The Effects of Medicaid Coverage on Children's

Health and Health Care Utilization

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Abstract

This paper analyzes the effects of Medicaid on children's health care utilization and health outcomes by utilizing remarkable expansions of Medicaid eligibility for low income children in the late 1980s and early 1990s using National Health Interview Surveys (NHIS). These Medicaid expansions provide a natural experiment in which insurance coverage varies in a way that is plausibly considered exogenous. The resulting instrumental variables (2SLS) models suggest that Medicaid coverage significantly increases the utilization of medical care by low-income children. Specifically, Medicaid is found to substantially decrease the probability of going without a visit to a doctor's office and significantly increase probability of hospitalization in the previous year. Increased Medicaid coverage is also associated with a significantly higher probability of going to a doctor's office than going to ER or hospital clinics. However, the estimation results provide no support for the hypothesis that Medicaid improves the health of low-income children.

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Introduction

Medicaid is the biggest health insurance program in the United States. Over 51 million people were enrolled in Medicaid at some time during 2002 (Holahan and Bruen 2003). Concerns over high rates of child morbidity and mortality and insufficiency of health insurance coverage for low-income children have led to a number of legislative changes that significantly expanded Medicaid eligibility in the late 1980s and early 1990s. These expansions doubled the fraction of children eligible for Medicaid between 1984 and 1992 (Currie and Gruber 1996a).

Historically, eligibility for Medicaid was contingent on eligibility for Aid to Families with Dependent Children (AFDC), that is, a person qualified for Medicaid and AFDC at the same time by having net income below a state's income eligibility limit. Therefore, eligibility was essentially limited to very low income women and children in single parent families. Starting in the mid-1980s, a series of federal legislations uncoupled Medicaid eligibility from eligibility for AFDC and substantially expanded the population eligible for Medicaid. By 1992, states were required to cover children under age 6 in families with incomes up to 133 percent of the federal poverty line, and all children under age 19 who were born after September 30, 1983 and whose family incomes were below 100 percent of the federal poverty level. States also had the option of covering infants up to 185 percent of the poverty line with federal matching dollars. The belief that increased health insurance coverage will increase utilization of medical services and improve the health of low-income children was the main motivating factor for these expansions. The expansions have transformed Medicaid from a narrowly targeted program for cash assistance recipients into a broad-based health insurance program for low-income children and pregnant women.

Expansions of Medicaid eligibility provide a natural experiment in which health insurance coverage varies in a way that is plausibly considered exogenous to health status and the same underlying factors that determine both health and consumption of medical care. This paper exploits this natural experiment and provides empirical evidence on how well Medicaid works in improving low-income children's health-care utilization and health outcomes using the National Health Interview Survey (NHIS) - a large, nationally representative data set.

This paper builds on Currie and Gruber (1996a) by estimating the relationship between Medicaid coverage and a number of health, health care access and use measures for children while controlling for selection into Medicaid. Unlike Currie and Gruber (1996a), I investigate the effects of Medicaid participation instead of Medicaid eligibility. Many eligible children actually fail to enroll in Medicaid. Therefore, studies like Currie and Gruber (1996a) that focus on the impact of Medicaid eligibility on health or utilization present only indirect evidence on the issue.

I first estimate the effects of Medicaid on children's medical care utilization. Consistent with the relevant literature, I find that Medicaid coverage is associated with substantially more medical care use. The point estimates from instrumental variables (2SLS) models are substantially larger than the original estimates of Currie and Gruber (1996a). Medicaid coverage decreases the probability of going without a doctor's visit in the previous year considerably. I also find that Medicaid coverage triples the likelihood of having had a visit in the last two weeks, and quintuples the probability of hospitalization in the previous year.

Secondly, I estimate the effects of Medicaid on the site of medical care and find that visits to a physician's office increase much more than visits to hospitals. Given that a doctor's office is generally considered to be the most efficient site of medical care, this finding suggests that there may be some efficiency gains produced by the Medicaid expansions.

Since the success of Medicaid should be evaluated not only by its effect on health-care utilization but also by its effect on children's health, I investigate the effect of Medicaid on various health measures available in the NHIS data. Unlike Currie and Gruber (1996a) who found sizeable and positive health effects of Medicaid in the aggregate data, the results of this paper do not provide any empirical evidence on the favorable effects of Medicaid coverage on children's individual health outcomes.

This paper proceeds as follows. Section I provides a summary of the relevant literature. Section II discusses Medicaid expansions that took place during this period. Section III describes the data and provides estimates of take-up of Medicaid among eligible children. Section IV describes the empirical specification. Section V presents the estimation results. Section VI concludes.

