davidoff *et al* (2000) examined hospital UC during 1990-1995 in response to the following changes: Medicaid coverage expansions, increased generosity of Medicaid payments, and increased Medicaid HMOs. Their findings suggest that FP and public hospitals lowered UC after Medicaid expansions, while NFP hospitals reduced UC in response to higher Medicaid HMO rates. Most recently, Lo Sasso and Seamster (2007) extended the study of Davidoff et al (2000) by including additional years of data (1996-2000) and more policy variables: SCHIP expansion, the Medicaid DSH program, and government subsidies through tax appropriations. They found a large positive relationship between government subsidies and hospital UC, but little or no impact of other Medicaid related policies. Although their findings indicated that hospitals are most responsive to financial incentive changes than any other Medicaid policies, they did not consider the BBA policy, the financial pressure that should have influenced hospitals' indigent care decision in the late 1990s. Nor did they take into account the effect of other hospitals' provision of indigent care.

The findings in these two studies are useful but not very informative, because changes in overall UC do not explain through which mechanisms hospitals changed their provision of indigent care. For example, increases in UC may not reflect hospitals willingness to increase indigent care, but rather capture reduced efforts in collecting bad debts. Here, in addition to UC, I examine admission patterns as well as type of services provided in order to explore how hospitals changed their provision of indigent care in the 1990s. Below, I summarize the findings of past studies about hospital indigent care related to coverage expansions, financial incentive changes, as well as market conditions.

(1) Expansion of public health insurance coverage for low-income patients

Apart from Davidoff *et al*. (2000) and Lo Sasso and Seamster (2007), Dubay *et al*. (1995) is the only peer-reviewed, national study that examined the impact of Medicaid expansions on hospital UC[63]. Their findings showed that the Medicaid expansions for pregnant women and infants in 1987 decreased the growth of UC by 5 percent. Blewett *et al* (2003), studying a state-subsidized health insurance program for the working poor (MinnesotaCare), also found a negative relation between expanded government coverage and hospital uncompensated care[64]. The major limitation of these studies is that they used aggregated measures for UC, at the county or state level, which cannot explain individual hospitals' behavior.

(2) Government hospital payments

There have been several policies that have changed hospital payment systems or amounts of hospital payment: the Medicare Prospective Payment System (PPS), Uncompensated Care Pool, the Medicare/Medicaid DSH program, and the BBA. Bazzoli *et al* (2006) is one of the major studies that examined the BBA impact on the provision of hospital UC. Instead of controlling for hospital ownership type, they

[63] As a working paper, McConnell *et al* (2005) measured the effect of the Oregon's Medicaid program (OMP) on hospital uncompensated care, and showed that disenrollment of one adult from the OMP leads to an increase of approximately $852 in hospital uncompensated care.
[64] APS healthcare (2006) is a working paper that studied Wisconsin's BadgerCare–state funded health insurance program for low-income working families with children–and showed that the expansion of this program accounted for a 6-year cumulative savings of $283.08 million in hospital UC spending.

focused on the safety-net status and the size of the financial pressure. They found that the adjustment to UC after the BBA was proportional to the degree of the financial pressure for each hospital: the largest decline in UC occurred at core safety-net hospitals, while the policy impact was minimal for non-safety-net hospitals. Campbell *et al* (1993) and Mann *et al* (1995), examining Medicaid payment cuts and the Medicare PPS respectively, showed that the decreased hospital payments reduced provision of hospital UC.

Spencer (1998) is the only study that examined distribution of indigent care burden across hospitals. In particular, she analyzed whether the establishment of an uncompensated care pool successfully redistributed indigent care burden across hospitals and increased the total amount of UC. Using New York hospital data in 1993, she found the redistribution effects only for routine care. Nakamura (2007) examined hospitalization of indigent patients without emergency conditions after the deregulation of the hospital rate-setting system, along with reduced state subsidies for charity care, in New Jersey in 1993. Defining indigent admissions without emergency conditions as voluntary indigent care, she found that lower government subsidies decreased indigent care, but only the voluntary portion.

(3) Other Factors (managed care, conversion, merger, and peer pressure)

There has been a great deal of research about the relationship between changes in market conditions and hospital indigent care. Gruber (1994) is a seminal paper that studied the effect of market competition on hospital charity care, using California hospital data during 1984-1988. He found that increased price competition decreased revenues from private payers, which consequently constrained the cost-shifting ability of hospitals and thereby led to decreases in hospital UC. Except for Currie and Fahr (2004), which found little evidence that higher HMO penetration reduced charity care, previous studies have shown evidence that increased price competition reduces hospitals' provision of indigent care (Thorpe *et al*, 2001; McKay and Meng, 2007).

Another intriguing factor that could affect hospitals' provision of indigent care is peer pressure, i.e., the provision of indigent care from other hospitals within markets. Banks *et al* (1997) and Clement *et al* (2002) found that the presence of public or major safety-net hospitals in the market create incentives for other hospitals to reduce indigent care. By contrast, Frank and Salkever (1991), Gaskin (1997), Clement *et al* (2002), and Rosko (2004) found that hospitals increased the provision of UC if other hospitals in the market provide UC, as part of non-price competition (rivalry on the supply of indigent care). Although these studies considered potential or actual provision of other hospitals' indigent care, they did not examine dynamics of the distribution of indigent care burden between hospitals.

V. Data and Empirical Strategy

Data

My primary source of data is Florida hospital discharge data sets along with the hospitals' financial data, obtained from the Agency of Health Care Administration. The hospital financial data sets provide information about charity care (Hill-Burton plus other), bad debt, ownership status, teaching status, number of licensed beds, revenues, admissions, county and zip code information. The revenues and admissions can be broken down by payer sources. The discharge data sets provide detailed patient information such as payer source, DRG code, diagnosis and procedure code, admission source, admission type, sex, age, residential county, and zip code.

Other variables are obtained from Area Resource Files (ARF), the Bureau of Labor Statistics (BLS), Current Population Survey (CPS), and Florida Agency for

Health Care Administration (AHCA). The ARF files provide hospital market information at the county level: number of active non-federal physicians, number of emergency care visits, number of births, population, population under 65, non-white population, population under poverty, per capita income, and unemployment rates. The BLS provides the Consumer Price Index (CPI) for medical care[65], while the CPS data is used to generate ELIG, the Medicaid policy variable, as well as trends of the uninsured population. From the Florida AHCA, I obtain Medicaid caseload data (for 1990-2000) and HMO penetration rates (only for 1996-2000) at the county level.

Estimation Model

Before examining the policy impact on individual hospitals' provision of indigent care, I test effects on the total amounts of indigent care at the county level. If most hospitals reduce provision of indigent care after coverage expansions or the BBA, the aggregated indigent care at the county level should decrease; however, if the county level indigent care does not change, this will imply that these policies merely redistributed contributions for indigent care among hospitals. The following is the estimation model for indigent care at the county level:

Model 0: $\text{Indigent Care}_{ct} = a_0 + \boldsymbol{a_1\, POST_t} + a_2\, \boldsymbol{POST_t{\times}MKT_{ht}} + a_3\, \mathbf{M_{ct}} + \text{county} + e_{ct}$

Where ***POST=POST92*** for Medicaid expansions, ***POST97*** for the BBA

MKT = [**solehosp**=1, **HighHHI**=1]

[65] The Producer Price Index (PPI) for hospital services seems to be a more appropriate index to deflate hospital uncompensated care. However, I use the CPI due to the data availability: CPI data for medical care is available from 1987 on, whereas PPI data for hospital services is available only after 1992.

The dependent variable is the sum of hospitals' indigent care in a given county, while hospital indigent care is quantified by three sets of measures: amount of uncompensated care in dollars, volume of uninsured patients, and quantity of unprofitable services provided. I examine aggregate amounts of indigent care provided within the same counties over time and compare the aggregated indigent care across three market types. For each policy, I separately estimate the model: impact of the Medicaid expansion is estimated with the hospital sample for 1990-1995, and the BBA impact with that for 1996-2000. ***POST*** is a policy variable: *POST92*=1 for the post Medicaid expansion period (1993-1995), and *POST97*=1 for the post BBA years (1998-2000). ***MKT*** consists of two indicator variables that control for the concentration level of indigent care burden at the market level: ***HighHHI*** and **solehosp**. If a market (county) consists of at least two hospitals, and its HHI is higher than the median value of all counties' HHI's, ***HighHHI*** takes a value of one, representing a market with high concentration of indigent care burden. If a market contains only one hospital, ***solehosp*** takes a value of one. Markets with low concentration of indigent care burden (*LowHHI*) are the reference group.

M is a vector of market conditions that could affect demand for, and supply of indigent care, the variables obtained from the ARF. On the demand side, I control for per capita emergency visits, number of births (log form), per capita income level (log form), unemployment rates, percentage of non-white population, percentage of population aged over 65, percentage of population below the poverty line, and Medicaid caseload (log form). On the supply side, I control for market concentration for paying patients, per capita active non-federal MD's (log form), presence of public hospitals in the market, as well as private HMO and Medicaid HMO penetration (only for the BBA).

Now, I introduce my main econometric models (Model 1 and Model 2) that examine individual hospitals' provision of indigent care in response to the policy changes. These are difference-in-difference and triple difference type regressions at the hospital level.

Model 1: $\text{Hospital Indigent Care}_{ht} = a_0 + \boldsymbol{a_1}\, \boldsymbol{POST_t} + \boldsymbol{a_2}\, \boldsymbol{OWNSH_{ht}} + \boldsymbol{a_3}\, \boldsymbol{POST_t} \times \boldsymbol{OWNSH_{ht}} + a_4\, \mathbf{H_{ht}} + a_5\, \mathbf{M_{ct}} + \text{county} + e_{ht}$

Model 2: $\text{Hospital Indigent Care}_{ht} = b_0 + \boldsymbol{b_1}\, \boldsymbol{POST_t} + \boldsymbol{b_2}\, \boldsymbol{OWNSH_{ht}} + \boldsymbol{b_3}\, \boldsymbol{MKT_{ct}} + \boldsymbol{b_4}\, \boldsymbol{OWNSH_h} \times \boldsymbol{MKT_{ct}} + \boldsymbol{b_5}\, \boldsymbol{POST_t} \times \boldsymbol{OWNSH_{ht}} + \boldsymbol{b_6}\, \boldsymbol{POST_t} \times \boldsymbol{MKT_{ct}} + \boldsymbol{b_7}\, \boldsymbol{POST_t} \times \boldsymbol{OWNSH_{ht}} \times \boldsymbol{MKT_{ct}} + \mathbf{H_{ht}} + \mathbf{M_{ct}} + e_{ht}$

Where ***OWNSH*** = [**FP**=1, **Public**=1]

My dependent variables are the three sets of measures that capture individual hospitals' supply of indigent care: UC, uninsured admissions, and unprofitable service provision. I will explain how to construct these dependent variables in the next section. Again, I separately estimate these models for the Medicaid expansion (with the sample of 1990-1995) and the BBA (with the sample of 1996-2000). In Model 1, I compare hospitals' supply of indigent care across three different ownership types—NFP, FP, and public hospitals—in a given market before and after the policy change. ***OWHSH*** consists of two binary variables: one for for-profit ownership (FP=1) and the other for public ownership (Public=1); NFP hospitals are the reference group. The policy indicator (POST) and market condition variables (M) are constructed in the same way as explained above. ***H*** is a vector of hospital attributes other than hospital ownership. I include teaching status (teaching=1), number of licensed beds (a dummy variable for hospitals with more than 200 licensed beds=1), and urban/rural status (rural=1). For the BBA, I control for the magnitude of the financial shock, measured by the Medicaid FPI and Medicare FPI. The coefficients of the interaction terms, $\boldsymbol{a_3}$, are the estimates that capture the differences in policy impacts across hospital ownership types.

In Model 2, I compare hospitals' supply of indigent care between markets that have different levels of concentration of indigent care burden, in addition to the ownership types. The DDD type estimates ($\boldsymbol{b_7}$) capture the difference in policy impacts across markets and across ownership types.

Construction of Dependent Variables

The three sets of dependent variables are constructed in the following way. For uncompensated care, I use four variables as follows: log of UC costs, log of charity care costs, UC costs as a percent of total operating expenses, and charity care costs as a percent of total operating expenses. UC or charity care costs are calculated by multiplying UC or charity care charges with hospital-specific cost-to-charge ratio[66]. The first two are inflation-adjusted, dollar based measures. I separately examine charity care for the following two reasons. First, the Florida State Statute[67] is very specific in defining charity care, which is universally applied to hospitals across the state (Jackson and Beatty, 2003): charity care is the portion of unpaid care which is exclusively offered to uninsured low-income patients, mostly those with incomes

[66] The American Hospital Association (AHA) defines cost-to-charge ratio as total expenses exclusive of bad debt to the sum of gross patient revenue and other operating revenue. I use the ratio of total operating expenses to the sum of gross patient charges and other operating revenues.
[67] Title XXIX (2): "'Charity care' or 'uncompensated charity care' means that portion of hospital charges reported to the agency for which there is no compensation for care provided to a patient whose family income for the 12 months preceding the determination is less than or equal to 150 percent of the federal poverty level, unless the amount of hospital charges due from the patient exceeds 25 percent of the annual family income. However, in no case shall the hospital charges for a patient whose family income exceeds four times the federal poverty level for a family of four be considered charity."

under 150% of the FPL, while a payer source for bad debt can vary. Therefore, I perceive charity care as a lower bound of hospitals' true willingness to provide indigent care. Second, even if there is no change in the amount of UC, hospitals may change the composition of UC.

For volume of the indigent, I use uninsured (selfpay) admissions as a proxy for indigent admissions. I first examine a proportion of uninsured admissions, a number of uninsured patients in log form, and uninsured inpatient days in log form. The proportion of uninsured admissions captures relative volume of indigent admissions, but can vary not only by changes in absolute number of uninsured admissions, but also by changes in insured admissions. Therefore, I also look at absolute number of uninsured admissions and their days of stay at hospital. Then, I isolate non-emergency patients from total admissions and break them down by payer source. The non-emergency uninsured admissions, the other set of dependent variables, are measured by number in log form as well as in proportion among non-emergency admissions of all payers. Lastly, following Nakamura (2007), I construct a ratio of non-emergency to emergency admissions for the uninsured. If hospitals decrease indigent care, the decrease should be larger for non-emergency patients than emergency patients, so this ratio should decrease. In order to control for other factors that could influence hospital admission patterns across all payer sources, such as service closure, a national trend of switching to outpatient care, or a type of illness, I difference out the same ratio associated with the privately insured from the ratio for the uninsured. This differenced ratio will decrease if hospitals reduce indigent care. In addition to these uninsured admissions, I examine admission patterns for Medicaid patients: number, proportion, and inpatient days of Medicaid patients.

For the analysis of Medicaid expansions, I divide Medicaid admissions into the target group (pregnant women and infants under age 1) and the non-target group of the policy, and classify uninsured admissions in the same manner. Then I look at how hospitals changed the composition of these four groups. If expansions of public coverage increase number of Medicaid patients in the target group, who are more profitable than uninsured patients, hospitals may increase Medicaid admissions at the expense of uninsured admissions within the target group or substitute Medicaid patients in the non-target group for those in the target group. However, if Medicaid expansions generate more revenues for hospitals, hospitals may increase admissions for uninsured patients who belong to the non-target group or for uninsured patients in the target group who still do not qualify for Medicaid.

For the service provision, I separately examine amounts of 16 services (10 profitable and 6 unprofitable services) in log forms. These are total amounts of services provided to patients in all payer sources, not restricted to the uninsured subgroup. Since these services are measured by five different units such as inpatient days, number of visits, minutes performed, number of procedures, and number of staff, my 16 dependent variables are as follows: log inpatient days for NICU, burn intensive care, coronary care, pediatric intensive care, psychiatric acute care, and substance abuse acute care; log visits of clinic services and emergency services; log minutes of open heart surgery; log number of staff for orthopedic surgery; log procedures of labor/delivery, cardiac catheterization, diagnostic radiology, CT, MRI, and ESW Lithotripsy. I also examine number of unprofitable services provided (from zero to six), as well as proportion of unprofitable services among those six (from zero to one). For profitable services, the total number (from zero to ten) and the proportion out of those ten are examined as well.

VI. Results

Descriptive Statistics

Table 2.4 presents descriptive statistics, as well as the methods of constructing all the dependent and independent variables. My sample consists of a total of 1739 hospital-year observations, coming from 168 short-term hospitals in Florida which did not change ownership status during 1990-2000. The state of Florida has 67 counties, among which six counties (Liberty, Jefferson, Wakulla, Dixie, Gilichrist, and Lafayette) in the west of Florida and the west part of the northeast Florida have no hospitals. In addition, Glades and Sumter counties in the central and south Florida do not have any short-term hospital. All of these counties without a hospital belong to non-Metropolitan areas. As the map in Figure 2.6 shows, most of the hospitals are located in south Florida and along the state’s east or west coast. Table 2.5 presents distribution of the hospitals in my sample across counties. Among the 67 counties, the number of counties with short-term hospitals that did not change ownership status over the years is between 48 and 51. The average number of hospitals within counties is about 3, and the majority of the counties consist of one or two short-term hospitals: 37 percent of the counties include only one hospital, while 63 percent include multiple hospitals (31 percent contain two hospitals, and 32 percent consist of more than two hospitals). The maximum number of short-term hospitals within a county is 18 in Miami-Dade and Broward counties.

The distribution of the uninsured, however, greatly varies across the state (see Figure 2.7). Three contiguous counties in the South East region—Miami-Dade, Broward, and Palm Beach Counties—are home to more than one half of the uninsured population in Florida—24.6%, 14.8%, and 15.1% of the state’s uninsured population, respectively (Census, 2000). Since they account for only 14.1%, 10.1%, and 7% of the

[Table 2.4] Construction of Variables and Descriptive Statistics

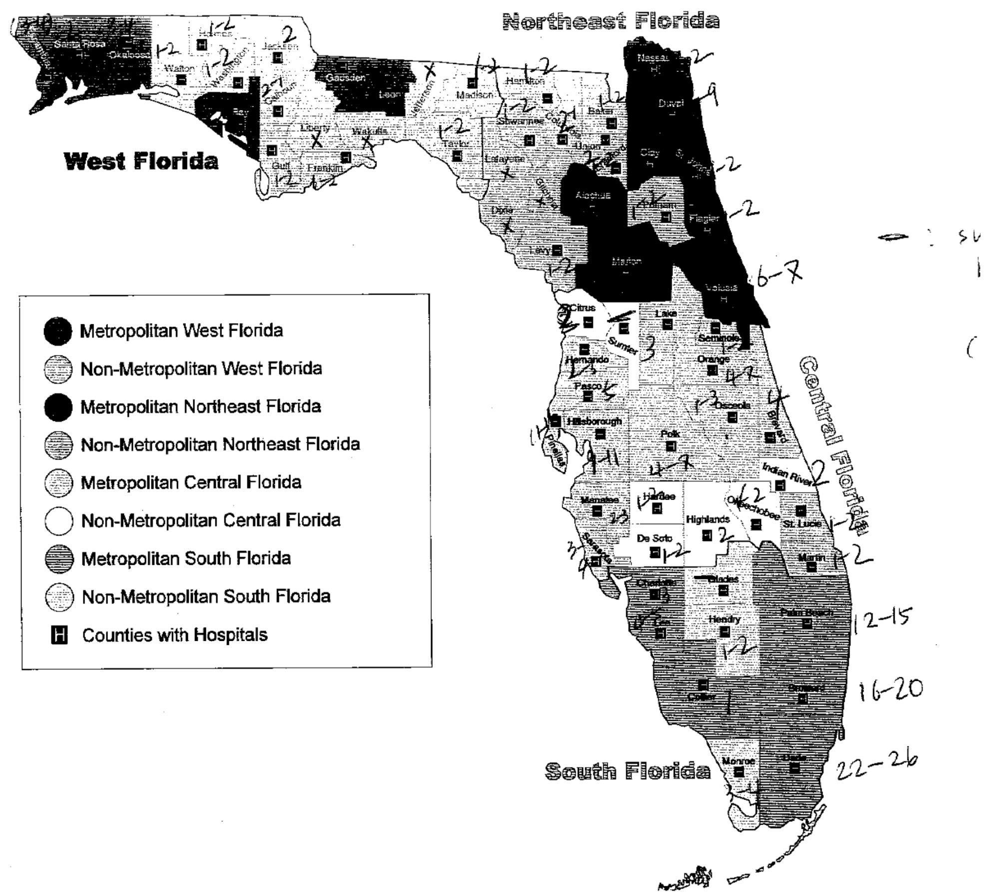
Variable	Construction	Obs	Mean	s.d.
Hospital Attributes (Independent Variables: Hospital Level)				
FP	Private, for-profit hospital	1739	0.47	0.50
Public	Public hospital	1739	0.11	0.32
Teaching	Hospital that has at least 10 residents	1739	0.14	0.47
Large Bed	Hospital with number of licensed beds>200	1739	0.47	0.50
Rural	Acute care hospital that is licensed under Florida Statute 395.602(2)(e). The statute can be found at http://www/flsenate.gov/statutes/.	1739	0.11	0.32
Policy Indicator				
POST92	Years after Medicaid expansion (1993-1995)	1739	0.71	0.45
POST97	Years after the BBA (1998-2000)	1739	0.25	0.43
McareFPI	Medicare FPI at the year of 1998 (p. 7)	147	-0.83	0.42
McaidFPI	Medicaid FPI at the year of 1998 (p. 7)	147	-0.06	0.12
Market Attributes (Independent Variables: County Level)				
HHI for the uninsured	sum of the squared market shares of predicted hospital admissions for indigent patients in each disease group and zip code	1739	0.29	0.29
High HHI for the uninsured	HHI for the uninsured is greater than its median value: high concentration of indigent care burden at the county level	1739	0.21	0.40
Sole hospital	the only hospital within county	1739	0.10	0.30
per capital emergency visit	ln(number of emergency visits /total population)	1739	0.38	0.19
ln(per capita income)	ln(per capital income)	1739	9.99	0.27
% of population aged 65 or over	Population aged 65+/total population	1739	0.19	0.07
% of population who are non-white	Non-white population/total population	1739	0.28	0.18
Unemployment rate (%)	Unemployment rate	1739	5.85	2.26
ln(active non-federal MD's)	ln(number of active non-federal physicians, MDs)	1739	6.58	1.71
Presence of public hospital in the market	At least one public hospital present in the market	1739	0.42	0.49
HHI with admissions of paying patients	sum of the squared market shares of hospital admissions for privately insured, Medicare, Medicaid, and other payer sponsored patients	1739	0.34	0.29
% population under the poverty line	Population under poverty line/total population	1739	0.14	0.04
ln(birth)	ln(number of birth)	1739	8.08	2.52
ln(Medicaid caseload)	ln(Medicaid caseload in total)	1739	10.48	1.34
Commercial HMO penetration	Commercial HMO penetration (only for 1996-2000)	759	0.21	0.11
Medicaid HMO penetration	Medicaid HMO penetration (only for 1996-2000)	759	0.02	0.01