I. Literature Review

The majority of Medicaid studies concentrated on the relationship between Medicaid and access to and use of health care. A number of previous studies have looked at the relationship between healthcare utilization and insurance status. Early studies tended to use descriptive methods to compare the patterns of access and health-care use by different insurance groups (Wilensky and Berk 1982; Hayward et al. 1988; Himmelstein and Woolhandler 1995). Some more recent studies have utilized a multivariate framework to control for factors that may confound estimates of the effect of insurance status on access and use (Freeman and Corey 1993; Marquis and Long 1996; Berk and Schur 1998; Newacheck et al. 1998; Long and Marquis 1999). Such factors consist of socioeconomic characteristics, health status, and local health market conditions such as the price and availability of private health insurance. The common finding of the studies was that having insurance including Medicaid is associated with improved access to care and a significant increase in the utilization of health-care services relative to being uninsured. Several papers have shown that children who are uninsured have lower utilization levels, a less efficient distribution of utilization across sites of care, and poorer health outcomes (Kasper 1986; Short and Lefkowitz 1992).

Although these studies account for a variety of variables that may influence health status, health-care access and use, they have a fundamental limitation: They do not separate the effects of who enrolls in Medicaid from the effects of Medicaid itself. This is a shortcoming because health insurance status is not a random occurrence; in contrast, a range of reasons may motivate an individuals' selection to enroll or not enroll in Medicaid. If these motives also directly affect the individuals' health, health care access and use, then observed differences in health, access and use between Medicaid and those with private insurance and the uninsured may be due, in part, to unmeasured differences between the individuals who choose Medicaid compared with those who choose private insurance or being uninsured rather than the individual's actual insurance status, biasing the estimates of the effects of health insurance. Therefore, those studies are not able to ascertain a causal relationship between health insurance and health. Causation is difficult to establish because we never observe truly random variation in health insurance status.

For example, ceteris paribus, we possibly expect individuals with greater health care needs or strong preferences for health care to be both more likely to choose insurance over uninsurance and to utilize more health-care, regardless of their health insurance status. In the case of Medicaid, children in poor health are more likely to enroll in Medicaid and more likely to use more health care. Therefore, we expect Medicaid to be associated with bad health and more health care use. Other potential factors that might bias estimates of the impacts of Medicaid include proximity to and availability of health-care providers, financial barriers, prior experience with private insurers or public programs, difficulties and costs associated with enrolling in Medicaid, and stigma associated with participation in public programs.

The RAND Health Insurance Experiment is the only study that randomly allocated people to different insurance plans and examined the outcomes. An important finding was that people who had received free health care utilized about 40 percent more health services than those who had some cost sharing, but the results showed “little or no measurable effect on health status for the average adult.” (Newhouse 1993) That is, lower utilization did not translate into worse health outcomes. An important exception to this general finding is that lower utilization by poorer people, who faced large co-payments, did have a measurable and harmful effect on health. However, the randomized trial included too few children making it impossible to draw any strong conclusion regarding child health.

Several studies have attempted to deal with selection bias in estimating the impacts of health insurance on health and access to and use of care for children. Hanratty (1996) studied the effect of Canada's national health insurance program on health outcomes. Her results suggested that there was a significant reduction of 4% in the infant mortality rate as a result of national health insurance and a smaller reduction in low birth weight of about 1.3%.

Currie and Gruber (1996a), which looked at the effects of Medicaid expansions of eligibility for children, established that making a child eligible for Medicaid considerably increases his/her utilization of medical care, especially the care delivered in physician's offices. They also found that increases in eligibility at the state level are associated with significant reductions in child mortality. In a related paper, Currie and Gruber (1996b), which considered the effects of Medicaid expansions for pregnant women, found a weakly significant effect of the Medicaid on the incidence of low birth weight and a larger and significant effect on infant mortality. Their estimates suggested that a 30 percentage point increase in eligibility was associated with an 8.5% decline in state-level infant mortality rate. This paper builds on this literature, especially on Currie and Gruber (1996a) by estimating the relationship between Medicaid coverage and a number of health, health care access and use measures for children while controlling for selection into Medicaid. Currie and Gruber (1996a) studied the effect of Medicaid eligibility instead of Medicaid participation. One apparent reason for this choice was that information on Medicaid coverage was not available in the authors' data in all years. A second reason for concentrating on Medicaid eligibility is that eligibility is an important tool of public policy. Finally, eligibility is less likely to be affected by individual behavior and as a result less likely to be endogenous.

There are, however, a few shortcomings associated with using eligibility. Estimates of the effect of Medicaid eligibility measure the impact of the "intention to treat", and not the effect of "treatment on the treated." It is known that many eligible children fail to enroll in Medicaid.[2] Therefore, studies that focus on the impact of Medicaid eligibility on health can only provide indirect evidence on the subject.

Another concern associated with using Medicaid eligibility is that eligibility is measured with significant error. For example, Currie and Gruber (1996a) assigned eligibility based on reported annual income in the past year, but actual Medicaid eligibility is determined based on a family's current monthly income. Moreover, in National Health Interview Survey (NHIS), income is reported in brackets and missing for a large number of households. To assign eligibility, they selected a random point within the bracket and imputed missing income. Therefore, eligibility is likely to be imprecisely assigned. In my analysis, I calculated Medicaid eligibility for each child in my sample of the NHIS data using exactly the same procedure as in their paper and found out that about 20 percent of children who were reported to be covered by Medicaid were actually deemed to be ineligible by the eligibility calculations. In this case, eligibility among children from high-income families who are truly ineligible will be correctly assigned, as will eligibility among children from very low-income families who are truly eligible. In each case, measurement error in reported incomes will have little consequence for assignment because the reported income is so far above or below the eligibility threshold that it doesn't generally affect the assignment. On the other hand, there is a significant

[2] See Selden et al. (1998) for an analysis of low take-up of Medicaid.

probability that eligibility among near-poor families will be incorrectly assigned because of measurement error (Yazici and Kaestner 1998). Under these circumstances measurement error will be non-random and estimates of the effect of Medicaid obtained using such a measure are biased in an unknown direction.

Currie and Gruber (1996a) used an instrumental variables (IV) procedure to address the measurement error problem in eligibility. However, as Yazici and Kaestner (1998) has shown, using the instrument "simulated eligibility," which is the average eligibility of a national sample of children determined by applying that state's eligibility rules to the national sample does not solve the problem because the same measurement error is also present in the national sample since income is poorly measured for this sample. Moreover, the average measurement error in the national sample is likely to be correlated with the individual measurement error in Medicaid eligibility. This is because in states with a relatively low-income eligibility threshold, the expected individual measurement error is also small since most people in that state will have incomes above the threshold. Therefore, using "simulated eligibility" do not purge the measurement error problem in Medicaid eligibility because this error is likely to come from inaccuracies in the programs used to input eligibility for each child.

In this study, I examine the effect of Medicaid coverage rather than Medicaid eligibility on child health and health care utilization. I address the endogeneity problem associated with participation by using an instrumental variables (IV) procedure that exploits the significant variation across states and over time in the timing and implementation of Medicaid expansions. This is the same identification strategy and IV procedure used by Currie and Gruber (1996a) to correct for measurement error and other statistical problems associated with Medicaid eligibility. However, since the measurement error in Medicaid coverage stems primarily from random individual response error, my analysis does not suffer from the aforementioned measurement error problem in Currie and Gruber as the error in the Medicaid coverage variable will credibly be uncorrelated with the error in the instrument.

II. The Medicaid Expansions

Medicaid is a joint state-federal program financed by state contributions and federal matching funds. Medicaid participants consist of three groups: low-income aged and disabled people; the “medically needy” (people who have recently incurred considerable medical expenses); and low-income families with dependent children. In this paper, I focus entirely on the last group whose members were the target of these legislative changes. Traditionally, this group included families who received cash assistance through the AFDC program. Thus, Medicaid eligibility and participation were directly associated with the eligibility standards for AFDC. In general, to qualify for AFDC a family must have had either a single parent or an unemployed primary earner (to be eligible for the AFDC-UP program). The family’s income and assets also had to be below the state-established thresholds, most of which were much less than the federal poverty line.

Beginning in early 1980s, a series of federal law changes significantly weakened the link between Medicaid eligibility and AFDC eligibility by lowering the restrictions on two-parent families and those with earned income, extending Medicaid coverage to families with incomes above the AFDC thresholds. Deficit Reduction Act of 1984

(DEFRA '84) eliminated the family structure requirements for Medicaid eligibility of young children, by requiring states to cover children who lived in families that were income-eligible for AFDC. DEFRA was followed by a series of measures that raised the income cutoffs for Medicaid eligibility, first at state option, and then by federal mandate. By Omnibus Budget Reconciliation Acts (OBRA) of 1986 and 1987, Congress gave states the authority to raise the income limits for Medicaid coverage of certain groups (such as infants and very young children) above the AFDC level. OBRA 1989 required coverage of pregnant women and children up to age 6 with family incomes up to 133 percent of the federal poverty level, and OBRA 1990 required states to cover children born after September 30, 1983 with family incomes below 100 percent of the federal poverty level. Additional expansions within certain guidelines for age and family income were permitted at state option.