[Table 2.4] continued

Dependent Variables (Hospital Indigent Care)				
Variable	Construction	Obs	Mean	s.d.
Uncompensated Care (UC)				
ln(UC cost)	ln(UC charges*cost-to-charge ratio)	1739	14.61	1.92
% UC cost	UC costs/total expenses	1739	0.07	0.05
ln(charity care)	ln(charity care charges*cost-to-charge ratio)	1739	12.34	3.96
% charity care	Charity care costs/total expenses	1739	0.05	0.08
Admission Patterns				
% Uninsured Adm	Uninsured admissions/total admissions	1739	0.06	0.05
ln(uninsured adm)	ln(number of uninsured admissions)	1739	5.72	1.44
ln(uninsured inpdays)	ln(uninsured inpatient days)	1739	7.20	1.46
ln(non-ER uninsured adm)	ln(number of uninsured patients with non-ER conditions)	1739	4.88	1.39
% Mcaid adm	Medicaid admissions/total admissions	1739	0.11	0.09
ln(Mcaid adm)	ln(number of Medicaid admissions)	1739	6.08	1.65
ln(Mcaid inpdays)	ln(Medicaid inpatient days)	1739	7.69	1.71
Δ ratio(non-ER/ER)	(ratio of non-ER to ER for uninsured patients) – (ratio of non-ER to ER for the privately insured)	1739	-0.46	0.80
ln(uninsured adm: target group)*	ln(number of uninsured maternity patients and uninsured infants under age 1)	980	2.72	2.35
ln(uninsured adm: non-target group)*	ln(number of uninsured patients above age 1 who demand non-maternity care)	980	5.67	1.46
ln(non-ER uninsured adm: non-target)*	ln(number of uninsured patients with non-ER conditions among non-maternity patients aged above 1)	980	4.81	1.52
ln(Mcaid adm: target)*	ln(number of Medicaid maternity patients or Medicaid infants under age 1)	980	3.70	2.86
ln(Mcaid adm: non-target)*	ln(number of Medicaid patients above age 1 who demand non-maternity care)	980	5.40	1.46
Service Provision				
Profitable Services				
ln(coronary)	ln(Coronary Care Inpatient Days)	1739	3.04	3.93
ln(CC)	ln(Cardiac Catheterization Procedures)	1739	4.52	3.67
ln(CT)	ln(Computed tomography Scanner Procedures)	1739	8.04	2.07
ln(Radiology/diagnostic)	ln(Diagnostic Radiology Procedures)	1739	10.53	1.10
ln(ESW)	ln(ESW Lithotripter Procedures)	1739	1.47	2.08
ln(MRI)	ln(Magnetic resonance imaging Procedures)	1739	4.05	3.43
ln(NICU)	ln(Neonatal Intensive Care Unit Inpatient Days)	1739	1.94	3.49
ln(Open Heart)	ln(Open Heart Surgery minutes)	1739	3.36	5.32
ln(Orthopedic)	Ln(Number of Staff for orthopedic surgery)	1739	1.91	1.18
ln(Pediatric Intensive Care)	Ln(Pediatric Intensive Care Inpatient Days)	1739	0.79	2.30
Num(Profitable service)	Number of Profitable Services (0-10)	1739	5.56	2.21
% Profitable service	(number of profitable Services)/10	1739	0.56	0.22

[Table 2.4] continued

Dependent Variables (Hospital Indigent Care): continued				
		Unprofitable Services		
Variable	Construction	Obs	Mean	s.d.
ln(Burn care)	ln(Burn Intensive Care Unit Days)	1739	0.14	6.04
ln(ER)	ln(Emergency Room Visits)	1739	9.63	1.87
ln(Free Clinic)	ln(Clinic+ Free Standing Clinic Visits)	1739	2.94	4.43
ln(Obstetric)	ln(Labor and Delivery Procedures)	1739	4.35	3.74
ln(Psych)	ln(Psychiatric Acute Care Days)	1739	2.91	4.22
ln(substance abuse)	ln(Substance Abuse Acute Care Inpatient Days)	1739	0.75	2.25
Num(unprofitable service)	Number of unprofitable services (0-6)	1739	2.34	1.11
% (unprofitable service)	(number of unprofitable services)/6	1739	0.39	0.18

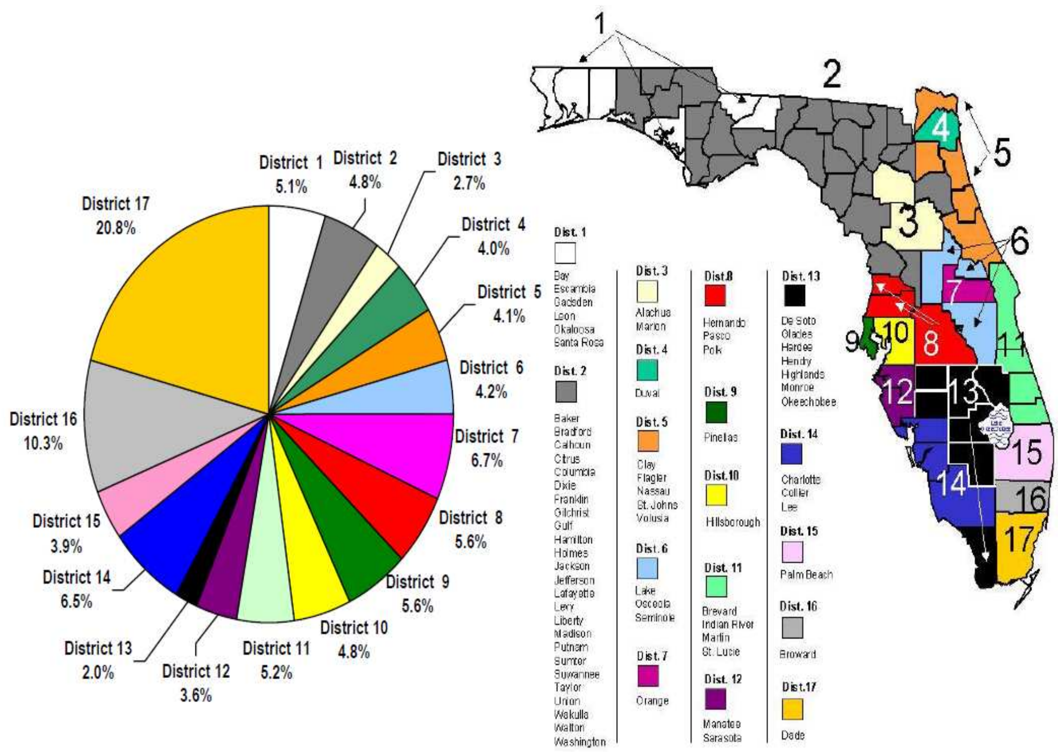


Source: Florida Hospital Service Guide (AHCA, 2003)
Note: Numbers in each county mean the number of hospitals during 1990-2000.
For example, the number of short-term hospitals in Miami-Dade County was between 22 and 26 during my sample period.

[Figure 2.6] Distribution of Florida Hospitals by County

[Table 2.5] Distribution of Hospitals across Counties

Year	Average # of Hospitals	# of County
1990	3.29	51
1991	3.29	49
1992	3.33	49
1993	3.33	48
1994	3.24	50
1995	3.32	50
1996	3.22	50
1997	3.18	49
1998	3.02	49
1999	3	49
2000	2.94	50

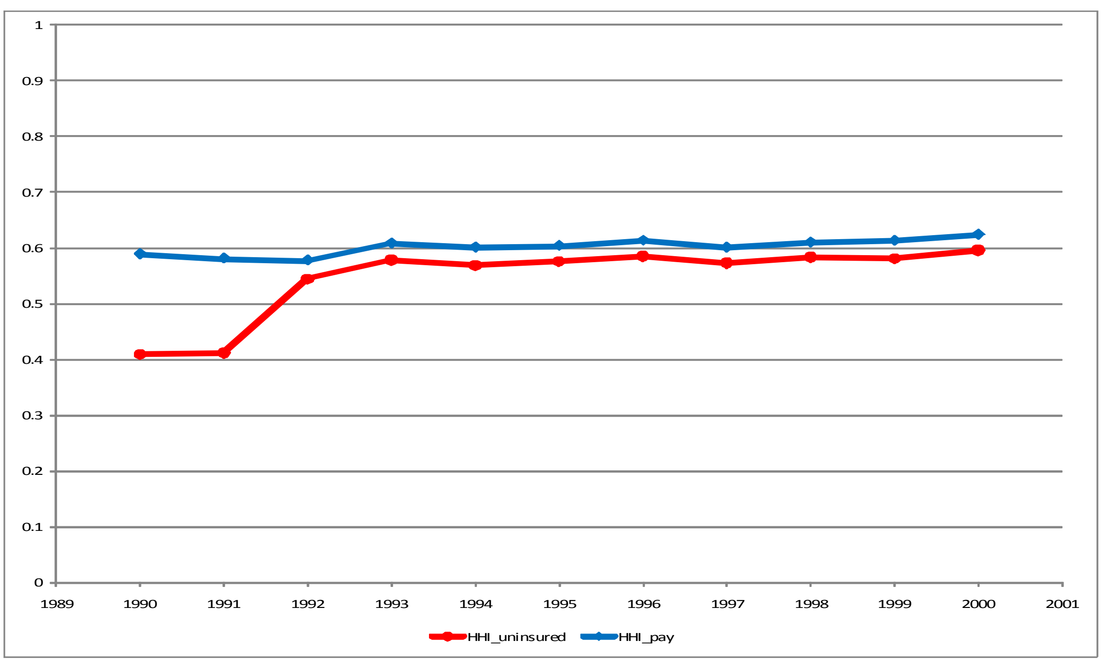


Source: Florida Health Insurance Study, 2004

[Figure 2.7] Distribution of Uninsured Residents under Age 65 by District

state's population, respectively, this means that hospitals located on the south coast face higher demand for indigent care. On the other hand, there are few uninsured persons in rural and sparsely populated counties: for example, the sum of uninsured residents in seven counties in Central Florida—DeSoto, Glades, Hardee, Hendry, Highlands, Monroe, and Okeechobee—makes up of only 2% of the uninsured population in the state. Within these counties, however, almost a quarter (24.4%) of the population lacks health insurance coverage, which implies that the role of safety-net providers is also important in these rural counties.

Now, I discuss distribution of the uninsured within counties for 1990-2000. Figure 2.8 shows the HHI for the uninsured (red line) and HHI for paying patients (blue line). The HHI for the uninsured (concentration of indigent care burden at the county level) increased in 1992 from 0.41 to 0.54, but has stayed almost the same since 1992. The HHI for paying patients has been constantly higher approximately at 0.6, and changed little over the years.

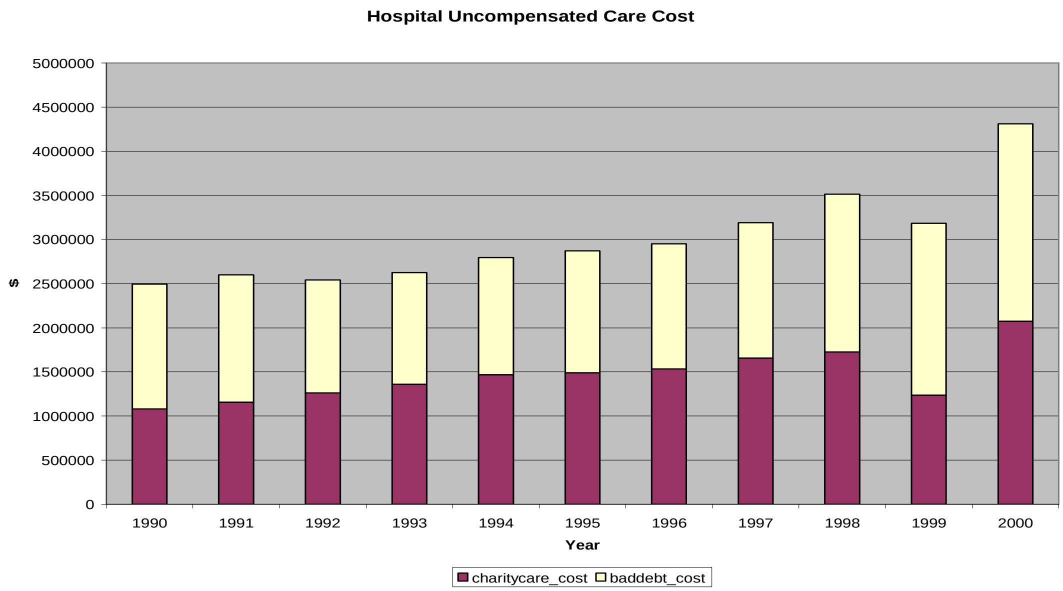


[Figure 2.8] Distribution of the Uninsured (HHI for the uninsured: county level)

The Florida hospital market mainly consists of FP and NFP hospitals, accounting for 47 and 41 percent of the study sample, respectively, while public hospitals are 12 percent of the hospital sample. Teaching hospitals, defined as those that have at least 10 residents, consist of 14 percent of my sample. Florida hospitals have an average of 289 licensed beds, and 89 percent are located in urban areas. 21 percent of the hospitals are located in counties where at least two hospitals operate and the indigent care burden is highly concentrated, whereas 10 percent are the only providers operating in their respective counties.

Hospital UC consists of 29 percent charity care and 71 percent bad debts (see Figure 2.9), and takes up 7 percent of operating expenses. The payer mix is as follows: 6 percent self-pay, 11 percent Medicaid, 26 percent private insurance, and 51 percent Medicare. While 60 percent of privately insured or Medicaid patients are admitted with non-emergency conditions, only 50 percent of self-pay patients come with non-emergency conditions.

On the demand side, the average per capita income is $21,222.7; the average unemployment rate at the county level is about 6 percent; the elderly (65 years or older) make up 19 percent of the population, whereas the non-white population makes up 28 percent. On the supply side, the average number of active non-federal physicians is 723 at the county level; the value of HHI with paying patients is 0.34; and 42 percent of hospitals were located in counties which had a public hospital.



Source: author's calculation based on the Florida hospitals' financial data set

[Figure 2.9] Hospital Uncompensated Care in Florida (1990-2000)

Results of Model 0 (county level)

Table 2.6 and Table 2.7 report the estimates of the county level analysis (Model 0) for the Medicaid expansion and the BBA, respectively. Here, the dependent variable is the aggregate of hospitals' indigent care at the county level.

(a) Results for the Medicaid Expansions (Model 0)

In Table 2.6, the results in the first panel show that the aggregate amounts of indigent care in terms of charity care costs and number of uninsured patients decreased, by 0.16 logs and 0.21 logs respectively, after the Medicaid expansion; however, neither change was statistically significant. Interestingly, the aggregate number of uninsured patients belonging to the non-target group increased after the expansion, by 0.29 logs, in a statistically significant manner.

[Table 2.6] Results of Model 0 (Medicaid Expansions)

Panel I	ln(UC cost)		ln(charity cost)		ln(uninsured adm)		ln(uninsured target)		ln(uninsured non-target)	
Post92	0.1 (0.08)	0.08 (0.09)	-0.16 (0.42)	-0.44 (0.59)	-0.21 (0.29)	-0.32 (0.46)	0.33 (0.75)	1.02 (0.83)	0.29** (0.12)	0.29** (0.14)
Post92× HHIhigh		-0.02 (0.06)		-0.04 (0.16)		0.16 (0.19)		-0.19 (0.57)		0.06 (0.10)
Post92× solehosp		0.05 (0.06)		0.64 (0.56)		0.11 (0.29)		-1.37 (0.83)		-0.04 (0.13)
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	297	297	297	297	297	297	297	297	297	297
R-sqr	0.99	0.99	0.85	0.86	0.85	0.85	0.87	0.87	0.97	0.97
F-stat	6.26	5.99	9.91	5.97	5.46	5.46	44.35	21.01	38.21	47.48
Prob>F	0	0	0	0	0	0	0	0	0	0

Panel II	ln(Medicaid Admission)		ln(Medicaid Adm: Target group)		ln(Medicaid Adm: Non-target group)	
Post92	-0.08	0.14	0.48	1.02	-0.18**	-0.05
	(0.09)	(0.13)	(0.53)	(0.64)	(0.08)	(0.10)
Post92× HHIhigh		-0.08		-0.46		-0.06
		(0.09)		(0.55)		(0.08)
Post92× solehosp		-0.42***		-0.85*		-0.25**
		(0.15)		(0.49)		(0.11)
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	297	297	297	297	297	297
R-sqr	0.98	0.98	0.89	0.89	0.98	0.98
F-stat	3.97	4.05	3.04	7	70.7	10.89
Prob>F	0	0	0	0	0	0

Panel III	Ln(ER visits)		Ln(clinic visits)		Ln(labor/delivery procedures)		Ln(NICU)		Ln(pediatric intensive care)	
Post92	0.04	0.09**	1.54	0.02	0.19	0.87	-0.21	0.13	-0.06	0.2
	(0.03)	(0.03)	(1.26)	(1.92)	(0.36)	(0.76)	(0.54)	(0.84)	(0.06)	(0.19)
Post92× HHIhigh		-0.05		0.83		-1.04		-0.05		-0.3
		(0.04)		(1.80)		(0.71)		(0.53)		(0.24)
Post92× solehosp		-0.05*		2.71		-0.71		-0.7		-0.34
		(0.03)		(2.02)		(0.69)		(0.71)		(0.27)
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	297	297	297	297	297	297	297	297	297	297
R-sqr	1	1	0.78	0.78	0.96	0.97	0.96	0.96	0.99	0.99
F-stat	27.11	27.9	31.71	26.23	3.14	3.58	72	127	340	1872
Prob>F	0	0	0	0	0	0	0	0	0	0

This implies hospital indigent care beneficiaries shifting from maternity to non-maternity patients after the Medicaid program covered more maternity patients. The aggregate of Medicaid patients in the target group, mostly involving births, increased, while the aggregate of Medicaid patients in the non-target group decreased by 0.18 logs; however, neither change was statistically significant. In markets with only one hospital, the admissions for Medicaid patients (in total, in the target group, and in the non-target group) actually decreased after the expansions: this may imply that patients residing in a county where a single hospital was operating may have moved to hospitals in a different county after the coverage gain.

In the third panel, I present results for the service provision at the county level. Here, I only report the estimates for services that were possibly affected by the expansion policy such as maternity and pediatric care. In a given county, the sum of labor/delivery procedures performed at hospitals increased, while the aggregate NICU days and the sum of pediatric intensive care days decreased. However, none of these changes was statistically significantly different from zero at the 10% level. Although I expect emergency room or clinic visits to decrease after the coverage expansion (because these are the entry points for uninsured patients), both increased, albeit by amounts that are not statistically significant. In particular, the total number of ER visits increased by 0.09 logs for counties with multiple hospitals, but decreased by 0.05 logs for those with only one hospital. Considering that these counties also increased the aggregate amount of care offered to uninsured patients in the non-target group, these increased ER visits were likely to originate from non-maternity patients.

(b) Results for the BBA (Model 0)

Panel I in Table 2.7 presents the estimates for the BBA regarding changes in UC and volume of the uninsured at the county level. As in Table 2.6, most of the

[Table 2.7] Results of Model 0 (the BBA)

Panel I	ln(UC cost)		Ln(Charity Cost)		Ln(Uninsured Admission)		Ln(Medicaid Admission)	
POST97	0.01	-0.04	0.14	0.07	0.37	0.34	-0.17	-0.16
	(0.07)	(0.08)	(0.17)	(0.19)	(0.59)	(0.65)	(0.12)	(0.12)
POST97 ×HHIhigh		0.1		0.12		0.08		-0.03
		(0.06)		(0.16)		(0.23)		(0.07)
POST97 ×solehosp		0.07		0.17		0.03		0
		(0.08)		(0.21)		(0.27)		(0.09)
Obs.	247	247	247	247	247	247	247	247
county F.E.	YES	YES	YES	YES	YES	YES	YES	YES
R-square	0.99	0.99	0.93	0.93	0.87	0.87	0.98	0.98
Prob>F	0	0	0.41	0	0	0	0	0

Panel II	ln burncare	ln (ER)	ln (clinic)	ln (labor)	ln (psych)	ln (subst)	ln(# of unprofit)
POST97	0.14	0.96	-0.67	-0.07	0.29	-0.45	0.34
	(0.14)	(0.85)	(2.27)	(0.12)	(0.39)	(1.02)	(0.40)
POST97 ×HHIhigh	-0.08	-0.12	4.33**	-0.12	0.01	0.22	0.03
	(0.09)	(0.19)	(1.95)	(0.15)	(0.27)	(0.87)	(0.09)
POST97 ×solehosp	-0.03	-0.05	0.35	-0.08	-1.05	-0.08	0.01
	(0.06)	(0.19)	(2.62)	(0.15)	(0.85)	(1.02)	(0.14)
Obs.	247	247	247	247	247	247	247
county F.E.	YES	YES	YES	YES	YES	YES	YES
R-square	0.96	0.85	0.8	1	0.98	0.9	0.91
Prob>F	0	0	0	0	0	0	0

Panel III	ln(CC)	ln (MRI)	ln (NICU)	ln openheart	ln (orthoped)	ln (pedinc)	ln(num of profit)
POST97	0.73**	-0.95*	0.21	-0.84	0.06	-0.4	0.43
	(0.29)	(0.53)	(0.21)	(1.52)	(0.17)	(0.82)	(0.39)
POST97 ×HHIhigh	0.87	1.42**	0.18	0.69	0.04	0.12	-0.01
	(0.65)	(0.68)	(0.29)	(2.04)	(0.11)	(0.67)	(0.10)
POST97 ×solehosp	0.4	-1.55*	0.52	0.03	0.37	-0.07	-0.02
	(0.62)	(0.92)	(0.59)	(1.61)	(0.26)	(0.35)	(0.10)
Obs.	247	247	247	247	247	247	247
county F.E.	YES	YES	YES	YES	YES	YES	YES
R-square	0.97	0.92	0.98	0.9	0.99	0.97	0.94
Prob>F	0	0	0	0	0	0	0

policy effects on the aggregate level of indigent care did not change in a statistically significant manner. Moreover, contrary to my hypothesis, the BBA did not reduce the indigent care provision at the county level: UC, charity care, and uninsured admissions at the county level all increased after the BBA, while the aggregate of Medicaid admissions decreased. For the unprofitable service provision, the BBA reduced county level clinic visits, substance inpatient days, and labor procedures. In contrast, many of the profitable services provided at the county level increased after the BBA: aggregate amounts of services related to cardiac care, CT, diagnostic radiology, ESW, NICU, and orthopedic care all increased after the supply shock.