In summary, the expansions raised the eligibility threshold from the AFDC level to at least 100 percent of the poverty line for all children and possibly higher, depending on age and state of residence. Age plays an important role because eligibility standards for younger children were generally less restrictive, while state of residence is important as states had the option of exceeding the federal minimum eligibility limits. These legislations are documented in Appendix A. As described in great detail by Currie and Gruber (1996a), states took up these options at different rates, so that there was a considerable amount of variation in Medicaid eligibility thresholds by state, year, and age of child that can be used to identify the effects of the expansions.

III. Data and Sample Characteristics

The National Health Interview Survey (NHIS) is a large and nationally representative cross-sectional dataset. The core survey collects information about demographic characteristics, labor force attachment and family income. In the survey supplements, there are also a number of questions about the utilization of medical care over the previous two weeks and the previous year. For the years 1984, 1986, 1989, and 1992, the NHIS included a supplement on health insurance. For the years 1990 and 1991, the family resources supplement included information on Medicaid coverage.[3] Thus, for those six years, it is possible to link information about child health and health-care utilization to data on Medicaid coverage status. I cannot extend my analysis to cover more recent years because state identifiers are not available in the public use NHIS data for those years. I drop children with missing Medicaid coverage information from the data. My total sample size is 145,357, which include approximately 25,000 children of ages 0 to 14 per year.

To make the results directly comparable, I use the same measures of utilization as Currie and Gruber (1996a) in the NHIS data. At least one doctor's visit per year is recommended for children by pediatricians. Therefore, the lack of a doctor's visit in the previous year is indicative of a true health-care access problem. This is the first utilization measure used in the analysis. I examine two other measures of utilization in the NHIS data: the probability of having had a doctor's visit in the past two weeks; and the probability of having had a hospitalization in the past twelve months. The former is helpful in evaluating the extent that Medicaid affects not only the likelihood of any

[3] Note that the question about Medicaid coverage is not fully consistent over the years. For 1984, 1986, and 1989, the question asks whether the child was covered by Medicaid any one time during the last 12 months. For the other three years, the question asks whether the child was covered by Medicaid last month.

contact, but also the frequency of contacts; the latter is helpful in assessing whether Medicaid increases the utilization of health-care providers other than physicians.

There are concerns over the health-care utilization of the uninsured for two main reasons. Uninsured people are more likely to have low number of medical contacts. They are also more likely to have inefficiencies in their patterns of utilization. It is a common belief that people lacking health insurance are less likely to have a regular source of care and more likely to use hospital outpatient departments or emergency rooms. Concern over high rates of hospital use among the uninsured arises not only from the fact that hospital care is more expensive, but also from the issues about the quality of care received in those settings as opposed to a doctor's office.

The NHIS reports the site of care if a child had a visit in the last two weeks. To examine the efficiency with which medical care is delivered to Medicaid patients, as Currie and Gruber (1996a), I consider three different sites of care: the physician's office; a hospital emergency room or outpatient clinic; and other sites, mainly private or public clinics.

In order to assess the effects of Medicaid on child health, I use three different health measures available in the NHIS data. In the NHIS, parents rate their children's health as excellent, very good, good, fair, or poor. The first health measure used in the analysis is whether the child has been reported by in fair or poor health. It is well documented in the literature that for adults, a poor self-report of health is a strong predictor of mortality, even when controlling for physician assessed health status and health-related behaviors. Moreover, Case, Lubotsky, and Paxson (2002) show that self-reported health status is strongly correlated with children's chronic conditions, bed days, and hospitalization episodes. Two other measures I employ are whether the child has spent more than seven days in bed in the last twelve months, and whether the child is limited in any way in his or her daily activities.

The means of my NHIS sample are presented in Table 1. Across all years and ages, 14.6% of children in the NHIS sample were reported to be covered by Medicaid. As expected, compared to the whole sample, children covered by Medicaid are significantly poorer. They are more likely to be minorities, they tend to live in one-parent households, and they are also more likely to live in central cities. Their mothers are more likely to be high-school dropouts and less likely to be college graduates. Moreover, children covered by Medicaid are younger as the eligibility rules for Medicaid are less restrictive towards infants and children of age under 6.

As Table I shows, children covered by Medicaid are significantly more likely to be reported in fair or poor health. They are also more likely to have spent more than seven days in bed in the previous year and they have a higher probability of being reported having an activity limitation. In terms of health care utilization, children covered by Medicaid use more services in all three measures I employ in the analysis. They are less likely to go without a visit in the last year and they are twice more likely to have been hospitalized in the past year and they are also more likely to have visited a health-care provider in the last two weeks. If they had a visit in the last two weeks, they are equally likely to have visited a physician's office but they are much more likely to have visited an emergency room or other sites of care compared to other children.

Take-up of Medicaid

Using the same algorithm and detailed state Medicaid rules as in Currie and Gruber (1996a), I impute eligibility for each child in my sample of NHIS. Figure 1 shows the trends in Medicaid eligibility and coverage for children of all ages over the years 1984-1992. There was a remarkable increase in Medicaid eligibility over this period; eligibility doubled between 1984 and 1992, and almost one third of all children in the sample were eligible by the end of the period. Medicaid coverage did also increase, but not nearly as sharply as eligibility; slightly less than one fifth of all children were covered by Medicaid by 1992. Both eligibility and coverage went up between 1984 and 1986; they were more or less flat from 1984 to 1989, and rose sharply thereafter. Some of the increase came from DEFRA and other state law changes between 1984 and 1986, but the majority came from the expansions to higher income groups between 1989 and 1992.

Since eligibility rules for Medicaid were less restrictive towards infants and children of age six and under, Figure 1 masks the substantial heterogeneity in eligibility and coverage trends across age groups. Figure 2 presents these trends for select age groups. Since Medicaid rules were most generous towards infants, about one half of all infants in the sample were eligible and approximately one third were covered by Medicaid by the end of the period. Because age 6 was an important for cutoff for expansions following OBRA 1989, Medicaid eligibility trends were different for children of age 5 and 6. However, there was not a substantial difference for Medicaid coverage rates for these two groups of children, suggesting that take-up of newly available insurance coverage was much less than full.

For higher age groups, the effects of Medicaid expansions were lower in terms of both eligibility and enrollment. It is also observed that the coverage and eligibility rates are close to each other for older children. This is not surprising because as Card and Shore-Sheppard (2004) shows OBRA 1989 and OBRA 1990, which differentially affected younger and older children, were not very effective in increasing Medicaid coverage because of the extremely low take-up rates of the newly available coverage.

In addition to reporting eligibility and coverage trends, I also estimate Medicaid take-up rates in my NHIS sample. The results are presented in Table 2. The first column shows results from an OLS model. The increase in Medicaid coverage cannot be automatically attributed to changes in Medicaid rules. In order to control for the business cycle, as well as for observable non-policy related determinants of individual eligibility, I estimate models of Medicaid coverage that include year and state dummies, controls for race, gender, mother's education, family income, central city or rural residence, and child age. It is estimated that making a child eligible for Medicaid over the 1984 to 1992 period increased the probability that he or she was covered by Medicaid by about 21 percent.

The OLS regression may be subject to some remaining omitted variables bias. For instance, an economic downturn in a state in a particular year may cause both eligibility and coverage to rise at the same time. As in Currie and Gruber (1996a), I address this issue by instrumenting eligibility in the second column of Table 2. The instrument is named to be “simulated eligibility” by the authors and it measures legislative generosity of Medicaid policy in a given state in a given year, for each child's age group. This instrument is described in detail in the econometric specification part below. The crucial point is that instrumental variables methods purge the regression of bias due to unobserved individual-level characteristics as well as omitted variables such as economic conditions in a specific state and year.

The 2SLS model in the second column of Table 2 shows a slightly lower take-up rate of 18 percent. Currie and Gruber (1996a), who estimated take up rates from the Current Population Survey (CPS), found higher take-up rates of 30 percent for the OLS model and 23 percent for the 2SLS model. My results are relatively closer to more recent estimates of Medicaid take-up in the literature. For example, using a regression discontinuity approach, Card and Shore-Sheppard (2004) estimated take-up rates for newly available Medicaid coverage under OBRA 1990 expansion to be around 7% - 11%. Their estimated take-up rates for coverage under the OBRA 1989 expansion were even smaller - 5% or less.

Consequently, despite the fact that the Medicaid expansions doubled the fraction of children eligible for Medicaid over the 1984 and 1992 period, the growth in the number of children covered was considerably lower. This result suggests that take-up can be a significant barrier to the success of the Medicaid expansions. Nevertheless, the increase in Medicaid coverage rates is not trivial, and there is still the possibility that the expansions had a significant impact on children's health and health-care utilization. The remaining of this paper investigates this possibility.