Results of Model 1 (Hospital Level)

Now, I discuss the policy effects on individual hospitals' supply of indigent care. Model I is the difference-in-difference type regression that enables me to compare policy impacts across ownership types. The coefficient of POST captures policy impacts on indigent care for NFP hospitals, while the estimates for two interaction terms (POST×FP and POST×Public) capture the differences in policy impacts between NFP and the respective ownership type (NFP vs. FP and NFP vs. Public).

(a) Results for the Medicaid Expansions (Model 1)

Table 2.8 through Table 2.10 present the results of Model I for the Medicaid expansion—UC measures, admission patterns, and types of services provided. In Table 2.8, I report the estimates for the four UC measures: UC costs in log form, UC as a percent of total operating expenses, charity care costs in log form, and charity care as a percent of total operating expenses. Prior to the Medicaid expansion, regardless of the choice of measures, I can confirm conventional wisdom concerning the

[Table 2.8] Results of Model I for Medicaid Expansion: Uncompensated Care

	ln (UC cost)	% (UC cost)	ln (charity care)	% (charity care)
POST92	-0.09	0	-1.16**	-0.01*
	(0.16)	(0.00)	(0.44)	(0.00)
POST92×FP	0.24	0.01*	1.58***	0
	(0.22)	(0.00)	(0.44)	(0.00)
POST92×Public	0.13	0	0.24	0.02*
	(0.16)	(0.01)	(0.24)	(0.01)
FP	-0.78***	-0.02***	-5.01***	-0.02***
	(0.22)	(0.01)	(0.59)	(0.01)
Public	1.43***	0.12***	2.60***	0.16***
	(0.32)	(0.02)	(0.85)	(0.02)
Teaching	0.57**	0.02*	-0.27	0.04**
	(0.23)	(0.01)	(0.71)	(0.02)
Large_bed	1.16***	0	2.71***	0.01*
	(0.16)	(0.01)	(0.55)	(0.01)
Rural	5.05**	0.12***	4.96	0.11***
	(2.29)	(0.03)	(3.16)	(0.03)
ln(mcaidcase)	-0.18	-0.01	1.23	0.01
	(0.40)	(0.01)	(1.04)	(0.01)
% pop65	0.6	0.16	9.51	0.24
	(8.51)	(0.14)	(22.22)	(0.21)
% nonwhite	-1.02	-0.32**	13.5	0.1
	(3.40)	(0.13)	(12.43)	(0.12)
capita_ERvisit	0.23	0	0.13	0
	(0.26)	(0.00)	(0.24)	(0.00)
unemployment	-0.05	-0.00*	0.11	0
	(0.05)	(0.00)	(0.09)	(0.00)
ln(birth)	-0.13	0	-0.17	0
	(0.17)	(0.00)	(0.32)	(0.00)
ln(capita_income)	1.06*	0.02	0.74	0.03
	(0.63)	(0.02)	(1.88)	(0.02)
ln(active MD)	0.72	0	3.37**	0.01
	(0.57)	(0.03)	(1.65)	(0.02)
% poverty pop	-2.45	0.17	15.24	0.22*
	(4.42)	(0.19)	(11.81)	(0.11)
Pres_public hosp	1.00*	0.03	2.51**	0.03
	(0.56)	(0.02)	(1.01)	(0.03)
HHI_pay	0.85	0.02	2.17	0.04
	(0.59)	(0.02)	(1.66)	(0.03)
Constant	2.32	-0.02	-37.09**	-0.51***
	(6.79)	(0.17)	(18.53)	(0.16)
Observations	980	980	980	980
County F.E.	YES	YES	YES	YES
R-square	0.54	0.58	0.51	0.54
Prob>F	0	0	0	0

Note: Standard errors (in parentheses) are heteroskedasticity robust and clustered at the hospital level.

relationship between hospital ownership type and provision of indigent care: compared to NFP hospitals, FP hospitals provide less indigent care, while public hospitals offer more. The first two columns show that after the Medicaid expansion, there was very little statistical evidence that hospitals changed UC, except for FP hospitals which increased UC costs as a percent of operating costs. The last two columns show that FP hospitals increased both charity care and bad debts, but the increase in bad debts was larger than that in charity care. The Medicaid expansion reduced the charity care burden for NFP hospitals both in log terms (by 1.16) and as a percent of operating expenses (1 percentage point). Public hospitals also reduced charity care costs by 1.16 logs, but relative to operating costs, charity care costs increased by 1 percentage point. My findings suggest that public and NFP hospitals benefited from the Medicaid expansion, by carrying a smaller charity care burden. However, no change in UC implies an increase in bad debt, so that the overall indigent care burden might not have been reduced for these hospitals.

Table 2.9 presents the results for the admission patterns after the expansion. The first three columns include the estimates for uninsured (selfpay) admission rates, number of uninsured admissions in log form, and uninsured inpatient days in log form. I expect uninsured admissions to decrease after the Medicaid expansion. Although hospitals of all ownership types admitted fewer uninsured patients, these decreases are not statistically significantly different from zero. However, uninsured inpatient days decreased by 0.27 logs across all ownership types (at the 10% level). Now, I separate uninsured patients into maternity and infant patients (the Medicaid target group) and the rest (the non-target group), and examine whether the Medicaid expansion decreased uninsured patients who belonged to the target group. The fourth column shows that the number of uninsured patients who were in the target group did decrease at NFP and public hospitals by 0.42 logs after the expansion, but FP hospitals

[Table 2.9] Results of Model I for Medicaid Expansion: Admission Patterns

Panel I (N=980)							
	%unins adm	ln(unins adm)	ln(unins Inpday)	ln (unins: target)	ln(unins: non-Target)	ln(unins: non-ER & non-target	Δ Ratio (nonER/ ER)
POST92	0	-0.09	-0.27*	-0.42**	0.27*	0.31**	0.19*
	(0.01)	(0.13)	(0.15)	(0.18)	(0.15)	(0.15)	(0.11)
POST92×FP	0.01	-0.13	0.01	0.44***	-0.35***	-0.42***	-0.07
	(0.00)	(0.12)	(0.12)	(0.16)	(0.13)	(0.12)	(0.11)
POST92×Public	-0.01	0.08	0.06	0.26	0.22*	0.24*	0.12
	(0.01)	(0.11)	(0.14)	(0.23)	(0.12)	(0.14)	(0.13)
FP	-0.02***	-0.62***	-0.54***	-1.99***	-0.26	-0.33**	0.04
	(0.01)	(0.17)	(0.16)	(0.39)	(0.16)	(0.16)	(0.12)
Public	0.10***	1.35***	1.66***	1.33	1.14***	1.13***	-0.09
	(0.02)	(0.28)	(0.30)	(0.81)	(0.26)	(0.28)	(0.22)
Teaching	0	0.32	0.39*	0.49	0.34	0.45**	-0.02
	(0.01)	(0.20)	(0.22)	(0.38)	(0.22)	(0.22)	(0.13)
Large Bed	0	1.24***	1.24***	1.28***	1.25***	1.24***	-0.27**
	(0.01)	(0.17)	(0.15)	(0.35)	(0.17)	(0.15)	(0.12)
Rural	0.08***	1.22	1.88*	-0.43	1.38	0.83	-0.01
	(0.03)	(0.98)	(0.95)	(1.26)	(0.95)	(0.96)	(0.18)
Other County Variables & County F.E.	YES	YES	YES	YES	YES	YES	YES
R-square	0.51	0.54	0.6	0.47	0.52	0.59	0.15
Panel II (N=980)							
	% Mcaid adm	ln (Mcaid Adm)	ln (Mcaid inpday)	ln (Mcaid: target)	ln (Mcaid: non-target)		
POST92	0	-0.18	-0.12	-0.36*	-0.14		
	(0.01)	(0.12)	(0.12)	(0.20)	(0.10)		
POST92×FP	0.02**	0.24*	0.24	0.47**	0		
	(0.01)	(0.14)	(0.18)	(0.20)	(0.12)		
POST92×Public	0.01	-0.12	-0.11	0.06	-0.09		
	(0.01)	(0.12)	(0.13)	(0.22)	(0.10)		
FP	-0.03*	-0.80***	-0.59***	-2.28***	-0.49***		
	(0.02)	(0.22)	(0.21)	(0.42)	(0.18)		
Public	0.10***	1.58***	1.68***	1.64*	1.37***		
	(0.03)	(0.33)	(0.33)	(0.86)	(0.26)		
Teaching	0.09***	0.91***	0.98***	1.07**	0.66***		
	(0.02)	(0.25)	(0.25)	(0.48)	(0.22)		
Large Bed	0.01	1.47***	1.63***	1.59***	1.45***		
	(0.01)	(0.20)	(0.19)	(0.42)	(0.17)		
Rural	0.08	0.99	1.18	-0.04	1.15		
	(0.07)	(1.26)	(1.33)	(1.62)	(1.07)		
Other County Controls & county F.E.	YES	YES	YES	YES	YES		
R-square	0.41	0.56	0.57	0.5	0.56		

increased it by 0.02 logs. However, the reason why the overall uninsured admissions did not change was because NFP and public hospitals admitted more uninsured patients in the non-target group, i.e., non-maternity patients above age 1, while FP hospitals decreased these admissions. In the last two columns, I find that the increase in indigent care at NFP and public occurred with those who had non-emergency conditions and seek non-maternity care, i.e., indigent care which hospitals could have chosen not to offer.

In order to check whether the decreased number of uninsured patients in the target group was matched with an increased number of Medicaid admissions, I also examine Medicaid admission patterns in Panel II. At first, I examine Medicaid admissions in total, not restricted to the target group of the expansion, and find that only FP hospitals increased the total number of Medicaid patients (by 0.24 logs) and their admission rates (by 2 percentage points). When I divide Medicaid patients into the target and non-target group, the fourth and fifth columns show that the increase in Medicaid admissions at FP hospitals was due to the increase in the number of maternity and pediatric patients, those in the target group.

My findings imply that the Medicaid expansion did not reduce the total number of uninsured patients, but did change distribution of uninsured patients across hospitals. NFP and public hospitals, which had taken care of a large number of low-income patients before the expansion, were able to reduce uninsured admissions among maternity patients and infants under age one, the target group of the policy change. However, they balanced out this decrease in uninsured admissions with the increase in admissions for uninsured patients who were in the non-target group. FP hospitals, which originally took care of few uninsured patients, became more interested in caring the patient group who were potentially eligible for Medicaid after the expansion: they increased admissions for low-income patients who were uninsured or on Medicaid, but only those in the target group, by sacrificing care to uninsured patients who were in the non-target group.

Table 2.10 reports the results of the expansion policy regarding service provision. For the Medicaid expansion, I do not expect hospitals to make large changes in types of services provided, and this is confirmed by Table 2.10. Neither profitable nor unprofitable services changed by statistically significant amounts, except for CT procedures, which decreased at FP hospitals. However, there may have been reallocation of maternity patients and infants under age 1 across hospitals, because the increased public insurance coverage provided payments to hospitals for treating those who became eligible for Medicaid. Therefore, I focus on three services particularly related to maternity and pediatric care: two profitable intensive care services (NICU days and pediatric intensive care) and one unprofitable service (labor procedures). Prior to the Medicaid expansion, FP hospitals provided smaller amounts of all of these three services than NFP and public hospitals. After the Medicaid expansion, FP hospitals provided relatively more labor and pediatric intensive care services than NFP hospitals, but the differences were not statistically significantly different from zero. Lastly, I examine whether the income effect motivated hospitals to increase provision of unprofitable services. Based on the number and proportion of unprofitable services, I do not find such effects.

(b) Results for the BBA (Model 1)

Next, I present the results of Model I for the BBA. First, I estimate Model I with the hospital sample for 1995-2000 with Medicare FPI and Medicaid FPI included (controlling for the size of the financial shock at the hospital level). However, the policy impacts may differ by the size of the financial shock, so I add interaction terms

[Table 2.10] Results of Model I for Medicaid Expansion: Service Provision

Profitable Services	POST92		POST92×FP		POST92×Public		Other Hosp. Var.	Other County Variables & F.E	R-square
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.			
ln(coronary)	-0.07	(0.36)	-0.15	(0.34)	-0.01	0.51	YES	YES	0.51
ln(CC)	0.18	(0.25)	-0.3	(0.28)	-0.44	0.55	YES	YES	0.55
ln(CT)	0.19	(0.25)	-0.37**	(0.15)	0.26	0.5	YES	YES	0.5
ln(radio/diag)	0.2	(0.19)	-0.12	(0.13)	0.02	0.38	YES	YES	0.38
ln(ESW)	0.14	(0.21)	-0.16	(0.21)	-0.02	0.4	YES	YES	0.4
ln(MRI)	0.42	(0.43)	0.18	(0.35)	0.58	0.43	YES	YES	0.43
ln(NICU)	0.14	(0.19)	-0.19	(0.16)	0.34	0.45	YES	YES	0.45
ln(openheart)	-0.07	(0.28)	0	(0.25)	-0.14	0.39	YES	YES	0.39
ln(orthopedic)	0.07	(0.09)	-0.12	(0.08)	0.13	0.58	YES	YES	0.58
ln(ped.int)	-0.15	(0.15)	0.01	(0.14)	0.3	0.32	YES	YES	0.32
# of profitable	0.16	(0.17)	-0.14	(0.15)	0.1	0.61	YES	YES	0.61
% of profit.	0.02	(0.02)	-0.01	(0.01)	0.01	0.61	YES	YES	0.61

Unprofitable Services	POST92		POST92×FP		POST92×Public		Other Hosp. Var.	Other County Variables & F.E	R-square
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.			
ln(burncare)	-0.02	(0.04)	-0.01	(0.04)	0.02	(0.04)	YES	YES	0.29
ln(ER)	-0.01	(0.23)	-0.19	(0.22)	-0.03	(0.12)	YES	YES	0.29
ln(freeclinic)	0.61	(0.56)	-0.65	(0.44)	0.01	(0.82)	YES	YES	0.37
ln(obstetric)	-0.49	(0.30)	0.39	(0.29)	0.14	(0.40)	YES	YES	0.45
ln (psychiatr)	-0.31	(0.27)	-0.09	(0.27)	-0.02	(0.31)	YES	YES	0.41
ln(substance)	-0.1	(0.29)	0.22	(0.27)	0.06	(0.37)	YES	YES	0.2
# of unprofit.	-0.01	(0.10)	-0.01	(0.09)	0.03	(0.12)	YES	YES	0.51
% of unprof.	0	(0.02)	0	(0.02)	0	(0.02)	YES	YES	0.51

between Medicaid FPI and each of the ownership types to Model I[68]. I construct a dummy variable for hospitals with high Medicaid FPI: HIGH_MCAIDFPI=1 if Medicaid FPI of a hospital is greater than the median value of all hospitals' Medicaid FPI. Table 2.11 through Table 2.13 present the three sets of results. The estimates in row (1)-(3) capture how hospitals with small financial shock responded to the BBA,

[68] I do not include interaction terms between Medicare FPI and ownership types because when I estimate Model I with Medicare FPI and Medicaid FPI included, the Medicare FPI did not have statistically significant impacts on hospital indigent care for most of my indigent care measures.

while the estimates in row (4)-(6) capture responses of hospitals with large financial shock (high Medicaid FPI) to the BBA. If those with larger shock reduced indigent care to a greater extent, these estimates would have negative values.

Table 2.11 reports the estimates for the four UC measures. Surprisingly, the BBA seemed to have had little effect on the amount of UC or charity care. Only FP hospitals made an adjustment to the log amount of charity care costs, but the adjustment was the increase in charity care costs by 0.56 logs. My results confirm that the decrease in indigent care was indeed larger at hospitals with greater financial shocks: For those with high Medicaid FPI, UC as a percent of operating expenses decreased by 1 percentage point, regardless of ownership type. For public hospitals with high Medicaid FPI, charity care as a percent of operating expenses also decreased by 8 percentage points.

[Table 2.11] Results of Model I for the BBA: Uncompensated Care

No.	Variables	ln (UC cost)	% (UC cost)	ln (charity care)	% (charity care)
(1)	POST97	0.16	0	0.22	0.01
		(0.10)	(0.00)	(0.30)	(0.01)
(2)	POST97×FP	-0.26	0	0.56*	-0.01
		(0.17)	(0.01)	(0.32)	(0.01)
(3)	POST97×Public	-0.04	0	-0.13	0.02
		(0.17)	(0.01)	(0.30)	(0.02)
(4)	POST97×HighFPI	-0.22	-0.01**	-0.15	-0.01
		(0.16)	(0.01)	(0.33)	(0.01)
(5)	POST97×FP×HighFPI	0.36*	0.01	0.41	0.02
		(0.19)	(0.01)	(0.37)	(0.02)
(6)	POST97×Public×HighFPI	-0.11	-0.01	-0.31	-0.08*
		(0.30)	(0.01)	(0.53)	(0.04)
	Other Hosp. Variables	YES	YES	YES	YES
	Other County Variables	YES	YES	YES	YES
	County F.E.	YES	YES	YES	YES
	Observations	729	729	729	729
	R-square	0.67	0.74	0.55	0.71
	Prob>F	0	0	0	0

Table 2.12 reports the estimates for admission patterns. My results show that NFP and public hospitals were more responsive to the BBA, and that hospitals with high Medicaid FPI reduced indigent care to a greater extent. Hospitals of all ownership types with high Medicaid FPI reduced uninsured admissions by 0.31 logs and Medicaid admissions by 0.47 logs. These account for a 1 percent decrease in uninsured admission rates for private hospitals, and 6 percent for public hospitals. There was no statistically significant change in uninsured inpatient days at hospitals in any ownership type. Now I isolate uninsured patients who did not have emergency conditions from total uninsured patients. I expect hospitals, with more financial pressure after the BBA, to reduce uninsured admissions, but only those who arrived with non-emergency conditions. The fourth and fifth column show that the size of the reductions in non-emergency uninsured admissions differs by ownership type and by the level of Medicaid FPI. Among those with low FPI, NFP hospitals decreased the log of uninsured admissions with non-ER conditions by 0.16, which accounted for 2 percentage points reductions in uninsured admission rates, but FP and public hospitals increased non-ER uninsured admissions by 0.26 and 0.31 logs, respectively (4 and 3 percentage-point higher than the rate for NFP hospitals). Among those with high Medicaid FPI, public hospitals seemed to have made the largest adjustments to indigent care: public hospitals lowered the rate of non-emergency uninsured admission by 5 percentage points (the largest), while FP hospitals lowered it by 1 percentage point (the smallest) and NFP hospitals by 2 percentage points. However, after taking into account the trend that might have occurred with privately insured patients (ΔRATIO), the changes in uninsured admissions with non-ER conditions became statistically insignificant.

In the last three columns, I examine Medicaid admission patterns: since the BBA specifically reduced Medicaid and Medicare hospital payments, it could directly

[Table 2.12] Results of Model I for the BBA: Admission Patterns

N=729	% unins adm	ln(unins adm)	ln(unins Inpday)	ln(nonER unins adm)	% (nonER unins adm)	Δ Ratio: nonER/ ER
POST97	-0.01	-0.04	-0.02	-0.16	-0.02*	-0.1
	(0.01)	(0.13)	(0.13)	(0.13)	(0.01)	(0.13)
POST97×FP	0.01	0	0.02	0.26*	0.04***	-0.07
	(0.01)	(0.14)	(0.13)	(0.15)	(0.01)	(0.14)
POST97×Public	0.02**	0.1	0.16	0.31*	0.03**	0.31
	(0.01)	(0.16)	(0.16)	(0.17)	(0.01)	(0.22)
POST97×HighFPI	-0.01	-0.31**	-0.23	-0.26	0.02	0.14
	(0.01)	(0.15)	(0.15)	(0.23)	(0.01)	(0.18)
POST97×HighFPI ×FP	0	0.17	0.13	0.04	-0.03*	0.1
	(0.01)	(0.22)	(0.21)	(0.30)	(0.02)	(0.24)
POST97×HighFPI ×Public	-0.05***	-0.38	-0.06	-0.63	-0.06**	-0.48
	(0.02)	(0.33)	(0.28)	(0.43)	(0.03)	(0.46)
Mcare FPI	0	0.02	-0.19	0.18	0	-0.15
	(0.01)	(0.35)	(0.24)	(0.32)	(0.01)	(0.19)
Mcaid FPI	-0.07	-1.49***	-1.47***	-1.44**	-0.12*	0.42
	(0.05)	(0.52)	(0.53)	(0.65)	(0.07)	(1.02)
FP	-0.02***	-0.62***	-0.81***	-0.82***	-0.03**	0.03
	(0.01)	(0.18)	(0.17)	(0.16)	(0.01)	(0.16)
Public	0.06***	1.02***	0.94***	0.86***	0.06***	0
	(0.02)	(0.29)	(0.27)	(0.27)	(0.02)	(0.35)
Teaching	0	-0.02	0.01	0.21	0.02	0.21
	(0.01)	(0.17)	(0.16)	(0.20)	(0.02)	(0.18)
Large bed	0	0.93***	0.96***	0.75***	-0.02**	-0.47***
	(0.00)	(0.19)	(0.16)	(0.17)	(0.01)	(0.14)
Rural	0.03***	-0.51	-0.38	-0.63**	0.09**	0.4
	(0.01)	(0.38)	(0.29)	(0.31)	(0.04)	(0.28)
Other County Variables & F.E.	YES	YES	YES	YES	YES	YES
R-square	0.61	0.67	0.74	0.7	0.39	0.32
Prob>F	0	0	0	0	0	0.06

[Table 2.12] continued

N=729	% Mcaid Adm	ln (Mcaid Adm)	ln(Mcaid Inpday)
POST97	0.02**	0.27*	0.26*
	(0.01)	(0.14)	(0.13)
POST97×FP	0.01	0.09	-0.01
	(0.01)	(0.18)	(0.16)
POST97×Public	-0.03**	-0.38*	-0.19
	(0.01)	(0.21)	(0.24)
POST97×HighFPI	-0.05***	-0.74***	-0.67***
	(0.01)	(0.19)	(0.18)
POST97×HighFPI ×FP	0	0.08	0.15
	(0.01)	(0.28)	(0.27)
POST97×HighFPI ×Public	0.02	0.26	0.19
	(0.02)	(0.47)	(0.49)
Mcare FPI	0.01	0.1	-0.04
	(0.01)	(0.29)	(0.24)
Mcaid FPI	-0.37***	-3.24***	-3.34***
	(0.06)	(0.66)	(0.62)
FP	-0.01	-0.49***	-0.40**
	(0.01)	(0.18)	(0.17)
Public	0.02	0.59*	0.64**
	(0.01)	(0.32)	(0.32)
Teaching	0.01	0.12	0.21
	(0.01)	(0.16)	(0.17)
Large bed	0	0.94***	1.07***
	(0.01)	(0.19)	(0.18)
Rural	-0.02	-1.05***	-1.11***
	(0.02)	(0.32)	(0.20)
Other County Variables & F.E.	YES	YES	YES
R-square	0.74	0.73	0.77
Prob>F	0	0	0

harm low-income patients even though they had Medicaid coverage. I find that NFP and FP hospitals with low Medicaid FPI increased the log of Medicaid admissions by 0.27 and the rate of Medicaid admissions by 2 percentage points. However, public hospitals with low FPI reduced the log and rate of Medicaid admissions by 0.11 logs and 1 percentage point, respectively. Compared to hospitals with low Medicaid FPI, those with high FPI significantly decreased the log and rate of Medicaid admissions, by 0.75 logs and 5 percentage points respectively. These findings imply that public hospitals, i.e., safety-net providers which were expected to experience a greater financial shock after the BBA, lowered indigent care to a greater extent, and hospitals which were hit hard by the BBA made larger adjustments to indigent care.