IV. Econometric Specification

The starting point for my econometric analysis is the following linear probability model:

$$H_{ista} = \alpha + \beta_1 Mdcd_{ista} + \beta_2 X_{ista} + \gamma_s + \tau_t + AGE_i + \gamma_s * AGP_a + \tau_t * AGP_a + \varepsilon_i$$

where H_{ista} is a measure of health or health-care utilization for child *i* in state *s* in year *t*, at age a, $Mdcd_{ista}$ is an indicator of Medicaid coverage, the regressor of primary interest, X_{ista} is a set of control variables, γ_s, τ_t, and AGE_i are a full set of state, year, and age dummies, AGP_a is a dummy for being in one of five age groups: 0-1, 2-4, 5-7, 8-11, and 12-14, and ε_i is a random error term. In this equation, the coefficient of interest is β_1. It measures the effect of Medicaid coverage on health and health-care utilization of children.

In the main specification, I use the same control variables as in Currie and Gruber's (1996a), which include child's gender, race, ethnicity, whether he or she is the oldest child, the number of siblings, income, the absence of a male head, the education of the mother, whether the mother or father was the respondent, the presence of other relatives, and whether the family lives in a central city or rural area. I include a full set of age dummies to capture differences in Medicaid coverage for different age groups, year dummies to account for national trends in Medicaid coverage, state dummies to capture long-standing differences across states in economic conditions and health care market characteristics, such as the availability of a health care safety net.

A problem with ordinary least squares estimation of these models is that there are unobserved factors correlated with Medicaid coverage that are likely to affect individual's health and health-care utilization even after conditioning on a detailed set of controls. For example, children covered by Medicaid are poorer and more likely to live in areas underserved by medical providers. This will lead to a spurious negative correlation between Medicaid coverage and health care utilization. It is also possible that poor health, or having a child who is in poor health, decreases labor supply and income and, thus, increases the likelihood of Medicaid coverage. In addition, Medicaid coverage is measured with error in surveys because parents do not always report insurance coverage of all children accurately or they may confuse public insurance with private plans. Thus, regressions that do not correct for endogeneity and measurement error will generate biased estimates of the coefficients for Medicaid coverage.

To address this problem, I implement the instrumental variables strategy used in several previous studies in the literature on Medicaid expansions (Currie and Gruber, 1996a and 1996b; Cutler and Gruber, 1996; Ham and Shore-Sheppard, 2001). This approach instruments for Medicaid coverage using a "simulated eligibility" measure, which represents the fraction of a nationally representative sample of children that would be eligible for public insurance in each state in each year. Specifically, I draw a random national sample of 300 children of each age from 0 to 14 from the Current Population Survey (CPS),[4] and for each member of the random sample I impute eligibility in each state–year combination. Simulated eligibility measure is defined to be the average imputed eligibility for each state–year–age combination. This instrument is strongly correlated with Medicaid coverage variable; the first stage F statistic is approximately 80.

This IV approach, however, will not yield unbiased estimates if state decisions regarding how much to increase income eligibility limits through Medicaid were based on anticipated state-specific trends in children's health status, i.e., if there is a problem of

[4] I choose to calculate this from the CPS instead of the NHIS because, income is reported in brackets in the NHIS and it is missing for a number of households. In addition, we can distinguish sources of income in the CPS. This is preferable because some forms of income can be disregarded in calculating Medicaid eligibility.

policy endogeneity. To deal with the potential problem of policy endogeneity, the 2SLS models also contain a complete set of dummy variables for states, years, and each single year of age. Interactions between 4 age groups and calendar year and between the same 4 age groups and states are also included. These interactions are included to control for changes in the utilization patterns of different age groups over time, as well as for fixed differences across states in the utilization patterns of different age groups. Consequently, final identification arises from two sources: changes within states over time; and changes within state-age groups over time. Both of these sources of variation are credibly exogenous to changes in child health care utilization and health status. It is also reasonable to fully interact state and year dummy variables to control not only for time-invariant state-specific factors, but also for unobserved time-varying state-specific factors that could be correlated with Medicaid coverage. However, including these variables eliminates a large amount of the interesting legislative variation in the data. In earlier years of the sample, changes in state policy affected children of all ages. Therefore, if state and year interactions are included, this interesting variation would be lost.[5]

V. Regression Results

V.1. Results on health-care utilization

The results on health-care utilization are presented in Table 3. I have two different estimation results for both OLS and two stage least squares (2SLS) models for each utilization measure. For each measure, the first two columns contain all the control variables mentioned above. I include these control variables to make estimation results

[5]Nevertheless, I also run models that include state and year interactions. It turns out that the point estimates are similar to those presented below but the standard errors blow up.

directly comparable to Currie and Gruber (1996a). For the other two columns, I repeat the same analysis after dropping the following variables from the regressions: central city residence, rural residence, mom is high school dropout, mom has some college, child is oldest, number of siblings, father present, respondent is mother, respondent is father, male relative present, female relative present, and the income variables. These are potentially endogenous variables that may be causally influenced not only by variables included as controls in the regression but also by factors not included in the model. I prefer this latter specification over the first one.