Table 2.13 shows the results for BBA impact on the type of services provided. I expect hospitals to provide more profitable services but less unprofitable services after the BBA, and hospitals with high FPI to make greater adjustments to their service provision. I find mixed results. The provision of profitable services increased at most hospitals, especially FP hospitals with high FPI and NFP hospitals with low FPI. However, only a few estimates have statistically significantly positive values: NICU days and orthopedic staffs increased by 0.93 and 0.31 logs, respectively, at NFP and FP hospitals with low FPI. Interestingly, FP hospitals with high FPI increased the number and proportion of profitable services by 0.92 logs and 0.09, respectively, which were due to the increases in orthopedic care and pediatric intensive care. The provision of unprofitable services decreased at FP hospitals with low FPI, as well as NFP and public hospitals with high FPI. However, many of the changes were not statistically significantly different from zero at the 10% significance level. Hospitals with a greater BBA shock, regardless of ownership types, decreased provision of obstetric services, the entry point for the indigent. In contrast, FP or public hospitals with high FPI increased provision of some of unprofitable services: public hospitals increased free clinic services by 5.36 logs; FP hospitals increased burn care, free clinic, and substance inpatient days. However, there is no clear pattern of hospitals cutting back the aggregate number of unprofitable services.

[Table 2.13] Results of Model I for the BBA: Service Provision

Panel I: Profitable Services						
N=729	ln (coronary)	ln(CC)	ln(CT)	ln (radio/diag)	ln(ESW)	ln(MRI)
POST97	0.46	0.18	-0.08	0.06	-0.17	0.33
	(0.58)	(0.41)	(0.32)	(0.11)	(0.33)	(0.46)
POST97×FP	-1.40*	-0.43	0.09	-0.21*	0.3	-0.03
	(0.75)	(0.63)	(0.32)	(0.12)	(0.40)	(0.53)
POST97×Public	-0.23	-0.41	0.51	-0.04	0.58	0.05
	(0.77)	(0.65)	(0.41)	(0.13)	(0.43)	(0.65)
POST97 ×HighFPI	-1.12	0.09	0.59	-0.13	0.18	0.06
	(0.85)	(0.59)	(0.54)	(0.11)	(0.47)	(0.70)
POST97×FP × HighFPI	1.84	1.29	-0.33	0.21	-0.07	0.07
	(1.16)	(1.02)	(0.56)	(0.17)	(0.61)	(0.88)
POST97×Public × HighFPI	1.2	-0.16	-1.11	-0.06	-0.9	-0.64
	(1.73)	(1.34)	(0.78)	(0.30)	(0.83)	(1.21)
Other Hosp. Variables	YES	YES	YES	YES	YES	YES
Other County Variables	YES	YES	YES	YES	YES	YES
County F.E.	YES	YES	YES	YES	YES	YES
R-square	0.47	0.63	0.58	0.72	0.45	0.46
Prob>F	0	0	0	0	0	0.01
N=729	ln(NICU)	ln (open heart)	ln (ortho pedic)	ln (pediac intens)	# of Profitable Service	% Profitable Service
POST97	0.93**	-0.83	0.31**	0.48	0.08	0.01
	(0.44)	(0.79)	(0.14)	(0.31)	(0.23)	(0.02)
POST97×FP	-1.11*	-1.17	-0.26	-0.91**	-0.24	-0.02
	(0.67)	(0.94)	(0.17)	(0.41)	(0.32)	(0.03)
POST97×Public	-1.57*	0.84	-0.25	0.14	0.25	0.03
	(0.82)	(1.36)	(0.19)	(0.69)	(0.40)	(0.04)
POST97 ×HighFPI	-1.51**	0.43	-0.09	-1.06**	-0.28	-0.03
	(0.72)	(1.18)	(0.17)	(0.46)	(0.35)	(0.03)
POST97×FP × HighFPI	2.20*	2.32	0.51**	1.77**	0.92*	0.09*
	(1.12)	(1.55)	(0.23)	(0.74)	(0.49)	(0.05)
POST97×Public × HighFPI	3.40*	-1.52	0.43	0.49	-0.32	-0.03
	(1.81)	(2.29)	(0.38)	(0.99)	(0.75)	(0.08)
Other Hosp. Variables	YES	YES	YES	YES	YES	YES
Other County Variables	YES	YES	YES	YES	YES	YES
County F.E.	YES	YES	YES	YES	YES	YES
R-square	0.56	0.47	0.7	0.54	0.67	0.67
Prob>F	0	0	0	0	0	0

[Table 2.13] continued

Panel II: Unprofitable Services								
	ln(burn care)	ln(ER)	ln(free clinic)	ln(obstetric)	ln(psychiat)	ln(sub abuse)	# of Unprof service	% Unprof service
POST97	0.06	0.2	0.48	0.36	0.52	-0.55*	0.09	0.01
	(0.14)	(0.13)	(0.81)	(0.40)	(0.52)	(0.30)	(0.13)	(0.02)
POST97 ×FP	-0.30*	0.02	-1.28	0.5	-0.63	-0.2	-0.12	-0.02
	(0.16)	(0.18)	(0.84)	(0.53)	(0.67)	(0.32)	(0.15)	(0.03)
POST97 ×Public	-0.18	-0.15	-0.07	-0.46	0.26	1.18**	0.09	0.02
	(0.21)	(0.23)	(0.86)	(0.83)	(0.72)	(0.55)	(0.19)	(0.03)
POST97 ×HighFPI	-0.07	-0.33	-0.79	-1.03*	-1.32	1.07**	-0.22	-0.04
	(0.24)	(0.22)	(1.03)	(0.61)	(0.90)	(0.44)	(0.18)	(0.03)
POST97×FP × HighFPI	0.51*	0.04	2.10*	-0.83	1.61	0.01	0.23	0.04
	(0.29)	(0.26)	(1.16)	(0.97)	(1.16)	(0.45)	(0.22)	(0.04)
POST97×Public × HighFPI	0.33	-0.08	5.36***	0.72	-0.51	-1.74**	0.46	0.08
	(0.48)	(0.48)	(1.50)	(1.98)	(1.54)	(0.73)	(0.43)	(0.08)
Other Hosp. Variables	YES	YES	YES	YES	YES	YES	YES	YES
Other County Variables	YES	YES	YES	YES	YES	YES	YES	YES
County F.E.	YES	YES	YES	YES	YES	YES	YES	YES
Observations	729	729	729	729	729	729	729	729
R-square	0.46	0.38	0.51	0.51	0.43	0.24	0.59	0.59
Prob>F	1	0	0	0	0	0.86	0	0

Results of Model 2 (Hospital Level)

In Model 2, I compare hospitals' provision of indigent care across three types of markets: markets with a single hospital, markets with multiple hospitals where the indigent care burden is equally spread out (low HHI, the reference group), and markets with multiple hospitals where the indigent care burden is highly concentrated at a few hospitals (high HHI). I expect hospitals operating in markets with high HHI or acting as sole providers to make smaller changes in indigent care, since alternative providers may be unavailable or unwilling to compensate for the decrease in indigent care.

(a) Results for the Medicaid Expansions (Model 2)

Table 2.14 through Table 2.16 present results for the Medicaid expansion. Table 2.14 reports the estimates for hospital UC regarding the Medicaid expansion policy. Panel (a), (b), and (c) indicate the three market types: markets with low HHI (reference group), with high HHI, and with a single hospital. Each panel consists of three blocks each of which represents a different ownership type: NFP (reference group), FP, and public hospitals. I make comparisons between panels, i.e., across markets in a given ownership type, as well as within panels, i.e., across ownership types in a given market type. In terms of UC and charity care costs, I find that UC costs declined by 1 percentage point after the expansion at hospitals of all ownership types and across all markets: among NFP hospitals, the decrease in UC costs was the largest in counties where multiple hospitals were operating; if hospitals were operating as sole providers, they decreased UC costs, but not in a statistically significant manner. However, FP hospitals actually increased charity care by 1.27 logs. No change or increase in charity care with the decrease in UC costs indicates that bad debts incurred by uninsured low-income patients decreased after the expansion. In other words, low-income maternity patients may have incurred bad debts before they were uninsured, instead of qualifying for charity care.

Table 2.15 presents results for admission patterns. The first three columns report the estimates regarding total uninsured admissions, and in the next four columns, uninsured patients are broken down into the target and non-target groups. I find that total uninsured admissions did not change much after the coverage expansions, while the composition of the uninsured admissions between the target and non-target group changed. The first three columns show that none of the changes in log amounts of uninsured admissions and uninsured inpatient days was statistically significant. However, the uninsured admission rates decreased at public hospitals

[Table 2.14] Results of Model 2 for Medicaid Expansion: Uncompensated Care

Panel	Explanatory Variables	ln (UC cost)	% (UC cost)	ln (charity care)	% (charity care)
(a)	POST92	-0.35	-0.01*	0.02	0.01
		(0.31)	(0.01)	(0.46)	(0.01)
	POST92×FP	0.01	0	1.27**	0
		(0.23)	(0.00)	(0.53)	(0.00)
	POST92×Public	0.09	-0.01	0.02	0.04
		(0.27)	(0.01)	(0.32)	(0.02)
(b)	POST92×HighHHI	-0.01	0	-0.05	0.01
		(0.24)	(0.00)	(0.30)	(0.01)
	POST92×FP×HighHHI	0.66	0	1.16	0.01
		(0.69)	(0.01)	(1.01)	(0.01)
	POST92×Public×HighHHI	0.29	0.01	0.92	-0.04
		(0.52)	(0.01)	(0.79)	(0.03)
(c)	POST92×solehosp	0.42	0	0.03	0
		(0.27)	(0.01)	(0.27)	(0.01)
	POST92×FP×solehosp	-0.29	0	0.52	0.01
		(0.37)	(0.01)	(1.53)	(0.01)
	POST92×Public×solehosp	-0.65	0.02	0.24	-0.03
		(0.64)	(0.02)	(0.69)	(0.03)
	Other Hosp. Variables	YES	YES	YES	YES
	Other County Variables	YES	YES	YES	YES
	Observations	980	980	980	980
	R-square	0.46	0.53	0.44	0.5
	Prob>F	0	0	0	0

[Table 2.15] Results of Model 2 for Medicaid Expansion: Admission Patterns

Panel I

N=980	%unins adm	ln(unins adm)	ln(unins Inpday)	ln (unins: target)	ln(unins: non-target)	ln(unins: non-ER & non-target	Δ Ratio (nonER/ER)
POST92	0	-0.11	-0.28	0.12	-0.03	-0.06	0.04
	(0.01)	(0.18)	(0.23)	(0.34)	(0.14)	(0.15)	(0.07)
POST92×FP	0.01*	-0.17	-0.02	0.55*	-0.41**	-0.51***	-0.11
	(0.00)	(0.15)	(0.14)	(0.30)	(0.18)	(0.16)	(0.12)
POST92×Public	-0.02*	-0.07	-0.1	-0.31	0.12	0.1	0.19
	(0.01)	(0.13)	(0.16)	(0.41)	(0.13)	(0.13)	(0.16)
POST92 ×HighHHI	0.01	0.09	0.1	-0.85*	0.14	0.1	0.18**
	(0.01)	(0.26)	(0.29)	(0.49)	(0.23)	(0.23)	(0.09)
POST92×FP ×highHHI	-0.02	-0.09	-0.2	0.25	0.05	0.12	-0.14
	(0.01)	(0.33)	(0.36)	(0.63)	(0.30)	(0.29)	(0.15)
POST92×Public ×highHHI	0.03*	0.35	0.41	1.55*	0.16	0.46	-0.63***
	(0.02)	(0.32)	(0.36)	(0.90)	(0.38)	(0.53)	(0.20)
POST92 ×solehosp	0.01	-0.05	0.01	-0.74**	-0.15	-0.14	0.16
	(0.02)	(0.37)	(0.44)	(0.29)	(0.17)	(0.18)	(0.10)
POST92×FP ×solehosp	-0.01	0.07	0.01	-0.4	0.41*	0.48**	-0.01
	(0.02)	(0.39)	(0.45)	(0.43)	(0.23)	(0.24)	(0.17)
POST92×Public ×solehosp	0.02	0.24	0.08	0.22	0.42*	0.38	-0.36*
	(0.03)	(0.37)	(0.45)	(0.69)	(0.22)	(0.28)	(0.20)
Other Hosp. and County Variables	YES	YES	YES	YES	YES	YES	YES
R-square	0.41	0.48	0.51	0.44	0.46	0.54	0.12
Prob>F	0	0	0	0	0	0	0

Panel II

	% Mcaid adm	ln(Mcaid Adm)	ln(Mcaid Inpday)	ln(Mcaid: Target)	ln(Mcaid: non-target)		
POST92	0	0.15	-0.09	0.86**	0.25		
	(0.02)	(0.23)	(0.24)	(0.42)	(0.16)		
POST92×FP	0.01	0.07	0.1	0.63*	-0.05		
	(0.01)	(0.18)	(0.23)	(0.33)	(0.14)		
POST92×Public	0	-0.34*	-0.27	-0.76*	-0.21		
	(0.02)	(0.18)	(0.19)	(0.42)	(0.14)		
POST92 ×HighHHI	-0.01	-0.49**	-0.3	-1.48***	-0.36**		
	(0.02)	(0.24)	(0.24)	(0.55)	(0.17)		
POST92×FP ×HighHHI	0.02	0.57	0.43	0.8	0.41*		
	(0.02)	(0.36)	(0.38)	(0.77)	(0.23)		
POST92×Public ×HighHHI	0.03	0.93**	0.86*	2.17**	0.68***		
	(0.03)	(0.43)	(0.46)	(0.85)	(0.25)		
POST92 ×solehosp	-0.05**	-0.73***	-0.60**	-1.20***	-0.68***		
	(0.02)	(0.27)	(0.29)	(0.41)	(0.23)		
POST92×FP ×solehosp	0.05*	0.51	0.46	-0.29	0.57*		
	(0.03)	(0.37)	(0.37)	(0.61)	(0.30)		
POST92×Public ×solehosp	0.04	0.90*	0.68	0.81	1.17*		
	(0.03)	(0.46)	(0.49)	(0.93)	(0.67)		
Other Hosp. and County Variables	YES	YES	YES	YES	YES		
R-square	0.32	0.5	0.5	0.45	0.53		
Prob>F	0	0	0	0	0		

which were operating in markets with low HHI or acting as sole providers by 2 percentage points, but increased by 1 percentage point if public hospitals were in markets with high HHI. On the other hand, the rate increased by 1 percentage point at FP hospitals across all three market types; this is mostly because they admitted more uninsured patients among maternity and infant patients, those who were potentially eligible for Medicaid.

Despite their lack of statistical significance, the changes in uninsured admissions and inpatient days support my hypothesis: hospitals operating in markets with low HHI reduced their numbers of uninsured admissions, by 0.11-0.28 logs, with the highest decrease at FP hospitals, while hospitals operating in markets with high HHI or as sole providers decreased uninsured admissions by smaller amounts or even increased them. Also, public hospitals clearly behaved differently across markets: in markets with low HHI, they reduced uninsured admission rates by 2 percentage points, while those in markets with high HHI or acting as sole providers increased them by 1 percentage point or did not change after the expansion.

In the next two columns, I divide uninsured patients into the target group (pregnant women and infants under age 1) and the non-target group (all other uninsured patients). After the expansion, hospitals acting as sole providers admitted fewer uninsured patients in the target group (by 0.74 logs for all ownership types), but more of those in the non-target group (by 0.41 logs at FP hospitals, and 0.42 logs at public hospitals). This finding implies that Medicaid revenues generated by the increased coverage enabled hospitals to extend indigent care to those who were not targets of the expansion policy. In contrast, FP hospitals in markets with low HHI began to admit more uninsured patients in the target group at the expense of those in the non-target group. In markets with high HHI, both FP and NFP hospitals experienced a reduction in uninsured patients in the target group, while public hospitals still provided more indigent care to maternity patients. The last two columns confirm that any change in uninsured admissions was made with those without emergency conditions.

Panel II continues to present the results for Medicaid admissions. Overall, FP and NFP hospitals increased total Medicaid admissions if they were in markets with low HHI, but decreased them in markets with high HHI or if they were only providers within markets. Public hospitals, however, appeared to act as lenders of last resort, compensating for the decreased indigent care by private hospitals, except for those operating in markets with low HHI. Not surprisingly, Medicaid admissions for those in the target group increased overall, by 0.01-1.49 logs, with the increase larger at FP and NFP hospitals that were operating in markets with multiple hospitals. In markets with high HHI, public hospitals were still the major providers for maternity and infant patients with Medicaid. In markets with a single hospital, Medicaid admissions for the target group increased if the single hospital had FP or NFP ownership, but decreased if the hospital was a public entity. This may indicate that maternity patients in counties with only one public hospital chose hospitals out of their county after obtaining Medicaid coverage. The expansion seemed to redistribute other Medicaid patients—non-maternity and non-infant patients with Medicaid—as well. For example, in markets with high HHI, FP and public hospitals provided more care for non-maternity Medicaid patients, while NFP hospitals saw fewer of them. My results suggest that Medicaid patients were reallocated across hospitals after the expansion: in markets with low HHI, Medicaid patients in the target group were more likely to use FP and NFP hospitals, but in markets with high HHI, they were more likely to use public or NFP hospitals. In markets that contained only one hospital, NFP and FP hospitals replaced non-maternity Medicaid patients with maternity Medicaid patients after the expansion policy.

In Table 2.16, I explore the impact of the Medicaid expansion on types of services provided. Since I was not able to isolate the quantity of services provided specifically to the uninsured, any changes that I would find here mean changes in total amounts of services provided at the hospital level. As a result, I find relatively small policy effects on the service provision. Since there is no reason that the coverage expansion would change service provision other than maternity and infant care, I focus on the three services related to pregnant women and infants—labor procedures, NICU days, and pediatric intensive care. Among these three, only labor procedures and NICU days changed in a statistically significant manner, and the policy changes differed by ownership status and across the three market types. My results suggest that the Medicaid expansion may have resulted in some patient reallocation across hospitals. In markets with low HHI, public hospitals lost their maternity patients to FP and NFP hospitals: public hospitals performed 0.24 logs fewer labor procedures, but FP and NFP hospitals performed 0.41 and 0.31 logs more. However, in markets with high HHI, FP and public hospitals increased their numbers of labor/delivery procedures, while NFP hospitals reduced them. For NICU care, public hospitals in all three types of markets increased NICU days (0.07-1.13 logs), but FP hospitals reduced them; NFP hospitals increased NICU days unless they were sole providers.

Among the remaining services, I will discuss changes in emergency room and clinic services, which are entry points for a majority of indigent patients. As expected, the coverage expansion significantly lowered the use of ER and clinic services for most hospitals. Except for NFP hospitals in markets with low HHI and FP hospitals in markets with high HHI, the number of ER visits decreased across all hospitals regardless of ownership or market types. Similarly, the number of free clinic visits decreased to some extent: the exceptions are NFP hospitals in markets with low HHI, public hospitals in markets with high HHI, and all hospitals that were sole providers.

[Table 2.16] Results of Model 2 for Medicaid Expansion: Service Provision

Panel I: Profitable Services						
N=980	ln (coronary)	ln(CC)	ln(CT)	ln (radio/diag)	ln(ESW)	ln(MRI)
POST92	-1.17**	0.28	0.54**	0.26	0.64**	0.91
	(0.57)	(0.36)	(0.25)	(0.17)	(0.30)	(0.57)
POST92×FP	-0.36	-0.47	-0.59***	-0.23	-0.31	0.04
	(0.39)	(0.34)	(0.20)	(0.16)	(0.22)	(0.45)
POST92×Public	-0.87	-0.53	-0.33	-0.05	-0.07	0.33
	(0.62)	(0.46)	(0.34)	(0.13)	(0.33)	(0.69)
POST92 ×HighHHI	-0.53	0.64	-0.44**	-0.43**	-0.17	0.71
	(0.70)	(0.64)	(0.21)	(0.19)	(0.53)	(0.66)
POST92×FP ×HighHHI	0.83	-0.17	0.69**	0.43	0.52	-0.33
	(0.99)	(0.83)	(0.34)	(0.30)	(0.69)	(0.91)
POST92×Public ×HighHHI	3.45***	0.17	2.41*	0.4	0.41	0.68
	(1.25)	(0.84)	(1.34)	(0.26)	(1.47)	(1.62)
POST92 ×solehosp	0.15	-0.46*	-0.50*	-0.27	0.09	-0.73*
	(0.39)	(0.25)	(0.27)	(0.17)	(0.42)	(0.43)
POST92×FP ×solehosp	-0.76	2.11**	1.16***	0.46*	0.75	1
	(0.92)	(1.03)	(0.36)	(0.24)	(0.74)	(0.75)
POST92×Public ×solehosp	1.48*	0.96	0.89*	0.41*	-0.24	0.55
	(0.78)	(0.67)	(0.54)	(0.23)	(0.66)	(1.13)
Other Hosp. & County Var.	YES	YES	YES	YES	YES	YES
N=980	ln(NICU)	ln (open heart)	ln (ortho pedics)	ln (pediac intens)	# of Profitable Service	% Profitable Service
POST92	0.38	-1.06	0.02	-0.07	0.22	0.02
	(0.37)	(0.71)	(0.13)	(0.34)	(0.23)	(0.02)
POST92×FP	-0.47**	-0.26	-0.16	0.02	-0.30*	-0.03*
	(0.19)	(0.29)	(0.11)	(0.20)	(0.16)	(0.02)
POST92×Public	0.01	-0.79*	0.27**	0.55	-0.13	-0.01
	(0.81)	(0.43)	(0.13)	(0.66)	(0.24)	(0.02)
POST92 ×HighHHI	-0.29	-0.7	0	0.01	0	0
	(0.30)	(0.65)	(0.14)	(0.22)	(0.26)	(0.03)
POST92×FP ×HighHHI	0.44	1.59	0.05	-0.04	0.22	0.02
	(0.36)	(0.98)	(0.19)	(0.26)	(0.44)	(0.04)
POST92×Public ×HighHHI	1.03	3.96***	-0.26	-0.45	1.02	0.1
	(1.36)	(1.43)	(0.23)	(0.69)	(0.78)	(0.08)
POST92 ×solehosp	-1.05	0.19	0.02	-0.02	-0.25	-0.02
	(0.68)	(0.42)	(0.10)	(0.18)	(0.17)	(0.02)
POST92×FP ×solehosp	0.95	0.22	0.07	-0.12	0.96**	0.10**
	(0.75)	(0.75)	(0.18)	(0.26)	(0.40)	(0.04)
POST92×Public ×solehosp	0.73	0.9	-0.25	-0.52	0.38	0.04
	(1.07)	(0.61)	(0.21)	(0.69)	(0.49)	(0.05)
Other Hosp. & County Variables	YES	YES	YES	YES	YES	YES

[Table 2.16] continued

Panel II: Unprofitable Services								
N=980	ln(burn care)	ln(ER)	ln(free clinic)	ln(obs tetric)	ln(psy chiat)	ln(sub abuse)	# of unpro fitable	% unpro fitable
POST92	0.18	0.02	0.62	0.41	0.13	-0.68	0.11	0.02
	(0.23)	(0.20)	(0.69)	(0.54)	(0.57)	(0.44)	(0.15)	(0.02)
POST92 ×FP	-0.02	-0.38	-0.6	-0.1	-0.3	0.11	-0.14	-0.02
	(0.05)	(0.24)	(0.53)	(0.40)	(0.30)	(0.33)	(0.11)	(0.02)
POST92 ×Public	0.06	-0.07	-0.7	-0.65	-0.71	-0.47	-0.30**	-0.05**
	(0.12)	(0.19)	(0.93)	(0.53)	(0.49)	(0.60)	(0.13)	(0.02)
POST92 ×HighHHI	0.02	-0.35**	-1.26	-1.51*	1	0.19	-0.28	-0.05
	(0.06)	(0.16)	(0.97)	(0.77)	(0.75)	(0.40)	(0.18)	(0.03)
POST92×FP ×HighHHI	0.07	0.74	1.25	1.95**	0.12	0.52	0.60**	0.10**
	(0.07)	(0.55)	(1.12)	(0.99)	(0.92)	(0.53)	(0.24)	(0.04)
POST92×Public ×HighHHI	-0.04	0.34	3.07	2.47**	1.37	2.07*	1.14***	0.19***
	(0.15)	(0.28)	(2.18)	(1.09)	(1.36)	(1.23)	(0.43)	(0.07)
POST92 ×solehosp	0.07	-0.16	1.55	-0.59*	-1.04	-0.03	-0.1	-0.02
	(0.07)	(0.12)	(1.15)	(0.34)	(0.78)	(0.73)	(0.31)	(0.05)
POST92×FP ×solehosp	0	0.34	-1	0.52	1.14	0.46	0.14	0.02
	(0.11)	(0.30)	(1.64)	(0.58)	(1.00)	(0.75)	(0.39)	(0.06)
POST92×Public ×solehosp	-0.22	0.19	-0.3	1.28	2.64*	1.22	0.6	0.1
	(0.20)	(0.24)	(1.67)	(0.92)	(1.53)	(0.96)	(0.42)	(0.07)
Other Hosp. & County Var.	YES	YES	YES	YES	YES	YES	YES	YES

Regarding the provision of unprofitable services, public hospitals in markets with low HHI or operating as sole providers offered fewer unprofitable services after the expansion (by 0.30 logs), but those in markets with high HHI provided more unprofitable services due to increases in maternity and substance abuse care. In the same markets, FP hospitals also increased provision of unprofitable services, entirely attributed to increased maternity care.

(b) Results for the BBA (Model 2)

Table 2.17 through Table 2.19 present results of Model 2 for the BBA. Table 2.17 reports the estimates for UC and charity care. Consistent with the results of Model I, I do not find any statistically significant reductions in UC or charity care after the BBA. In fact, I find that charity care increased at FP hospitals in all markets

[Table 2.17] Results of Model 2 for the BBA: Uncompensated Care

N=729	ln (UC cost)	% (UC cost)	ln (charity care)	% (charity care)
POST97	0.07	0	-0.07	0
	(0.07)	(0.00)	(0.12)	(0.01)
POST97×FP	-0.05	0	1.13***	0
	(0.13)	(0.00)	(0.38)	(0.00)
POST97×Public	-0.02	-0.01	-0.02	-0.01
	(0.08)	(0.00)	(0.11)	(0.01)
POST97×highHHI	0.09	0.01	0.41***	0.02*
	(0.09)	(0.01)	(0.15)	(0.01)
POST97×FP×highHHI	-0.04	0	-1.33***	-0.01
	(0.17)	(0.01)	(0.43)	(0.01)
POST97×Public×highHHI	0.1	0.02	-0.41	-0.01
	(0.15)	(0.02)	(0.49)	(0.02)
POST97×solehosp	0.23*	0.01	0.43	0.02
	(0.12)	(0.01)	(0.26)	(0.01)
POST97×FP×solehosp	-0.26	-0.02	-0.61	-0.03
	(0.21)	(0.01)	(1.03)	(0.02)
POST97×Public×solehosp	-0.13	-0.01	-0.46	-0.02
	(0.16)	(0.01)	(0.41)	(0.03)
Other hosp & county variables	YES	YES	YES	YES
R-square	0.58	0.54	0.47	0.46
Prob>F	0	0	0	0

(0.21-1.13 logs), and at hospitals of all ownership types in highly concentrated markets (0,21-0.41 logs). Also, hospitals operating as sole providers increased UC costs by 0.23 logs. It is surprising to see that the BBA had such minimal effects on UC and charity care or even increased them.

In Table 2.18, I present the estimates for admission patterns. Again, I do not find large or significant reductions in uninsured admissions. Hospitals acting as sole providers actually increased uninsured inpatient days by 0.36 logs, and uninsured admissions by 0.18-0.64 logs, with the smallest increase at FP hospitals. After the BBA, public hospitals admitted more uninsured patients across all market types. The next three columns show that non-emergency patients among uninsured admissions decreased at NFP hospitals in markets where there were at least two hospitals. However, public hospitals and those that are single providers within markets did not reduce admissions for non-emergency uninsured patients.

In addition to uninsured admissions, hospitals may have also made adjustments to Medicaid admissions. The last three columns show that FP hospitals increased care for Medicaid patients: Medicaid admission rates, numbers of Medicaid admissions and Medicaid inpatient days increased, except at hospitals operating as sole providers. My findings imply that, contrary to my hypothesis, the hospital market conditions did not generate differential policy effects. Moreover, neither UC nor uninsured admissions seemed to decrease after the BBA.

[Table 2.18] Results of Model 2 for the BBA: Admission Patterns

N=729	% unins adm	ln(unins adm)	ln(unins Inpday)	ln(nonER unins adm)	% (nonER unins adm)	Δ Ratio: nonER/ ER
POST97	0	0.01	-0.05	-0.05	0	0.23
	(0.00)	(0.09)	(0.09)	(0.14)	(0.01)	(0.18)
POST97×FP	0	0.08	0.06	0.27*	0.01	-0.18
	(0.00)	(0.11)	(0.12)	(0.14)	(0.01)	(0.16)
POST97×Public	0.01	0.15*	0.15	0.19	-0.01	-0.1
	(0.01)	(0.09)	(0.09)	(0.14)	(0.01)	(0.14)
POST97 ×HighHHI	-0.01	-0.02	0	-0.06	-0.02	-0.24
	(0.01)	(0.13)	(0.13)	(0.17)	(0.02)	(0.17)
POST97×FP ×HighHHI	0.02**	0.15	0.1	0.12	0.03*	0.32*
	(0.01)	(0.20)	(0.19)	(0.23)	(0.02)	(0.18)
POST97×Public ×HighHHI	0	-0.29	0.14	-0.54	0.02	0.32
	(0.01)	(0.22)	(0.39)	(0.39)	(0.02)	(0.20)
POST97 ×solehosp	0.01	0.49***	0.36**	0.49**	-0.02	-0.11
	(0.01)	(0.15)	(0.14)	(0.21)	(0.02)	(0.15)
POST97×FP ×solehosp	0	-0.46**	-0.22	-0.66**	0.01	0.12
	(0.01)	(0.20)	(0.19)	(0.27)	(0.02)	(0.18)
POST97×Public ×solehosp	0	-0.14	0.26	-0.02	0.04*	0.14
	(0.02)	(0.20)	(0.35)	(0.22)	(0.02)	(0.14)
Other Hosp. & County Variables	YES	YES	YES	YES	YES	YES
R-square	0.44	0.57	0.65	0.6	0.27	0.18
Prob>F	0	0	0	0	0	0

[Table 2.18] continued

N=729		% Mcaid Adm	ln (Mcaid Adm)	ln(Mcaid Inpday)
POST97		0	0.14	0.11
		(0.01)	(0.10)	(0.10)
POST97×FP		0.02***	0.22**	0.17**
		(0.01)	(0.09)	(0.08)
POST97×Public		-0.01	-0.08	-0.1
		(0.01)	(0.11)	(0.11)
POST97 ×HighHHI		0.02*	0.12	0.08
		(0.01)	(0.12)	(0.11)
POST97×FP ×HighHHI		-0.02	-0.26	-0.29
		(0.01)	(0.20)	(0.19)
POST97×Public ×HighHHI		-0.03	-0.36	-0.04
		(0.02)	(0.22)	(0.23)
POST97 ×solehosp		0.03*	0.56***	0.66***
		(0.02)	(0.20)	(0.19)
POST97×FP ×solehosp		-0.04**	-0.83***	-0.83***
		(0.02)	(0.19)	(0.19)
POST97×Public ×solehosp		0.03	0.14	0.9
		(0.02)	(0.33)	(0.73)
Other Hosp. & County Variables		YES	YES	YES
R-square		0.35	0.55	0.59
Prob>F		0	0	0

Next, Table 2.19 presents the BBA effects for the service provision. With the BBA aggravating hospitals' financial distress, I expect hospitals in markets with low HHI to make the largest adjustments to the service provision. NFP hospitals did reduce many of their unprofitable services after the BBA, with the decrease largest in markets with low HHI. Notably, NFP hospitals cut down free clinic visits by 1.67 logs if they were operating in markets with low HHI or acting as sole providers, but increased them in markets with high HHI. Interestingly, public hospitals increased provision of unprofitable services when NFP hospitals decreased it, but decreased it when NFP hospitals increased unprofitable services. For example, ER visits increased at NFP hospitals in markets with high HHI, but decreased at public hospitals in the same types of markets. This finding implies that NFP and public hospitals took the

[Table 2.19] Results of Model 2 for the BBA: Service Provision

Panel I: Profitable Services						
N=729	ln coronary	ln CC	ln CT	ln rad/diag	ln ESW	ln MRI
POST97	-0.16	0.47*	0.50**	0.05	0.06	0.78*
	(0.36)	(0.27)	(0.25)	(0.05)	(0.25)	(0.40)
POST97×FP	-0.36	0.2	-0.15	-0.12**	0.34	0.03
	(0.40)	(0.31)	(0.22)	(0.05)	(0.31)	(0.33)
POST97×Public	0.51	-0.71***	0.04	0.03	0.14	0.19
	(0.33)	(0.25)	(0.17)	(0.06)	(0.28)	(0.49)
POST97 ×HighHHI	0.26	0.02	-0.01	0.06	-0.2	0.12
	(0.38)	(0.39)	(0.23)	(0.07)	(0.43)	(0.67)
POST97×FP ×HighHHI	-0.04	0.17	-0.22	-0.11	-0.34	-0.59
	(0.78)	(0.65)	(0.29)	(0.09)	(0.56)	(0.76)
POST97×Public ×HighHHI	-0.32	0.02	0.11	-0.41*	-0.34	-0.5
	(0.55)	(0.49)	(0.40)	(0.23)	(0.52)	(0.87)
POST97 ×solehosp	0.45	-0.24	-0.5	-0.2	0.01	-0.34
	(0.39)	(0.32)	(0.37)	(0.28)	(0.33)	(0.47)
POST97×FP ×solehosp	-0.81	0.25	0.9	0.16	-0.18	-0.11
	(1.82)	(0.58)	(0.99)	(0.30)	(0.46)	(0.68)
POST97×Public ×solehosp	-0.92	0.63	0.51	0.25	-0.08	-0.53
	(0.63)	(0.41)	(0.66)	(0.33)	(0.40)	(1.31)
Other Hosp. & County Var.	YES	YES	YES	YES	YES	YES
N=729	ln NICU	ln open heart	ln ortho pedic	ln pediac intens	# of profit. service	% profit. service
POST97	0.13	0.33	0.04	-0.22	0.11	0.01
	(0.31)	(0.44)	(0.09)	(0.21)	(0.16)	(0.02)
POST97×FP	-0.09	0.05	0.05	0.06	0.27	0.03
	(0.21)	(0.40)	(0.12)	(0.17)	(0.17)	(0.02)
POST97×Public	-0.05	0.3	-0.01	0.6	0.23	0.02
	(0.28)	(1.07)	(0.14)	(0.68)	(0.22)	(0.02)
POST97 ×HighHHI	0.01	-0.26	-0.08	0.01	-0.01	0
	(0.45)	(0.41)	(0.16)	(0.37)	(0.24)	(0.02)
POST97×FP ×HighHHI	0.3	-0.56	-0.07	-0.2	-0.21	-0.02
	(0.58)	(0.84)	(0.21)	(0.42)	(0.36)	(0.04)
POST97×Public ×HighHHI	-0.26	-0.55	-0.2	-0.58	-0.34	-0.03
	(0.66)	(1.17)	(0.20)	(0.79)	(0.35)	(0.03)
POST97 ×solehosp	0.21	-0.27	-0.08	-0.31	0.12	0.01
	(0.35)	(0.92)	(0.11)	(0.20)	(0.21)	(0.02)
POST97×FP ×solehosp	0.16	1.61	0.13	-0.05	0.07	0.01
	(0.78)	(1.38)	(0.30)	(0.32)	(0.40)	(0.04)
POST97×Public ×solehosp	-0.51	-1.41	-0.19	-1.16	-0.56*	-0.06*
	(0.58)	(1.36)	(0.18)	(0.86)	(0.32)	(0.03)
Other Hosp. & County Variables	YES	YES	YES	YES	YES	YES

[Table 2.19] continued

Panel II: Unprofitable Services								
N=729	ln(burn care)	ln(ER)	ln(free clinic)	ln(obs tetric)	ln(psy chiatr)	ln(sub abuse)	# of unprof serv	% unprof serv
POST97	-0.03	0.04	-1.67***	0.31	-0.15	-0.06	-0.14	-0.02
	(0.11)	(0.07)	(0.58)	(0.33)	(0.40)	(0.16)	(0.10)	(0.02)
POST97×FP	0.09	0.11	0.46	0.1	0.52*	-0.01	0.14	0.02
	(0.08)	(0.14)	(0.65)	(0.30)	(0.27)	(0.27)	(0.10)	(0.02)
POST97×Public	-0.02	0	2.49***	-0.05	0.2	0.58	0.35***	0.06***
	(0.15)	(0.07)	(0.69)	(0.28)	(0.31)	(0.42)	(0.11)	(0.02)
POST97 ×HighHHI	0.37	0.13*	3.15***	-0.14	0.51	0.62*	0.49**	0.08**
	(0.29)	(0.08)	(1.15)	(0.42)	(0.57)	(0.33)	(0.19)	(0.03)
POST97×FP ×HighHHI	-0.43	-0.36**	-2	-0.33	-0.83	-0.75	-0.49**	-0.08**
	(0.33)	(0.17)	(1.22)	(0.54)	(0.65)	(0.50)	(0.22)	(0.04)
POST97×Public ×HighHHI	-0.15	-0.26**	-2.83	-0.32	-0.25	-0.73	-0.47*	-0.08*
	(0.25)	(0.12)	(1.90)	(0.50)	(0.75)	(0.52)	(0.25)	(0.04)
POST97 ×solehosp	0.05	-0.04	0.97	0.49	0.34	0.15	0.23	0.04
	(0.11)	(0.09)	(1.52)	(0.47)	(0.44)	(0.17)	(0.20)	(0.03)
POST97×FP ×solehosp	-0.14	-0.07	-2.43	-0.64	-1.97*	0.04	-0.56*	-0.09*
	(0.18)	(0.15)	(2.21)	(0.70)	(1.03)	(0.31)	(0.30)	(0.05)
POST97×Public ×solehosp	-0.05	0.15	-0.72	0.75	-0.07	-0.88*	0.07	0.01
	(0.26)	(0.20)	(2.52)	(0.67)	(0.67)	(0.51)	(0.26)	(0.04)
Other Hosp. & County Var.	YES	YES	YES	YES	YES	YES	YES	YES

role of substitute providers in the provision of unprofitable services. The number of unprofitable services, which take a value between zero to six, increased at public hospitals across all three market types, but decreased at FP hospitals acting as sole providers. In the case of NFP hospitals, the number of unprofitable services increased in markets with high HHI.

The BBA seemed to increase provision of profitable services at all hospitals, regardless of ownership type or market structure. However, most of the changes were not statistically significantly different from zero. Among the profitable services, cardiac catheterization, CT, and MRI procedures increased statistically significantly at hospitals of all ownership types across all three markets. Interestingly, numbers and proportions of profitable services increased at NFP and FP hospitals regardless of market type, albeit these changes were not statistically significant. However, public hospitals which were operating as single providers actually reduced provision of profitable services. My results suggest that FP and NFP hospitals, regardless of market structure, reduced indigent care if their financial situations worsened, while the financial shock did not force public hospitals to make large reductions in indigent care.

VII. Robustness Check

In this section, I conduct several tests to check the robustness of my main results. My first robustness check uses hospital fixed-effect models. The hospital fixed-effect models control for all unobserved, time-invariant heterogeneity across hospitals: for example, inconsistency in UC measurement, hospitals' treatment styles (preference for outpatient care for the uninsured), or a degree of commitment to indigent care, will be controlled for in this fixed-effect model. The results of the hospital fixed-effect models are consistent with those in the main analysis. This implies that my main results are not confounded by those unobserved, time-invariant, hospital-specific factors. Here, I will discuss differences in the results between the hospital fixed-effect models and the main analysis.

For Model I, the hospital fixed-effect models produced identical results for the Medicaid expansion, but a few of the BBA effects become weak: the decreases in the number of selfpay admissions at hospitals of all ownership type and the increases in the number of profitable services at FP hospitals are no longer statistically significant at the 10% level in the hospital fixed-effect estimation.

For Model 2, the hospital fixed-effect models produced the following differences. For the Medicaid expansion, I find more evidence that the policy change decreased hospitals' indigent care burdens by reducing charity care and selfpay inpatient days. Hospitals of private ownership were more actively involved with reducing indigent care: hospitals of FP and NFP ownership across all markets, as well as public hospitals in markets with high HHI, decreased charity care by 1 percentage point, while public hospitals in other two types of markets (markets with low HHI or markets with a single hospital) increased them by 3 percentage points. Particularly, FP hospitals reduced the number of non-emergency, selfpay admissions across all three types of market. Several estimates regarding the service provision become statistically insignificant at the 10% level or changed the signs. Among the three services related to maternity and infant care, only labor procedures are correctly estimated. The policy impacts remain statistically significant at public hospitals, and the sizes of the impacts differ across markets: public hospitals in markets with low HHI decreased labor procedures after the expansion, while public hospitals in markets with high HHI or those operating as sole providers increased the procedures. My findings imply that maternity patients might have been more easily reallocated across hospitals if they resided in markets where every hospital fairly shared the indigent care burden. In the hospital fixed-effect models, I find no statistical evidence for the decreased amounts of unprofitable services, while the increased provision of profitable services remained statistically significant (at the 5% level) at FP hospitals operating as sole providers.

For the BBA, the hospital fixed-effect analysis produces qualitatively similar results to those in the main analysis, but some of the differences are as follows: first, the decreases in selfpay admissions become statistically insignificant; second, selfpay admissions with non-emergency conditions increased at hospitals of all ownership types if they were sole providers within markets, while NFP hospitals decreased them if there were another hospitals within markets; third, FP hospitals, if not sole providers, reduced Medicaid admissions, while FP hospitals operating in markets which consisted of at least two hospitals increased Medicaid admissions with no change in non-emergency, selfpay admissions. Most results regarding service provision are the same, except for the following three: first, there was no change in the number or proportion of profitable services at the 10% significance level in the hospital fixed-effect models; second, the number and the proportion of unprofitable services increased at public hospitals after the BBA across all three types of market; third, FP and NFP hospitals also increased their provision of unprofitable services if they were in markets with high HHI.

The second robustness check uses different policy measures for the Medicaid expansion. Instead of using the POST92 dummy variable, I use the fraction of the Medicaid eligible population (ELIG), which changes over time due to the generosity of the Medicaid program. My results remain qualitatively similar to those in the main analysis. Since the policy impact could be larger in counties where the eligible population actually took up coverage, I use another specification in which I replace POST92 with Medicaid caseload, and include interaction terms between the caseload and hospital ownership types. The results from this estimation were also qualitatively the same as the main results. Finally, I re-estimate the baseline models with year fixed effects, instead of POST92 or POST97. The results with the year fixed-effects are identical to those in the main analysis.

VIII. Discussion and Conclusion

Hospital indigent care represents the safety-net of last resort for the majority of indigent and uninsured patients (Weissman, 2005). This paper examines how hospitals adjusted their provision of indigent care in response to a demand shift (Medicaid expansion) and a supply shock (the BBA). It is difficult to measure indigent care because it refers to care offered to uninsured patients who are poor. In this paper, I measure indigent care based on amounts of uncompensated care, admissions for the uninsured, and quantities of unprofitable services provided. Although none of them perfectly measures the care provided specifically to the uninsured who are poor, these are good proxies available for hospital indigent care. Uncompensated care is the sum of charity care (for low-income uninsured patients) and bad debts (for patients of all payer sources). Uninsured admissions are defined based on payer source (self-pay) and include all admissions for the uninsured who could be low- or high- income. Considering that a majority of the uninsured are poor, particularly those with hospitalizations according to the analysis of the MEPS in 2003, using admissions for total uninsured patients as a proxy for admissions for uninsured patients who are poor is reasonable. Unprofitable services are defined based on Horwitz (2005) and measured by total amounts of care provided to patients, regardless of payer source.

I hypothesize that the policy impacts on indigent care will differ by hospitals' ownership type and by markets' level of concentration of indigent care burden among hospitals. By estimating OLS regressions with the Florida hospital sample for 1990-2000, I find that the policy effects were heterogeneous according to ownership types: public and NFP hospitals were more responsive to the demand shift, but FP hospitals were more responsive to the supply shock. Regarding the market level of concentration of indigent care burden at hospitals, I do not find statistical evidence that hospitals operating in markets with low concentrations of indigent care burden made larger adjustments to indigent care than those operating in markets with high concentrations of indigent burden or acting as sole providers.