The OLS estimation results in the first column suggest that Medicaid coverage decreases the probability of going without a visit in the previous year by 10 percentage points. The corresponding 2SLS model in column 2 implies that Medicaid coverage decreases the probability of going without a visit in the previous year by about 50 percentage points. This is an astonishing finding especially when compared to the baseline probability of having no visit in the last year, which is about 19 percent. When I drop the potentially endogenous variables and redo the analysis, as columns 3 and 4 show, the estimated effects diminish to approximately 5 and 40 percentage points for OLS and 2SLS models, respectively.

The estimation results illustrate a similar pattern on the probability of having had a visit in the last two weeks. OLS models in columns 5 and 7 suggest that Medicaid coverage increases the probability of having had a visit in the last two weeks by about 6 and 3 percentage points, respectively. The 2SLS models in column 6 and 8 imply that Medicaid coverage substantially increases the probability of a visit in the previous two weeks by about 43 and 32 percentage points. Compared to the baseline probability, this implies that Medicaid coverage approximately triples the likelihood of having had a visit in the last two weeks.

In terms of the likelihood of hospitalization, OLS models in columns 9 and 11 indicate that Medicaid coverage increases the probability of hospitalization in the previous year by the same 3 percentage points. The 2SLS models in column 10 and 12 imply that Medicaid coverage significantly increases the probability of hospitalization by about 29 and 20 percentage points. Compared to the baseline probability of hospitalization, this implies that Medicaid coverage is associated with a fivefold increase in the probability of hospitalization in the previous year.

Consequently, being covered by Medicaid has large and significant effects on the utilization of medical care. This conclusion emerges both from OLS models, and much more strongly from 2SLS models. The coefficient estimates from 2SLS models are five to ten times larger than Currie and Gruber's (1996a) original estimates of Medicaid eligibility on children's utilization of medical care. This suggests that their estimates were providing only indirect evidence on the utilization effects of Medicaid and take-up of Medicaid is indeed an important barrier to the effectiveness of Medicaid expansions.
One other important observation about the results is that 2SLS estimates are substantially larger than the corresponding OLS estimates. This may be due to the fact that instrumental variables analysis provides estimates of local average treatment effect (LATE), i.e., the average treatment effect for the subset of the treated population influenced by the Medicaid expansions instead of the average effect on the whole population, which is what OLS provides us. Since the instrument, simulated eligibility, affects a small segment of the population, the IV results may not be generalized to the

entire population. Nonetheless, the IV results are typically more important to policymakers because they are more interested in knowing the outcome of the treatment on population targeted by the policy.

The control variables in the regressions indicate some interesting differences in utilization patterns across demographic groups. Blacks and Hispanics are both more likely to go without a visit in the previous and they are less likely to have had a visit in the last two weeks. There are also apparent differences associated with mother's education. Children whose mothers are high school dropouts are less likely to have had any visits in the past year, and less likely to have had a visit in the past two weeks. On the contrary, mothers with some college education are more likely to take their children to the doctor. As expected, children whose family incomes are in the bottom part of the income distribution are far more likely to go without a visit in the previous and they are less likely to have had a visit in the last two weeks.

The regression estimates above show that while having Medicaid coverage reduced the probability of going without a visit; it also increased hospitalizations. This raises concerns that medical care is supplied inefficiently to Medicaid patients. The purpose of the next section is to empirically investigate the efficiency with which health care is provided to Medicaid patients.

V.2. Results on Site of Care

One rationale for increased hospitalization rates in response to the Medicaid expansions is that hospitals may be better prepared at screening eligible patients and helping them complete often lengthy and complex application forms. According to

United States General Accounting Office, a lot of hospitals have created special offices, or contract with private companies, to assist Medicaid eligible patients in completing the necessary steps in enrollment. Hospitals have strong incentives to do that because of the increasing costs of uncompensated care generated by people using emergency rooms and not paying for the services.