After the Medicaid expansion (the demand shift), hospitals reduced their amount of charity care, but total uninsured admissions did not necessarily fall. Provision of charity care decreased at hospitals of all ownership types across all three types of markets, with this decrease larger at NFP and public hospitals. Although hospitals' financial burdens for maternity and infant patients lowered after the expansion, revenues generated from these patients appeared to extend care for non-maternity and non-infant patients who were uninsured and had non-emergency conditions, particularly at NFP and public hospitals in all three types of markets and at FP hospitals which were sole providers. The increased coverage also influenced the service provision related to maternity and pediatric care, which varied by ownership status and market structure, but these changes did not support my hypothesis.

For the BBA, the adjustments to indigent care were made mostly by manipulating uninsured admissions and service provision, rather than uncompensated care. In fact, it is surprising to see that FP hospitals across all markets increased their charity care provision after the BBA, as did all hospitals in markets with high concentrations of indigent care burden. However, NFP hospitals, if operating in markets in which alternative providers existed, reduced non-emergency uninsured admissions after the BBA. Public hospitals and those acting as sole providers within markets seemed to have more constraints on reducing indigent care (uninsured admissions). NFP hospitals in all markets also cut back unprofitable services (primarily clinic services), more so if they were operating in markets in which the indigent care burden is spread out. In contrast, public hospitals in all three types of markets seemed to compensate the decreased indigent care by other hospitals by providing more unprofitable services. Interestingly, FP hospitals decreased provision of unprofitable services only when they were sole providers, but increased provision of profitable services in all three market types.

The contribution of this paper is as follows: unlike previous studies (Davidoff et al, 2000; Lo Sasso and Seamster, 2007) that have examined only hospitals' uncompensated care, I examine several aspects of hospital indigent care such as admission patterns and service provision, in addition to uncompensated care.

Moreover, I control for effects of other hospitals' supply of indigent care and separately examine the BBA effects.

Finally, I will discuss several issues that merit further consideration, some of which will be left for a future research agenda. First, there may be concerns about crowding-out effects of private insurance coverage due to the presence of charity care. If the availability of hospital charity care gives incentives to marginally low-income individuals to drop out of private health insurance and seek hospital charity care, demand for charity care could increase in markets where hospitals generously provide charity care. According to Rask and Rask (2000), Herring (2005), and Lo Sasso and Mayer (2006), however, hospital uncompensated care does not crowd out private insurance, although health center uncompensated care may do so. Second, I was not able to control for hospital payments that might have significant effects on the supply of indigent care. However, Florida hospitals are generally believed to have had no changes in Medicaid payments (Lipson *et al*, 1997); their Medicaid reimbursements relative to costs stayed relatively constant at 82-83 percent in the 1990s.

Third, I did not consider hospital system membership status in the construction of the concentration measure, due to unavailability of data. The potential bias from ignoring this system status is to decrease the value of the HHI. According to Alexander *et al* (2009), who studied all hospitals in Florida, California, and Texas for 1989-2003, system-affiliated hospitals provide less community benefits. Although proportion of Florida hospitals affiliated with health care systems increased from 52% in 1989 to 62% in 2003, this increase occurred in the mid 1990s, and they noted that the system membership status has been relatively continuously maintained among hospitals which were already affiliated with systems (p.77). Therefore, I do not expect that the policy impacts that I find are caused by a change in system status among Florida hospitals.

Fourth, this paper does not examine long-term consequences of the policy changes such as conversions, closures, or mergers, which could possibly affect provision of indigent care. While Needleman *et al* (1999) and Thorpe *et al* (2000) found that hospitals converting from public to FP significantly decreased provision of uncompensated care, Sloan (2002) found no such evidence in uninsured or Medicaid admissions. Since I restricted my hospital sample to those which did not convert during the study period, I can rule out any conversion effects. However, we need more research in the areas of hospital mergers and closures related to indigent care. Finally, my analysis is based on Florida, a single state. As is usually the case, I cannot generalize my findings to the national level. Since both the BBA and the Medicaid expansions were nationwide health policies that should have influenced all American hospitals and low-income patients, the extension of this study to the national setting will provide better understanding of hospitals' behavior regarding provision of indigent care. Using the AHA Annual Survey data linked to the State Inpatient Database (SID), future research can extend this analysis to the national setting.

REFERENCES

Alexander, Jeffrey, Gary Young, Bryan Weiner, and Larry Hearld, "How Do System-Affiliated Hospitals Fare in Providing Community Benefit?" *Inquiry*, Vol. 46, Issue 1, Spring 2009: pp. 72-91.

American Hospital Association (AHA), Trend Watch Chartbook, Chapter 4: Trend in Hospital Financing, 2003: downloaded at http://www.aha.org/aha/trendwatch/2003/cb2003chapter4.ppt#45

American Hospital Association (AHA), Uncompensated Hospital Care Cost Fact Sheet, November 2008: downloaded at http://www.aha.org/aha/content/2008/pdf/08-uncompensated-care.pdf

APS Healthcare, "The Impact of BadgerCare on Hospital Uncompensated Care in Wisconsin," the State of Wisconsin's State Planning Grant (SPG) initiative, June 2006.

Banks, Dwayne, Mary Paterson, and Jeanne Wendel, "Uncompensated Hospital Care: Charitable Mission or Profitable Business Decision?" *Health Economics* 6(2), 1997.

Bazzoli, Gloria, Richard Lindrooth, Romana Hasnain-Wynia, and Jack Needleman, "The Balanced Budget Act of 1997 and U.S. Hospital Operations," *Inquiry – Journal of Health Care Organization Provision and Financing* 41 (4), Winter 2004.

Bazzoli, Gloria J., Richard C. Lindrooth, Ray Kang, and Romana Hasnain-Wynia, "The Influence of Health Policy and Market Factors on the Hospital Safety Net," *Health Service Research* 41 (4), Part 1, August 2006: pp. 1159-1180.

Blewett, Lynn A, Gestur Davidson, Margaret E. Brown and Roland Maude-Griffin, "Hospital Provision of Uncompensated Care and Public Program Enrollment," *Medical Care Research and Review* 60 (4), DEC 2003: pp. 509-527.

Chakravarty, Sujoy, Martin Gaynor, Steven Klepper, and William B. Vogt, "Does the Profit Motive Make Jack Nimble? Ownership Form and the Evolution of the U.S. Hospital Industry," *Health Economics*, Vol. 15, Issue 4, 2006: pp.345-361.

Campbell, Ellen S., and Melissa W. Ahern, “Have Procompetitive Changes Altered Hospital Provision of Indigent Care?” *Health Economics*, Volume 2, Issue 3, 1993.

Chang, Tom, and Mireille Jacobson, “What Do Not-For-Profit Hospitals Maximize? Evidence from California’s Seismic Retrofit Mandate,” MIT Working paper, 2008.

Clement, Jan P., Kenneth R. White, and Vivian Valdmanis, “Charity Care: Do Not-for-Profits Influence for-Profits?” *Medical Care Research and Review*, Vol. 59, No. 1, 2002.

Currie, Janet, and Jonathan Gruber, “The Technology of Birth: Health Insurance, Medical Interventions, and Infant Health,” NBER Working Paper No. W5985, 1997.

Current Population Reports, “Income, Poverty, and Health Insurance Coverage in the United States: 2006,” Census Bureau, August 2007.

Currie, Janet and John Fahr, “Hospitals, Managed care, and the Charity Caseload in California,” *Journal of Health Economics* 23 (3), May 2004: pp. 421-442.

Dafny, Leemore, “How Do Hospitals Respond to Price Changes?” *American Economic Review*, 95(5), December 2005: pp. 1525-1547.

Davidoff, Amy, Anthony LoSasso, Gloria Bazzoli, and Stephen Zuckerman, “The Effect of Changing State Health Policy on Hospital Uncompensated Care,” *Inquiry – the Journal of Health Care Organization Provision and Financing* 37 (3), Fall 2000.

Dranove, David, Richard Lindrooth, William White, and Jack Zwanziger, “Is the Impact of Managed Care on Hospital Prices Decreasing?” *Journal of Health Economics*, Volume 27, Issue 2, March 2008: pp. 362-376.

Dubay, Lisa C., Stephen Norton, and Marilyn Moon, “Medicaid Expansions for Pregnant Women and Infants – Easing Hospitals Uncompensated Care Burden” *Inquiry –the Journal of Health Care Organization Provision and Financing* 32 (3), 1995: pp. 332-344.

Duggan, Mark, “Hospital Ownership and Public Medical Spending,” NBER Working Paper No. 7789, July 2000.

Duggan, Mark, “Hospital Market Structure and the Behavior of Not-for-profit Hospitals,” *RAND Journal of Economics* 33, 2002: pp. 433-446.

Frank, Richard G. and David S. Salkever, “The Supply of Charity Services by Nonprofit Hospitals: Motives and Market Structure,” *The RAND Journal of Economics*, Vol. 22, No. 3, Autumn 1991: pp. 430-445.

Gaskin, Darell, “Altruism or Moral Hazard: The Impact of Hospital Uncompensated Care Pools,” *Journal of Health Economics* 16, 1997: pp. 397-416.

Government Accountability Office (GAO), “Emergency Care: EMTALA Implementation and Enforcement Issues,” GAO-01-747, June 2001.

Government Accountability Office (GAO), Nonprofit, For-Profit, and Government Hospitals: Uncompensated Care and Other Community Benefits, GAO-05-743, Washington, D.C.: May 2005.

Gowrisankaran, Gautam, and Robert J. Town, “Competition, Payers and Hospital Quality,” *Health Services Research* 38, 2003: pp. 1403–1421.

Gruber, Jonathan and David Rodriguez, “How Much Uncompensated Care Do Doctors Provide?” NBER, Working Paper No. 138585, 2007.

Gruber Jonathan, “The Effects of Competitive Pressure on Charity-Hospital Response to Price Shopping in California,” *Journal of Health Economics*, Vol. 13, Issue 2, 1994.

Hadley, Jack and Peter Cunningham, “Availability of Safety Net Providers and Access to Care of Uninsured Persons,” *Health Service Research* 39(5), October 2004.

Hadorn, David, “Setting Health Care Priorities in Oregon,” JAMA, Vol. 265, Issue 17, May 1991: pp. 2218-2225.

Healthcare Cost and Utilization Project (HCUP), “Trends in Uninsured Hospital Stays, 1997–2006,” Statistical Brief #67, April 2009.

Herring, Bradley, “The Effect of the Availability of Charity Care to the Uninsured on the Demand for Private Health Insurance,” *Journal of Health Economics* 24 (2), 2005.

Hirth, Richard, “Competition between for-Profit and Nonprofit Health Care Providers: Can it Help Achieve Social Goals?” Medical Care Research and Review, Vol. 54, No. 4, 1997: pp. 414-438.

Horwitz, Jill, “Making Profits and Providing Care: Comparing Nonprofit, For-profit, and Government Hospitals,” *Health Affairs* 24 (3), May-June 2005: pp. 790-801.

Horwitz, Jill, and Austin Nichols, “Peer Pressure: Hospital Ownership Mix and Service Provision,” NBER Working Paper, April 2007.

Jackson, Catherine, and Amanda Beatty, “Organization and Financing of Indigent Hospital Care in South Florida,” RAND, December 2003.

Kessler, Daniel, and Mark McClellan, “Is Hospital Competition Socially Wasteful?” *Quarterly Journal of Economics*, Vol. 115, No. 2, May, 2000, pp. 577-615.

Lindrooth, Richard, Gloria Bazzoli, Jack Needleman, and Romana Hasnain-Wynia, “The Effect of Changes in Hospital Reimbursement on Nurse Staffing Decisions at Safety Net and Nonsafety Net Hospitals,” *Health Services Research*, Vol. 41, No. 3, 2006.

Lipson, Debra J., Stephen Norton, and Lisa Dubay, “Health Policy for Low-Income People in Florida?” Urban Institute, Research Report, 1998.

Lo Sasso, Anthony T., and Bruce D. Meyer, “The Health Care Safety Net and Crowd-Out of Private Health Insurance,” NBER Working Papers 11977, January 2006.

Lo Sasso, Anthony T., and Dorian G. Seamster, “How Federal and State Policies Affected Hospital Uncompensated Care Provision in the 1990s,” *Medical Care Research Review*, 64(6), December 2007: pp. 731-744.

Lynk, William and Rachelle Alcain, “the Level of Hospital Charges and the Income of the Uninsured Patient,” *International Journal of Health Care Finance and Economics*, Vol. 8, No. 1, March 2008: pp. 53-72.

Mann, Joyce, Glenn Melnick, Anil Bamezai, and Jack Zwanziger, “Uncompensated Care, Hospitals Responses to Fiscal Pressure,” *Health Affairs* 14, 1995: pp. 263-270.

McConnell, John, “Oregon’s Cost-Shift: The Effect of Public Insurance Coverage on Uncompensated Care,” Report to the Oregon Office for Health Policy and Research, OHSU Center for Policy & Research in Emergency Medicine, 2005.

McKay, Niccie L., and Xiaoxian Meng, “The Effect of Managed Care on Hospitals' Provision of Uncompensated Care,” *Inquiry –the Journal of Health Care Organization Provision and Financing* 44 (1), Spring 2007: pp. 114-124.

Nakamura, Sayaka, “Voluntary and Not So Voluntary Provision of Hospital Uncompensated Care,” Job Market Paper, Rice University, October 2007.

Needleman, Jack, JoAnn Lamphere, and Deborah Chollet, “Uncompensated Care and Hospital Conversions in Florida,” *Health Affairs*, July/August 1999.

Nicholson, Sean, Mark V. Pauly, Lawton R. Burns, Agnieshka Baumritter, and David A. Asch, “Measuring Community Benefits Provided By For-Profit And Nonprofit Hospitals,” *Health Affairs*, Vol. 19, No. 6, 2000.

Norton, Edward, and Douglas Staiger, “How Hospital Ownership Affects Access to Care for the Uninsured,” *Rand Journal of Economics,* Vol. *25,* No 1, Spring 1994.

Rask, Kevin, and Kimberly Rask, “Public insurance substituting for private insurance: new evidence regarding public hospitals, uncompensated care funds, and Medicaid,” *Journal of Health Economics*, 19 (1), JAN 2000: pp. 1-31.

Rosko, Michael, “The Supply of Uncompensated Care in Pennsylvania Hospitals: Motives and Financial Consequences,” *Health Care Management Review* 29 (3), JUL-SEP 2004: pp. 229-239.

Rosner, Fred, Pieter Kark, and Samuel Packer, “Oregon’s Health Care Rationing Plan,” *Journal of General Internal Medicine*, Vol. 11, 1996.

Sasse, Kent C., “The Rationing of Health Care Services: The Case of Alameda County, California,” HEC Forum: an interdisciplinary journal on hospitals' ethical and legal issues, Vol. 2, No. 3, May 1990: pp. 145-155.

Saywell, Robert, Terrell Zollinger, David Chu, Charlotte MacBeth, and Mark Sechrist, “Hospital and Patient Characteristics of Uncompensated Hospital Care: Policy Implications,” *Journal of Health Politics, Policy and Law* 14(2), 1989: pp. 287-307.

Seshamani, Meena J., Sanford Schwartz, and Kevin G. Volpp, “The Effect of Cuts in Medicare Reimbursement on Hospital Mortality,” *Health Services Research*, Vol. 41, No. 3, Part I, June 2006.

Shen, Yu-Chu, Vivian Wu, and Glenn Melnick, "The Changing Effect of HMO Market Structure: An Analysis of Penetration, Concentration, and Ownership Between 1994-2005," *NBER* Working Paper 13775, February 2008.

Silverman, Elaine, and Jonathan Skinner, “Medicare Upcoding and Hospital Ownership,” *Journal of Health Economics*, Volume 23, Issue 2, March 2004.

Sloan, Frank A., *Handbook of Health Economics*, Chapter 21: Not-for-profit Ownership and Hospital Behavior, Volume 1, Part 2, 2000, pp. 1141-1174.

Sloan, Frank A., “Hospital Ownership Conversions: Defining the Appropriate Public Oversight Role,” Forum for Health Economics & Policy, Frontiers in Health Policy Research, Volume 5, Article 6, 2002.

Spencer, Christine S., “Do Uncompensated Care Pools Change the Distribution of Hospital Care to the Uninsured?” *Journal of Health Politics, Policy and Law*, Vol. 23, No. 1, Feb. 1998.

Tamara, Konetzka, Jingsan Zhu, and Kevin G. Volpp, “Did Recent Changes in Medicare Reimbursement Hit Teaching Hospitals Harder?” *Academic Medicine*, Vol. 80, No. 11, November 2005.

Thorpe, Kenneth, Curtis Florence, and Eric Seiber, “Hospital Conversions, Margins, and the Provision of Uncompensated Care,” *Health Affairs*, Vol. 19, No. 6, 2000.

Thorpe, Kenneth, Eric Seiber, and Curtis Florence, “The Impact of HMOs on Hospital-Based Uncompensated Care,” *Journal of Health Politics, Policy and Law*, Vol. 26, No. 3, June 2001.

Volpp, Kevin, Jonathan D. Ketcham, Andrew J. Epstein, and Sankey V. Williams, “The Effects of Price Competition and Reduced Subsidies for Uncompensated Care on Hospital Mortality,” *Health Services Research* 40 (4), 2005: pp. 1056-1077.

Weissman Joel, Darrell J. Gaskin, and James Reuter, “Hospitals’ Care of Uninsured Patients During the 1990s: the Relation of Teaching Status and Managed Care to Changes in Market Share and Market Concentration,” Inquiry, 40(1), 2003: pp. 84-93.

Weissman, Joel, “The Trouble with Uncompensated Hospital Care,” *New England Journal of Medicine* 352 (12), March 2005: pp. 1171-1173.

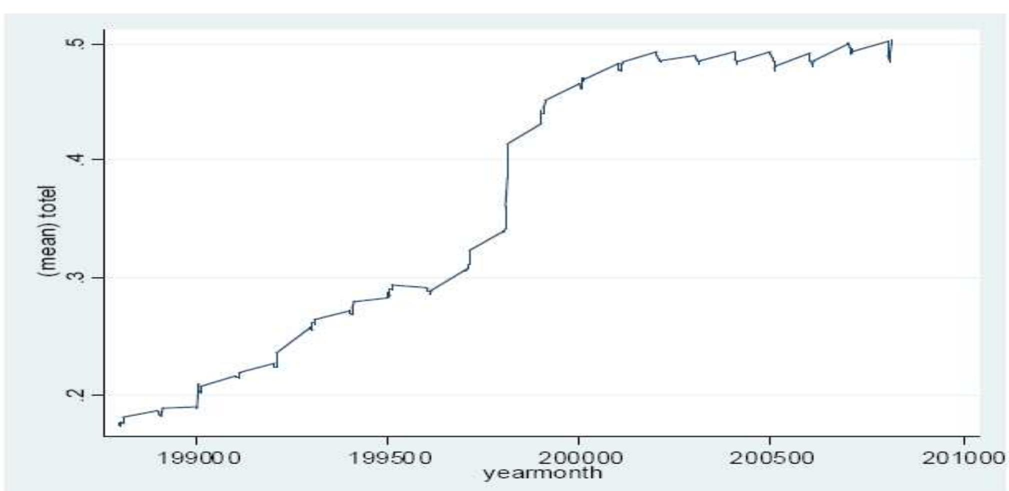
Zuckerman, Stephen, Gloria Bazzoli, Amy Davidoff, and Anthony LoSasso, “How Did Safety-Net Hospitals Cope in the 1990s?” *Health Affairs*, Vol. 20, Issue 4, Jul/Aug 2001.

CHAPTER 3

The Impacts of SCHIP on Hospital Care for Low-income Children

I. Introduction

Since the mid 1980s, the U.S. government has made tremendous efforts to provide public insurance coverage for more low-income children. As a result of the implementation of Medicaid and SCHIP (henceforth "Medicaid") from 1965 to the late 1990s, the fraction of the nation's children that are eligible for free or drastically reduced-cost health care has gone from less than 15 percent to about 50 percent; Medicaid is the single largest source of public health insurance for low-income children. Expansions in Medicaid have taken place in two waves since 1965. The first took place in the late 80s and early 90s. The second was in the late 1990s, through the CHIP legislation. Figure 3.1 shows the magnitude of these expansions.



Note: This shows the average state, average child age level policy change, as captured by a simulated eligibility calculator that processes the sample sample through changing state rules. The y axis measures the percent of the constant sample of children who are eligible for coverage.

[Figure 3.1] Trend in Children's Eligibility

The goal of this paper is to examine impacts of the CHIP expansion on hospital care for low-income children. Previously, two papers have examined the effects of the earlier Medicaid expansions on children's hospitalizations, but there has been no evaluation of the effect of the most recent expansions on children's hospitalization, other than a few studies focusing on California (Azer, 2007; Bermudez and Baker, 2005). Exploiting variations in public insurance eligibility rules for children by age, state, and year, we investigate net impacts of the coverage expansions on hospitalization rates, and intensity of care provided during hospital visits for a data set representing over 30 states. If the expansion of public insurance coverage increases access to primary and preventive care for low-income children (Newacheck et al, 1998; Dubay and Kenny, 2001; Stevens et al, 2006; Perry and Kenny, 2007), then these early medical interventions may reduce hospitalizations for ambulatory care sensitive (ACS) conditions, as well as intensity of care conditional on admission to a hospital (efficiency effect). On the other hand, the gain of public insurance lowers the marginal cost of hospitalization for families, which may increase hospital visits as well as intensity of care demanded (price effect) for all types of hospitalizations, depending on the elasticity of demand. A third possibility is that coverage expansions could shift some hospitalizations that were previously uninsured or privately insured to public insurance, and this could decrease or increase the intensity of services, depending on financial incentives that result for the hospital.

We study children's hospitalizations from 1996 to 2002 in the Nationwide Inpatient Sample (NIS). We restrict our sample to children aged 0-15 and divide them into four age categories—children under 1 year (excluding newborns), 1-5 years, 6-10 years, and 11-15 years—at the state and year levels[69]. For each age group/state/year cell, we create a simulated eligibility measure of Medicaid/CHIP that is the fraction of

[69] We also repeat this by single age of child, state, and year.

a nationally representative sample of children (from the CPS) in each age group who would be eligible for public health insurance in a given state and year. Using age of patient, year, and state identifiers of hospitals, we merge this state-year-age group level policy data with the NIS to study CHIP expansions.

Our main econometric model is based on a reduced form approach with the simulated measure as a policy variable. We also use the instrumental variables method of Dafny and Gruber (2005), which instrumented the eligibility measure for the CPS group with the simulated measure. First, we study the impact of policy expansions on hospitalization rates for children, which we then break down into ACS and non-ACS hospitalizations. We expect that the expansion of public insurance coverage will have an ambiguous effect on hospitalizations for ACS conditions (since there are two opposing forces at work), but increase hospital care for non-ACS conditions (which should only experience the price effect). In addition to these hospitalization rates, we study intensity of care during hospital visits, using number of days spent in the hospital and number of procedures performed per admission. Depending on a child's counterfactual insurance status had the expansion not happened, we expect different impacts from the expansion. If the child would have been uninsured but is publicly covered due to the expansions, i.e., the target group of the CHIP, we expect intensity of care to decrease for ACS hospitalizations, but increase for non-ACS hospitalizations. This is because of the efficiency and price effects explained above. However, if the child's counterfactual insurance status would have been privately insured, but is now public coverage (crowding-out effect), we expect intensity of care to decrease. This is because private insurance would have provided higher reimbursements and thus greater access. We also estimate effects of policy separately by insurance status, using the fraction of all hospitalizations for children that are public, private, or uninsured. We find that prior work did not look at insurance status

(Kaestner et al, 2001; Dafny and Gruber, 2005), presumably due to the uncertainty regarding the time that the payer source was recorded, upon admission or at discharge; we too proceed cautiously with this analysis as insurance coding might be not entirely reliable.

We find that children's hospitalization rates increased by 3.9 percent in response to a 10 percentage-point increase in eligibility for public health insurance. The entire increase comes from hospitalizations categorized as non-ACS. We also find that intensity of care increases both overall and among hospitalizations in the non-ACS category: if the fraction of the eligible population increases by 10 percentage points, length of stay increases by 0.12 days, while number of procedures increases by 0.06. For ACS hospitalizations, neither length of stay nor number of procedures is affected in a statistically significant manner (the coefficients are small and negative). Our results also suggest that the increases in hospitalizations are due to an increase in publicly insured cases. The fraction of Medicaid hospitalizations increases by 0.10 as the fraction of children in a state/year/age group made eligible increases from 0 to 1, while the fraction of uninsured hospitalizations declines by 0.06. The fraction with private coverage does not display a statistically significant impact; the coefficient sign and magnitude are -0.04.

The rest of the paper is laid out as follows: in Section II, we explain background information about public health insurance programs for children and pediatric hospitalizations. Section III reviews previous literature, and Section IV describes our data and empirical strategy. We discuss empirical results in Section V, and conclude the paper in Section VI.

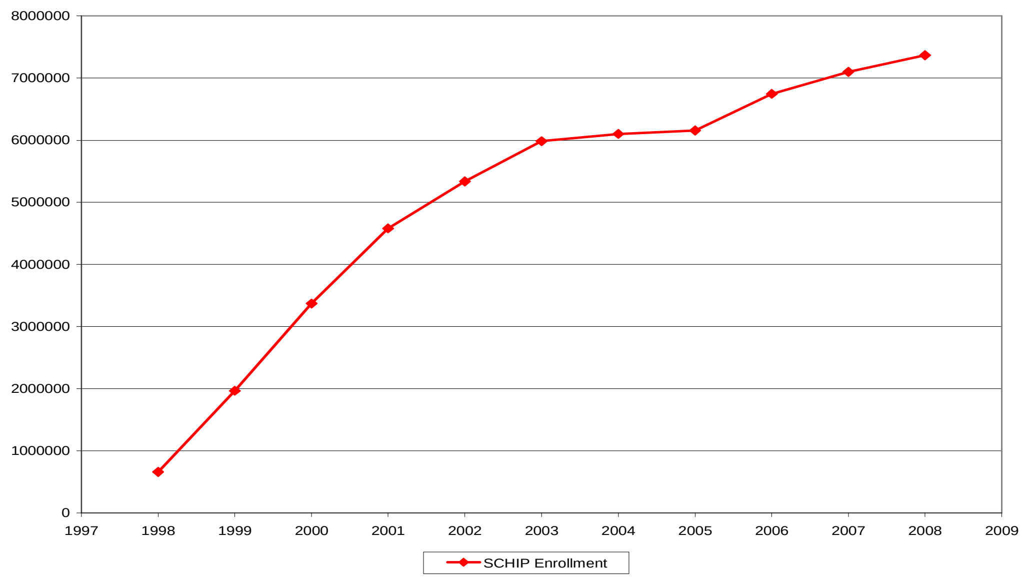
II. Background

(a) Public Health Insurance Programs for Children

The Medicaid program was implemented in 1965 with the aim of providing health insurance coverage for low-income individuals. Low-income children are its major beneficiary group, representing about a half of Medicaid beneficiaries (as of 2006). From the early days to the mid 1980s, Medicaid coverage was available for children of welfare mothers, which means that the income threshold for Medicaid eligibility was extremely low (below 100% of the FPL). In the late 1980s and early 1990s, however, eligibility income thresholds increased to 133-185 percent of the FPL, depending on a child's age and state of residence. These Medicaid expansions resulted in coverage for a greater number of low-income children.

Despite this increased generosity of Medicaid, concerns remain about a significant number of children who are still uninsured, i.e., those who are too poor to afford private insurance, but too rich to qualify for Medicaid. In 1997, the U.S. Congress created the State Children's Health Insurance Program (SCHIP) in an attempt to extend the public insurance safety net for those remaining uninsured, near-poor children. States were required to further increase their eligibility income thresholds, with their own choice of administrative model among the following three types: expansion of the Medicaid program, a separate SCHIP program, or a combination of these two[70]. By 2002, most states had increased their income thresholds up to the minimum of 200 percent of the FPL. As a result, Figure 3.2 shows that SCHIP enrollment has more than quadrupled during 1998-2008: it had increased rapidly for the first five years, from 900,000 in 1998 to 4 millions in 2003, but has

[70] As of June 2007, 14 states expanded the Medicaid program, 19 states created a separate SCHIP program, and 18 states run a combination program (the Kaiser Commission on Medicaid and the Uninsured, available at http://www.kff.org/medicaid/7642.cfm).



Data Source: SCHIP Statistical Enrollment Data System (SEDS) 01/20/2009. Downloaded at http://www.cms.hhs.gov/NationalCHIPPolicy/downloads/CHIPEverEnrolledYearGraph.pdf

[Figure 3.2] SCHIP Enrollment

stabilized since 2003; the annual percentage change in the SCHIP enrollment was 101.2% in 1999, 48.6% in 2000, 28.1% in 2001, 9.7% in 2002, and 4.1% in 2003.

The children's public insurance programs reimburse both physicians and hospitals, although their reimbursement rates are lower than those of private payers. If Medicaid/SCHIP reimbursed hospital care alone, hospital care would increase regardless of type of diseases. However, since Medicaid/SCHIP cover physician care as well, better access to primary physician care for low-income children will prevent some hospitalizations for ambulatory care sensitive conditions. Moreover, having adequate amounts of physician care before hospitalization is likely to prevent diseases' development into advanced stage, so that intensity of care during hospital visits may decline. Another factor that could affect hospital care is a hospital payment system. The public insurance programs reimburse hospitals at a lower level than private payers

(AAP report[71], 2001; Zuckerman et al, 2009), while a majority of uninsured, low-income children create hospital uncompensated care (Hadley and Holahan[72], 2004). Therefore, children who were previously uninsured but obtain public insurance coverage are likely to have more hospital care, while those who were previously privately insured but switch to public insurance coverage are likely to have less hospital care: even though Medicaid DSH payments, extra payments to hospitals that treat a disproportionately large number of low-income patients, as well as dominance of managed care in private insurance market, are taken into account, private payer reimbursements are significantly higher than Medicaid payments (See if there is any reference: this info is based on a conversation with a hospital administrator, John Rudd).

Like the Medicaid expansions, the SCHIP expansions raised two important issues: low take-up rates and large crowd-out effects (Shore-Shepard, 2000; Cunningham et al, 2002; Lo Sasso and Buchmueller, 2004; Hudson et al, 2005). States have made great efforts to address these issues: to encourage take-up and improve retention, states have developed innovative outreach programs, through which they have disseminated information about their programs, simplified application and enrollment processes, and assisted with those procedures (Aizer, 2007; Buchmueller et al, 2008). To reduce crowding-out effects, several states have chosen a waiting period strategy such that a child is required to be uninsured for a certain period of time (2-12 months) prior to enrolling in SCHIP (Kronebusch and Elbel, 2004; Kenny, 2007).

[71] The ratio of Medicaid to Medicare payments for hospital care (initial hospitalization with low complexity, CPT code=99221) is $47.91/$71.54=0.67 in 2001.
[72] Based on Hadley and Holahan's analysis of 1998-2000 MEPS, 29.3% of total pediatric care ended up with uncompensated care.

(b) Pediatric Hospitalization: ACS vs. non-ACS Hospitalization

Children's hospitalizations account for about 8 percent of total inpatient episodes. Primary causes of pediatric hospitalizations are diseases of the respiratory system (asthma, pneumonia, and bronchitis), various infections, appendicitis, general symptoms, as well as digestive and kidney diseases. Hospitalizations can be divided into two broad categories—ambulatory care sensitive (ACS) and non-ACS cases—based on whether or not they might have been prevented by better primary care and greater early medical interventions: ACS conditions are potentially preventable with timely and effective primary care, while non-ACS conditions are not. The ACS conditions are often called "avoidable," "discretionary," or "preventable" ones, while non-ACS conditions are called "unavoidable," "non-discretionary", or "non-preventable" ones; however, we believe that both ACS and non-ACS conditions have some room for discretion, although the scope of discretion for ACS conditions are relatively larger. These ACS hospitalizations are used as an indicator of quality and quantity of primary care or as an objective measure for children's health (Kaestner et al, 2001; Dafny and Gruber, 2005; Aizer, 2007; Cousineau et al, 2008). Examples of ACS conditions are asthma, pneumonia, gastroenteritis, diabetes, nutritional deficiencies, dehydration, severe ENT infections, immunization preventable conditions, and so on. According to McConnochie et al (1997), 18 to 28 percent of pediatric hospitalizations are believed to be ambulatory care sensitive.

We define ACS conditions based on International Classification of Diseases-9-Clinical Modification (ICD-9-CM) codes listed in Dafny and Gruber (2005), Weisman et al (1992), as well as Billings et al (1993). Panel (a) in Table 3.1 includes the ICD-9 codes used to define ACS conditions, while the rest are considered non-ACS conditions. Obviously, these non-ACS conditions can be further broken down according to the scope of discretion. In this paper, we first examine non-ACS

[Table 3.1] ICD-9 Codes for Children's Hospitalization

Panel (a): Ambulatory Care Sensitive Conditions	
Condition	**ICD-9 Codes**
Immunization preventable conditions	032, 033, 037, 045, 055, 056, 072, 390, 391, 070.3, 041.5, 320.0
Grand Mal status and other epileptic convulsions	345, 780.3, 642.6
Severe ENT infections	382, 462, 463, 465, 472.1, 461, 475, 383.0
Bacterial pneumonia	481-487
Asthma	493
Tuberculosis	011-018
Cellulitis	681, 682, 683, 686
Diabetes	250.0, 250.1, 250.2, 250.3, 250.4, 250.5, 250.6, 250.7, 250.8, 250.9
Hypoglycemia	251.0, 251.2
Gastroenteritis	276.5, 558.9
Kidney/urinary infection	590, 598.0, 599.0, 599.9
Dehydration-volume depletion	276.5
Iron deficiency anemia	280.1, 280.8, 280.9
Nutritional deficiencies	260, 261, 262, 265, 266, 280, 281, 268.0, 268.1
Failure to thrive	783.4
Chronic Obstructive Pulmonary Disease (Acute bronchitis and bronchiolitis)	491, 492, 494, 496, 490, 466.0, 466.1
Other acute and subacute forms of ischemic heart disease	411.1, 411.8, 413
Hypertensive Disease	401.0, 401.9, 402.00, 402.10, 402.90, 402.0, 403.0, 404.0
Ulcer	531-534
Pelvic Inflammatory Disease	614
Dental	521, 522, 523, 525, 528
Other abnormal heart sounds	785.3
Congenital syphilis	090
Panel (b): Extremely Unavoidable Cases	
Condition	**ICD-9 Codes**
Broken bones	800-829
Injuries	861-897
Crushing injuries	925-929
Foreign Body Entering Through Orifice	930-939
Burns	940-949
Appendicitis	540-542

hospitalizations as a whole. Then, among the non-ACS conditions, we specify conditions that would unequivocally require hospitalization, such as broken bones, burns, and serious injuries (from car accidents, gun shots, etc). Panel (b) in Table 3.1 shows the ICD-9 codes for these extreme cases, which have absolutely no room for discretion. Although we expect "ACS" hospitalizations to decrease, and "non-ACS" hospitalizations to increase after the coverage expansions, these extremely mandatory hospitalizations are not expected to change.

III. Literature Review

Many studies have examined policy impacts on take-up of Medicaid, its effect on uninsurance among children as well as substitution of Medicaid for private coverage (Dubay et al, 2000; Baughman, 2004; LoSasso and Buchmueller, 2004; Hudson and Selden, 2007; LoSasso and Buchmueller, 2008; Shore-Sheppard, 2008), changes in medical care utilization (Lave et al, 1998; Joyce and Racine, 2005; Davidoff et al, 2005; Duderstadt et al, 2006; Seden and Hudson, 2006; Wang et al, 2007; Currie et al, 2008), and health outcomes (Currie and Gruber 1996; Kenny et al, 2000; Szilagyi et al, 2000; Lykens and Jargowsky, 2002; Currie et al, 2008). Studies about take-up rates and crowding-out effects examined a linear relationship between a fraction of the public insurance eligible population and a probability for each coverage type among persons in the CPS March sample: the probability of having public insurance indicates take-up, and the probability of having private insurance suggests crowding-out. They presented different levels of take-up rates and crowding-out effects. Based on various data sources[73] and subgroup of children[74], past studies unanimously found a positive

[73] Most studies used the National Health Insurance Survey (NHIS), while a few used the Medical Expenditure Panel Survey, National Survey of Children' Health, and National Immunization Survey.
[74] Most studies examined all children under 19, but several studies restricted their sample to infants under age 2, immigrant children, or those with chronic illness.

association between public insurance expansions and health care utilization, although it is debatable whether the expansions improved health outcomes.

There have been two national studies of the effect of expansions on children's hospitalizations, and both studied the early expansions before 1996. Kaestner et al (2001) examined the impact of the first wave of Medicaid expansions on children's hospitalizations and health outcomes. Using NIS data in 1988 and 1992, they found that Medicaid expansions decreased the incidence of ACS hospitalizations among children aged 2-6 from very low-income zip code areas. Dafny and Gruber (2005) studied the impact of Medicaid expansions in the 1980s and early 1990s on children's hospital care. Using the National Hospital Discharge Survey (NHDS) for 1983-1996, they found both efficiency and price effects: Medicaid expansions for low-income children increased total hospitalization rates and number of procedures performed at hospital, while length of hospital stay decreased, and avoidable hospitalizations did not display a statistically significant change.

We find only three recent papers that specifically study the impact of the SCHIP expansions on hospitalization rates; all three studied the state of California alone: Aizer (2007), Bermudez and Baker (2005), and Cousineau et al (2008). Cousineau et al (2008) studied Children's Health Initiatives (CHIs), a supplement program to Medicaid and SCHIP in California, which have been developed in 26 counties since 2001. Their findings are also consistent with those in the previous literature: showing a negative relationship between increases in public insurance coverage and ACS hospitalization rates. Bermudez and Baker (2005) and Aizer (2007) are two studies that examined SCHIP enrollment, and its relation to ACS hospitalization rates in California. Both studies found that higher SCHIP enrollments reduced avoidable hospitalization rates. In particular, Aizer (2007) identified administrative hassle and insufficient knowledge as major reasons for low take-up rates and used number and presence of bilingual administrative staff who could help parents to enroll their children in SCHIP, as well as bilingual advertisements, as instruments for enrollment rates. Given the unique nature of California, it is hard to learn how children's hospitalization has been affected in the nation as a whole.

IV. Data and Empirical Strategy

<u>Data</u>

Our primary source of data is the Nationwide Inpatient Sample (NIS), part of the Healthcare Cost and Utilization Project (HCUP), sponsored by the Agency for Healthcare Research and Quality (AHRQ). The NIS is a nationally representative sample with all patients' discharge records for 20% of U.S. community hospitals in each of several states. The greatest advantages of this data set are its large sample size and provision of detailed information about patients—age, DRG codes, diagnosis and procedure codes, payer source, and length of stay.

We use the discharge records from 1996 to 2002, which encompasses both the pre- and post- expansion period, and includes 19-35 states: for 2002, the NIS contains about 8 million hospital discharges (1.4 million for children's hospitalizations) from 35 states (the 35 states represented here contain 83% of the U.S. population)[75]; for 1996, it contains 6.5 million discharges (1.2 million for children's hospitalizations) from 19 states (59% of the U.S. population). This sample size is 20 times greater than that of the NHDS, the other national discharge data source, used by Dafny and Gruber (2005) (8 million in NIS vs. 375,000 in NHDS in 2005). Although the NIS does not include all discharge records, using discharge weights provided by the NIS, we are

[75] Kaestner *et al* (2001) studied 8 states in 1988, which represent 40% of the U.S. population, and 11 states in 1992, which represent 53% of the U.S. population.

able to produce estimates for the universe of hospitalizations at the national level. We obtain population estimates from the Census Bureau, which we use as a denominator in calculation of hospitalization rates.

We select children aged 0-18 who were hospitalized during 1996-2002. After we drop newborns[76], who have a different hospitalization pattern, our sample size is 3.6 million. For the main analysis, we further restrict our sample to those aged 0-15 (2.7 million) and divide them into four age subgroups: children less than 1 year of age (no newborns), 1-5 years, 6-10 years, and 11-15 years. Children within each age category are under the same eligibility rules, and their causes of hospitalizations are similar. Here, we do not include those aged 16-18, in order to make our sample consistent with Dafny and Gruber (2005), but we later include this older age group for a robustness check. We also examine the further breakdown of our sample into single year of age (16 age groups for 0-15 years) in the robustness section.

Empirical Strategy

Our objective is to examine the impact of the SCHIP expansions on hospitalization rates for children and intensity of care during hospital visits. Model I is our baseline econometric model, following the specification in Dafny and Gruber (2005).

Model I: $Y_{AST} = \alpha + \beta_1\, ELIG_{AST} + \beta_2\, AGE\_GROUP_A + \beta_3\, STATE_S + \beta_4\, YEAR_T + \beta_5\, STATE \times YEAR + e_{AST}$

Y_{AST} is the rate of hospitalizations for age group A, state S, and year T, or another dependent variable of our interest: hospitalization rates of each type (ACS or non-ACS), length of stay, and number of procedures. The hospitalization rate is the number of hospitalizations in the age group/state/year cell divided by the population

76 DRG code 385-391. 5.7 million among 9.3 million pediatric discharges (61%) are dropped.

estimate for that age group, state, and year. All dependent variables are used in log forms: log hospitalization rates, log length of stay, and log number of procedures.

The explanatory variable of our primary interest is ELIG, generosity of public insurance programs. Our aim is to have a measure that reflects the magnitude by which public health insurance eligibility expanded for each group. Following the algorithm of Currie and Gruber (1995) and many other researchers, we simulate eligibility for public health insurance (Medicaid and SCHIP) among children under 19, using a constant national sample from the CPS March supplements of 1997-2003. $ELIG_{AST}$ is the fraction of children in age group A who would be eligible for Medicaid/SCHIP had they lived in state S in year T. This year/state/age group instrument captures the generosity of the states' public health insurance programs, which is attributed only to eligibility rules, independent of other factors such as differences in income, race, or age distribution of children in each state.

We include a full set of dummy variables for states, years, and age groups in order to control for any underlying correlation between SCHIP eligibility and hospitalizations within these groups. As in Dafny and Gruber (2005), we also include a full set of State×Year interaction terms in order to control for other time-varying, state-specific trends that might be correlated with SCHIP eligibility policy.

Here, we assume that marginal effects on hospitalizations result from beneficiaries of public insurance coverage, so that we examine patterns of hospital care for all children. In order to check whether changes in hospitalizations did originate from those who obtain public insurance coverage, we break down total hospitalizations by coverage type—public, private, and uninsured—and estimate Model I separately by insurance status. We use the fraction of hospitalizations for each coverage type, as well as the log number of admissions by insurance type, as alternative dependent variables.

V. Results

Descriptive Statistics

Table 3.2 presents descriptive statistics. The average hospitalization rate is 7.61%, and the ACS hospitalization rate is 3.38%. On average, children under 16 who were hospitalized during 1996-2002 stayed for 3.85 days and received 0.79 procedures during their hospital stays.

[Table 3.2] Descriptive Statistics

(N=732)	Mean	Standard Deviation
Hospitalization Rates	7.61%	0.10
ACS	3.38%	0.05
non-ACS	4.23%	0.06
ELIG (Simulated)	0.47	0.14
ELIG for CPS	0.40	0.14
Length of Stay (days)	3.85	1.46
Number of Procedures	0.79	0.36

Hospitalizations

Table 3.3 reports the estimates of ELIG for the numbers of hospitalized children and hospitalization rates for total, ACS, and non-ACS cases. Panel I shows that the total number of hospitalizations increased by 4.6 percent if ELIG increased by 10 percentage points. However, this increase is entirely attributed to the increase in the number of non-ACS hospitalizations: the number of ACS hospitalizations increased by 0.1 percent, but the estimate is small and statistically insignificant; the number of non-ACS hospitalizations increased by 8.5 percent, which is statistically significantly different from zero.

[Table 3.3] Results for Hospitalization

Panel I (Counts=# of hospitalizations)			
1996-2002	ln(# of total hospitalizations)	ln(# of ACS hospitalizations)	ln(# of non-ACS hospitalizations)
ELIG (Simulated)	0.46**	0.1	0.85***
	(0.19)	(0.15)	(0.23)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
Average (unlogged)	18237.45	7417.58	10819.87
Observations	732	732	732
Adjusted R-square	0.98	0.99	0.97
F test	555.81	618.39	409
p value	0	0	0

Panel II (Rates: # of hospitalizations/population)			
1996-2002	ln(total hosp'n rate)	ln(ACS_rate)	ln(non-ACS_rate)
ELIG (Simulated)	0.39**	0.04	0.79***
	(0.18)	(0.16)	(0.22)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
Average (unlogged)	0.076	0.034	0.042
Observations	732	732	732
Adjusted R-square	0.98	0.99	0.96
F test	367.16	587.99	417.08
p value	0	0	0

Note: Robust standard errors in parenthesis
*** significant at 1%; **significant at 5%; * significant at 1%

In Panel II, our dependent variable is hospitalization rates, number of hospitalized children divided by population estimates for each age group/state/year cell. The first column shows that an increase in public insurance coverage of 10 percentage points increased the total hospitalization rates by 3.9 percent. Our estimate is about half the size of the estimate obtained by Dafny and Gruber (2005), who studied earlier Medicaid expansions with the NHDS. Considering that SCHIP beneficiaries have lower take-up rates than their Medicaid counterparts, the size of our estimate seems reasonable. Since the fraction of children who are eligible for public insurance coverage increased by 0.20, from 0.31 in 1996 to 0.51 in 2002, this estimate implies that total hospitalizations increased by 7.8 percent, or 5.9 additional hospitalizations per 1000 children (based on average hospitalization rates for all children aged 0-15 during 1996-2002). Our findings imply that the price effect outweights any efficiency gain from better access to primary care.

In the next two columns, we decompose total hospitalizations into ACS and non-ACS cases. As with the number of hospitalizations above, we find that the increase in total hospitalization rates was due to the increase in non-ACS hospitalization rates, but not ACS cases: a 10 percentage-point increase in ELIG increased non-ACS hospitalization rates by 7.9 percent (6.6 additional hospitalizations per 1000 children[77]), while ACS hospitalization rates increased by 0.4 percent, which is small and not statistically significant.

Intensity of Care

So far, we have studied the policy impact on a chance of being hospitalized, i.e., hospitalization decision before admissions. Expansions of public insurance coverage can also influence intensity of care when a child is hospitalized, i.e., amount of care after admissions. Table 3.4 presents estimates for ELIG for length of stay and number of procedures, two measures for intensity of care. Intensity of care increased overall after the SCHIP expansion, but this impact originated from non-ACS hospitalizations. A 10 percentage-point increase in ELIG increased hospital stays by 3.2 percent and number of procedures by 8.2 percent: with average values of each measure used as a baseline, our estimates indicate 0.12 days longer hospital stays and

[77] 0.20 (increases in ELIG) * 0.042 (average unavoidable hospitalization rates) * 1000 * 0.079 (the estimate)

[Table 3.4] Results for Intensity of Care

	ln(length of stay)			ln(# of procedures)		
1996-2002	Total	ACS	Non-ACS	Total	ACS	Non-ACS
ELIG (Simulated)	0.32	-0.02	0.33	0.82***	-0.09	0.73***
	(0.24)	(0.19)	(0.28)	(0.26)	(0.33)	(0.27)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y	Y	Y	Y
STATE×YEAR	Y	Y	Y	Y	Y	Y
Average (unlogged)	3.85	2.71	4.55	0.79	0.28	1.11
Observations	732	732	732	732	732	732
Adjusted R-square	0.77	0.67	0.66	0.84	0.74	0.68
F test	30.45	38.16	26.01	28.72	72.21	29.56
p value	0	0	0	0	0	0

0.06 more procedures. Compared to Dafny and Gruber (2005), who found mixed results regarding intensity of care—decreased length of stay (0.13 days) and increased number of procedures (0.04 procedures)—after Medicaid expansions, we consistently find that overall intensity of care increased after the SCHIP expansions, although the increase in length of stay is not statistically significantly different from zero.

When we break down these two measures by ACS and non-ACS conditions, however, we find evidence that seems to support the efficiency theory because intensity of care increased only for non-ACS hospitalizations, while there was no statistically significant change for ACS hospitalizations. In fact, those who were hospitalized with ACS conditions were released more quickly (by 0.005 days) and had fewer procedures (by 0.003) during hospital visits, although these estimates are very small and statistically insignificant at the 10% level. For those who were hospitalized with non-ACS conditions, however, intensity of care increased in both measures: length of stay increased by 0.15 days (which is not statistically significant), and number of procedures increased by 0.08 in a statistically significant manner. Our findings give stronger evidence for both the price and efficiency effects: the coverage expansions increased access to care in overall (the price effect); patients whose hospitalization decisions were marginal had better primary care and thus enhanced health outcomes before being hospitalized, so that their hospital stays became shorter, and they needed fewer procedures (the efficiency effect).

Hospitalizations by Coverage Types

In this section, we examine hospitalizations separately by coverage type. We expect that marginal increases in hospitalizations originate from low-income children who have public insurance coverage. That means, among pediatric hospitalizations, the number of children who come with public health insurance should increase after the SCHIP expansions. Here, we divide total hospitalizations into three subgroups—Medicaid, privately insurance, and uninsured—and count admissions for each coverage type.

Table 3.5 shows that the number of Medicaid admissions increased after the SCHIP expansion, as did the number of privately insured admissions. However, the increase in hospitalizations was larger for Medicaid admissions: in response to a 10 percentage-point increase in ELIG, the number of Medicaid admissions increased by 418, while the number of privately insured admissions increased by 357. The number of uninsured admissions decreased by 9.3 percent, but the estimate is not statistically significantly different from zero. In Panel II, we use a fraction of hospitalizations for each coverage type as our dependent variables: for example, the fraction of Medicaid hospitalizations is the number of Medicaid hospitalizations divided by total hospitalizations for each age group/state/year cell. Again, we find that the fraction of Medicaid hospitalizations increased, by 0.10 if ELIG increased from 0 to 1, while the fraction of uninsured hospitalizations decreased by 0.06. Both are statistically significant at the 5% level. The fraction of privately insured hospitalizations decreased

[Table 3.5] Results for Hospitalizations by Coverage Type

Panel I (counts)			
	ln (# of Medicaid)	ln (# of the privately insured)	ln (# of the uninsured)
ELIG (Simulated)	0.64***	0.39**	-0.93
	(0.24)	(0.19)	(0.61)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
Average (unlogged)	7508	9157	882
Observations	732	732	732
Adjusted R-square	0.97	0.98	0.82
F test	347.86	474.45	280.68
p value	0	0	0

Panel II (proportions)			
Proportion of	Medicaid	Private insurance	Uninsured
ELIG (Simulated)	0.10**	-0.04	-0.06**
	(0.04)	(0.05)	(0.03)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
Observations	732	732	732
Adjusted R-square	0.87	0.86	0.72
F test	80.67	115.43	48.07
p value	0	0	0

by 0.04, based on which we can infer crowding-out effects, but this change is not statistically significantly different from zero.

VI. Robustness Check

We conduct several robustness checks and find that our results are highly robust to alternative measures and specifications. First, we use the instrumental variables method, following Dafny and Gruber (2005). Here, we create ELIG_CPS, a fraction of children for each age group in a given year and state who are actually eligible for public insurance coverage in the CPS March sample. This fraction is different from the simulated policy measure (ELIG) because we do not use the same set of national sample across states. Since ELIG_CPS is endogenous by nature, we use ELIG as an instrument variable for the CPS group level measure of eligibility. This IV method produces results almost identical to those from the reduced form.

Second, we include interaction terms between year and age group, and then state-age group interaction terms as in Dafny and Gruber (2005). These Year×Age group interaction terms control for confounding effects that could be attributed to different time trends across age groups, while the State×Age group interaction terms control for time-invariant heterogeneity across state and age group cells. Our results in Table 3.6 report the estimates for ELIG. When we add the Year×Age group interaction terms, the magnitude of the estimates and their standard errors both increase. In the case of ACS hospitalizations, the estimate increases by a substantial amount and becomes statistically significant. Finally, when we add the State×Age group interaction terms, the estimates for total and non-ACS hospitalizations become negative and statistically insignificant, while the estimate for ACS hospitalizations remains positive and statistically significant. These findings imply that the changes in ACS hospitalizations are sensitive to the specifications.

Third, we adjust our standard errors for correlation within states, clustering standard errors at the state level. Most of the results, except for those concerning the fractions of hospitalizations by coverage type, remain statistically significant. Fourth, among unavoidable hospitalizations, we separately examine admissions for extreme conditions that would unequivocally require hospitalization, such as broken bones. At the margin, we do not expect any changes in these extreme cases. Table 3.7 does show that there is no statistically significant change in this type of hospitalization; the result is robust to the inclusion of Year×Age group and State×Age group interaction terms.

[Table 3.6] Robustness Check for Hospitalization Rates

Hospitalization Rates	ln(Total hosp'n rate)	ln(Total hosp'n rate)	ln(ACS hopt'n rate)	ln(ACS hopt'n rate)	ln(non-ACS hopt'n rate)	ln(non-ACS hopt'n rate)
ELIG (Simulated)	0.64**	-0.05	0.64***	0.61**	0.74**	-0.47
	(0.27)	(0.37)	(0.22)	(0.30)	(0.32)	(0.46)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y	Y	Y	Y
STATE×YEAR	Y	Y	Y	Y	Y	Y
Age Group×YEAR	Y	Y	Y	Y	Y	Y
Age Group×STATE	N	Y	N	Y	N	Y
Observations	732	732	732	732	732	732
R-square	0.98	0.99	0.99	1	0.98	0.99
F test	357.22	3113.69	695.65	3833.92	370.25	4737.29
p value	0	0	0	0	0	0

[Table 3.7] Robustness Check for Hospitalization Rates of Extreme Cases

Hospitalization Rates for Extreme Cases (broken bones, burns, injuries, etc)	ln(extreme cases)	ln(extreme cases)	ln(extreme cases)
ELIG (Simulated)	0.6	0.97	-0.37
	(0.62)	(0.68)	(1.01)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
AGE Group×YEAR	N	Y	Y
Age Group×STATE	N	N	Y
Observations	732	732	732
R-square	0.53	0.52	0.6
F test	74.01	52.79	233.69
p value	0	0	0

This result strengthens our earlier findings about the policy impact on the increase in non-ACS hospitalizations. In other words, the coverage expansions help children who may not seek heath care without coverage to receive necessary hospital care when they get sick.

Fifth, we include the upper age group of 16-18 year olds, and redo all of the estimations in the main analysis. We mentioned that we did not include this upper age group in the main analysis in order to construct a consistent sample with that of Dafny and Gruber (2005). Moreover, the primary cause of hospitalizations for female teens aged above 15 is pregnancy-related or maternity care, so that the pattern of their hospital use may be different from that of children in other age groups. For the SCHIP expansions, however, the increases in income thresholds were larger for older children, those aged above 11. Therefore, the magnitude of policy impacts may increase when we add this older age group to our original sample. Table 3.8 presents estimates for the five age groups including 16-18 year olds. These results are consistent with our main results. For hospitalization rates, the magnitude of our estimates is slightly smaller: when ELIG increases by 20 percentage points, there are 5.5 additional hospitalizations per 1000 children. For intensity of care, however, the estimates are larger and statistically significantly positive for both measures: in response to a 10 percentage-point increase in ELIG, length of hospital stay increased by 0.17 days, and number of procedures performed per admissions increased by 0.10.

[Table 3.8] Results for the Five Age Groups (16-18 year-olds included)

Panel I (Hospitalization Rates=# of hospitalizations/population)			
	ln(total hosp'n rate)	ln(ACS hopt'n rate)	ln(non-ACS hopt'n rate)
ELIG (Simulated)	0.35*	0.07	0.73***
	(0.18)	(0.15)	-0.21
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
Average (unlogged)	0.078	0.029	0.049
Observations	915	915	915
Adjusted R-square	0.96	0.98	0.94
F test	208.07	417.72	173.52
p value	0	0	0

[Table 3.8] continued

Panel II (Intensity of Care)						
	ln(length of stay)			ln(# of procedures)		
	Total	ACS	Non-ACS	Total	ACS	Non-ACS
ELIG (Simulated)	0.44**	0.30	0.51**	1.15**	0.42	1.05**
	(0.19)	(0.15)	(0.22)	(0.23)	(0.26)	(0.22)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y	Y	Y	Y
STATE×YEAR	Y	Y	Y	Y	Y	Y
Average (unlogged)	3.76	2.75	4.33	0.91	0.31	1.19
Observations	915	915	915	915	915	915
Adjusted R-square	0.68	0.67	0.66	0.75	0.71	0.62
F test	24.07	38.03	19.72	19.83	50.02	14.25
p value	0	0	0	0	0	0

For non-ACS hospital visits, the magnitude of the estimates is even larger: 0.22 days longer hospital stays and 0.12 more procedures.

Finally, we estimate our model with individual age fixed-effects (single year of age between 0 and 15 constructs each age dummy), instead of the 4 age group dummies. In Table 3.9, we find the same patterns as our main results: total and non-ACS hospitalizations increased in a statistically significant manner, while intensity of care overall and for non-ACS cases also increased after the expansions. The estimates for hospitalizations are smaller than those in the main results, but the estimates for intensity of care are larger and become statistically significant. For ACS conditions, both hospitalizations and intensity of care decreased, albeit not statistically significant. These findings clearly suggest that the SCHIP expansions provide greater access to hospital care and better access to primary care.

[Table 3.9] Results for Each of 0-15 Age group (16 Age Groups)

Panel I (Hospitalization Rates=# of hospitalizations/population)			
	ln(total hosp'n rate)	ln(ACS hopt'n rate)	ln(non-ACS hopt'n rate)
ELIG (Simulated)	0.27***	-0.14	0.70***
	(0.10)	(0.10)	(0.12)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y
STATE×YEAR	Y	Y	Y
Average (unlogged)	0.045	0.018	0.027
Observations	2895	2895	2895
Adjusted R-square	0.96	0.96	0.94
F test	636.93	668.09	414.83
p value	0	0	0

Panel II (Intensity of Care)						
	ln(length of stay)			ln(# of procedures)		
	Total	ACS	Non-ACS	Total	ACS	Non-ACS
ELIG (Simulated)	0.43***	-0.09	0.54***	0.89***	-0.59*	1.09***
	(0.11)	(0.09)	(0.14)	(0.15)	(0.34)	(0.20)
Main effect (Age group, state, and year fixed-effects)	Y	Y	Y	Y	Y	Y
STATE×YEAR	Y	Y	Y	Y	Y	Y
Average (unlogged)	3.64	2.63	4.16	0.80	0.28	1.09
Observations	2895	2892	2894	2889	2892	2894
Adjusted R-square	0.67	0.51	0.63	0.78	0.56	0.51
F test	55.87	42.87	40.98	65.52	55.26	40.74
p value	0	0	0	0	0	0

VII. Conclusion and Discussion

This paper examines how expansions of public insurance coverage for low-income children influence incidence of hospitalization as well as intensity of care during hospital visits. Since its inception in 1997, the SCHIP has increased numbers of children with public insurance coverage. We hypothesize that this coverage expansion could increase or decrease hospital care for low-income children because of two counterbalancing effects. First, low-income children who were previously uninsured but gained coverage, the major coverage gain group, are likely to have better access to primary and preventive care. This earlier medical intervention will enhance their health outcomes, so that some hospitalizations may be avoidable (the efficiency effect). On the other hand, families who now face lower out-of-pocket costs with the gain of public insurance coverage may be more willing to seek hospital care when they get sick (the price effect). Based on the same logic, children who are hospitalized may need less care if earlier medical interventions effectively improve their health status, while they may demand more care if intensity of care received at hospitals before gaining coverage was lower than the optimal level.

Our findings show that the coverage expansions for low-income children result in greater access to and higher intensity of hospital care. When the fraction of the eligible population among children aged 0-15 increased by 0.20 percentage points from 1996 to 2002, we find that 5.9 per 1000 additional children were hospitalized, and that they stayed 0.24 days longer at hospitals and had 0.12 more procedures performed. These findings indicate that the CHIP expansions provided better access to hospital care as well as increased intensity of care during hospital visits. However, we also find that these increases in hospitalization rates and intensity of care were entirely attributable to those with non-ACS conditions, but not those with ACS conditions. This finding implies that the price effects balanced out the efficiency effects: all of the increase in hospital care came from children whose conditions were not preventable with primary care (those with only the price effects), but children at the margin (those with both the price and efficiency effects) did not increase hospital care after gaining coverage. This also suggests that increased public insurance coverage may reduce inefficiency in the provision of care: those without coverage are more likely to delay seeking care, which jeopardizes their health and incurs needlessly higher costs when they show up in advanced stages of illness, or arrive at emergency rooms with non-emergency conditions. However, the coverage gain encourages patients to have more access to primary and preventive care and seek needed care in a timely manner, which prevents development of disease into advanced stages or unnecessary use of emergency rooms. As a result, increased public insurance coverage may reduce potentially high medical costs in the future. Reassuringly, we find no statistically significant effect of the policy on hospitalization rates for extreme conditions (such as broken bones) which should not have been affected at the margin. Also, our results are robust to various specifications and different sets of samples.

The impact we estimate for the CHIP expansions is smaller than that found by Dafny and Gruber (2005) for earlier Medicaid expansions. Taking into account lower take-up rates and larger crowding-out effects for the CHIP expansions, however, the size of our estimate seems reasonable. Our next step is to examine policy impact by race and age of children as well as further breakdowns of types of hospitalization by their scope of discretion. Since non-whites are overrepresented among beneficiaries of public insurance coverage, we expect a larger policy impact on non-white, low-income children.

REFERENCES

Aizer, Anna, "Public Health Insurance, Program Take-up, and Child Health," *Review of Economics and Statistics*, Vol. 89, Issue 3, 2007: pp. 400-415.

Baughman, Reagan, "Differential Impacts of Public Health Insurance Expansions at the Local Level," *International Journal of Health Care Finance Economics*, Vol. 7, No. 1, 2007.

Bermudez, Dustin and Laurence Baker, "The Relationship between SCHIP Enrollment and Hospitalizations for Ambulatory Care Sensitive Conditions in California," *Journal of Health Care for the Poor and Underserved* 16, 2005: pp. 96-110.

Billings, John, Lisa Zeitel, Joanne Lukomnik, Timothy Carey, Arthur Blank, and Laurie Newman, "Impact of Socioeconomic Status on Hospital Use in New York City," *Health Affair*, Vol. 12, Issue 1, 1993: pp. 162-173.

Buchmueller, Thomas, Anthony Lo Sasso, and Kathleen Wong, "How Did SCHIP Affect the Insurance Coverage of Immigrant Children?" *The B.E. Journal of Economic Analysis & Policy*, Volume 8, Issue 2, Article 3, 2008.

Cousineau, Michael, Gregory Stevens, and Trevor Pickering, "Preventable Hospitalizations among Children in California Counties after Child Health Insurance Expansion Initiatives," *Medical Care*, Vol. 46, Issue 2, Feb. 2008: pp. 142-147.

Cunningham, Peter J., Jack Hadley, and James Reschovsky, **"**The Effects of SCHIP on Children's Health Insurance Coverage: Early Evidence from the Community Tracking Study," *Medical Care Research and Review*, Vol. 59, No. 4, 2002.

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

Currie, Janet, Sandra Decker, and Wanchuan Lin, "Has Public Health Insurance for Older Children Reduced Disparities in Access to Care and Health Outcomes?" *Journal of Health Economics,* Volume 27, Issue 6, 2008: pp. 1567-1581.

Dafny, Leemore, and Jonathan Gruber, “Public Insurance and Child Hospitalizations: Access and Efficiency Effects,” *Journal of Public Economics*, 89(1), 2005.

Davidoff, Amy, Genevieve Kenney, and Lisa Dubay, “Effects of the State Children's Health Insurance Program Expansions on Children with Chronic Health Conditions,” *Pediatrics*, Vol. 116, No 1, July 2005: pp. e34-e42.

Dubay, Lisa, and Genevieve M. Kenney, **“**Health Care Access And Use Among Low-Income Children: Who Fares Best?” *Health Affairs*, Vol. 20, No. 1, 2001.

Duderstadt, Karen, Dana Hughes, Mah-J Soobader, and Paul Newacheck, “The Impact of Public Insurance Expansions on Children’s Access and Use of Care,” *Pediatrics*, Vol. 118, 2006: pp. 1676-1682.

Hudson, Julie L., and Thomas M. Selden, “The Impact of SCHIP on Insurance Coverage of Children,” *Inquiry*, 42(3), 2005: pp. 232-54.

Joyce, Ted, and Andrew Racine, “CHIP Shots: Association between the State Children's Health Insurance Programs and Immunization Rates,” *Pediatrics*, Vol. 115, No. 5, May 2005: pp. e526-e534.

Kaestner Robert, Ted Joyce, and Andrew Racine, “Medicaid Eligibility and the Incidence of Ambulatory Care Sensitive Hospitalizations for Children,” *Social Science & Medicine*, Volume 52, Issue 2, January 2001: pp. 305-313.

Kenney, Genevieve, and Justin Yee, “SCHIP At a Crossroads: Experiences To Date And Challenges Ahead,” *Health Affairs* 26, No. 2, 2007: pp. 356–369.

Kronebusch, Karl, and Brian Elbel, “Simplifying Children’s Medicaid and SCHIP,” *Health Affairs*, Vol. 23, No. 3, 2004: pp. 233-246.

Lave JR, Keane CR, Lin CJ, Ricci EM, Amersbach G, LaValle CP, “Impact of Children’s Health Insurance Program on Newly Enrolled Children,” *JAMA* 279, 1998.

Lo Sasso, Anthony T., and Thomas C. Buchmueller, “The Effect of the State Children’s Health Insurance Program on Health Insurance Coverage, *Journal of Health Economics*, Volume 23, Issue 5, 2004: pp. 1059-1082.

Newacheck, Paul, Jeffrey Stoddard, Dana Hughes, and Michelle Pearl, "Health Insurance and Access to Primary Care for Children," *New England Journal of Medicine*, Vol. 338, No. 8, 1998: pp. 513-519.

Perry, Cynthia D., and Genevieve M. Kenney, "Preventive Care for Children in Low-Income Families: How Well Do Medicaid and State Children's Health Insurance Programs Do?" *Pediatrics*, Vol. 120, No. 6, 2007: pp. e1393-e1401.

Selden, Thomas, and Julie Hudson, "Access to Care and Utilization Among Children," *Medical Care*, 44(5 suppl.), May 2006.

Selden, Thomas, Julie Hudson, and Jessica Banthin, "Tracking Changes in Eligibility and Coverage among Children, 1996–2002," *Health Affairs*, 23(5), 2004: pp. 39-50.

Shore-Sheppard, Lara, "Stemming the Tide? The Effect of Expanding Medicaid Eligibility on Health Insurance Coverage," *B.E. Journal of Economic Analysis and Policy*, Vol. 8, Issue 2, 2008.

Stevens, Gregory, Michael Seid, and Neal Halfon, "Enrolling Vulnerable, Uninsured but Eligible Children in Public Health Insurance: Association with Health Status and Primary Care Access," *Pediatrics*, Vol. 117, No. 4, April 2006.

Szilagyi, Peter, Andrew Dick, Jonathan Klein, Laura Shone, Jack Zwanziger, Alina Bajorska, and H. Lorrie Yoos, "Improved Asthma Care After Enrollment in the State Children's Health Insurance Program in New York," *Pediatrics* 117(2), 2006.

Wang, Hua, Edward C. Norton, and R. Gary Rozier, "Effects of the State Children's Health Insurance Program on Access to Dental Care and Use of Dental Services," *Health Service Research*, 2007.

Weissman JS, Gatsonis C, Epstein AM, "Rates of Avoidable Hospitalization by Insurance Status in Massachusetts and Maryland," JAMA, Vol. 268, 1992: 2388-2394.