In order to assess whether the eligibility expansions increased visits to doctor's offices, arguably the most cost-effective site of care, I estimate models with the dependent variable equal to one if the child visited any one of the following three sites in the last two weeks: doctor’s office, ER or hospital outpatient clinic, and other sites of care. The estimation results are presented in Table 4. 2SLS models suggest that the probability of a visit to a doctor's office rises by 26 to 40 percentage points, which is about twice as large as the baseline probability. The corresponding OLS estimates are substantially lower but still positive and statistically significant.

As suggested by both OLS and 2SLS models, the probability of a visit to a hospital also rises but the magnitude of the increase is much smaller than that of the visits to a physician’s office. Moreover, 2SLS estimates for these measures are not statistically significant. While OLS models imply a statistically significant increase in visits to other care settings, 2SLS models shows a fall in visits to other sites but it is not statistically significant.

In conclusion, the fact that visits to a physician’s office increase much more than visits to hospitals and visits to a physician’s office is being the only site of care where IV estimation produces statistically significant results suggests that there may be some efficiency gains produced by the Medicaid expansions. However, the finding should be interpreted with some caution. Since I do not consider the underlying reason for the visit to a particular site; for some cases, it is life-saving and in fact much more efficient to go to ER instead of a doctor's office.

V.3. Results on Health

The effectiveness of Medicaid should be evaluated not only by its effect on utilization, but also by its effect on children's health. Relatively little is known about the effects of Medicaid on health outcomes. The RAND Health Insurance Experiment (RHIE), the only study that randomly allocated people to different insurance plans, provide little support for the hypothesis that increased utilization associated with greater health insurance coverage improves children's health

Currie and Gruber (1996a) used state-level aggregate data on child mortality from vital statistics to test whether Medicaid eligibility influences child health. They found that higher rates of Medicaid eligibility were associated with reduced child mortality, particularly for black children. Their analysis focuses on an objective measure of health, child mortality. The benefits of using an objective measure of health over more subjective measures are clear, but the use of child mortality is not ideal. Child mortality is a relatively rare incidence and the majority of child deaths are not medically preventable. In their case, random variation in aggregate child mortality may obscure the effect of changes in Medicaid eligibility that affects only a fraction of the aggregate population.

In order to assess the effects of Medicaid on child health, I use three different individual-level health measures available in the NHIS data. It is well documented in the literature that a poor self-report of health is a strong predictor of mortality for adults, even when controlling for physician assessed health status and health-related behaviors. Moreover, Case, Lubotsky, and Paxson (2002) show that self-reported health status is strongly correlated with children's chronic conditions, bed days, and hospitalization episodes. Accordingly, the first measure I utilize is whether the child has been reported in fair or poor health. The two other outcome variables I use are whether the child has spent more than seven days in bed in the last twelve months, and whether the child is limited in any way in his or her daily activities.

The estimation results are presented in Table 5. First of all, the results on the probability of being reported in fair and poor health show that OLS estimates, which do not control for selection into Medicaid, are indeed biased. They indicate that Medicaid causes worse health outcomes. The corresponding instrumental variables estimation results, which controls for selection bias, still do not show any significant or even positive effect of Medicaid coverage on children's reported health status. When I consider the two other measures of health, whether the child has spent more than seven days in bed in the last twelve months, and whether the child is limited in any way in his or her daily activities, I arrive at a similar conclusion. Both the OLS and IV estimates (although IV ones are not statistically significant) point to worse health outcomes associated with Medicaid coverage. The results suggest that increased health care access and use do not lead to better health. However, as the results of section V.1 suggest, Medicaid coverage greatly increased utilization of medical care. As those children have more contacts with doctors, they may learn about an underlying limitation or condition that they were previously unaware of. Therefore, those health measures are not ideal and better and more objective measures of health are needed.

Another explanation for the lack of positive health effect of Medicaid is that relating current child health to current insurance status may not be appropriate if health care does not have an immediate effect on child health. It is easy to imagine a situation where a previously uninsured child, who currently receives Medicaid, may be in poor health because the child's health had deteriorated during the period he was uninsured. Alternatively, we may examine whether there are long term benefits of health insurance. These could be quite substantial, especially among children since children obtain mostly preventive care, the effects of which can only be measured over the long run. In fact, long-term health effects of Medicaid is the subject of my current research.

V.4. Results on Health-care Utilization and Health by Race

African-American children are known to be in worse health and consume less medical care when compared with their white peers. One of the main objectives of Medicaid is to equalize access to health-care. In order to explore whether increases in Medicaid coverage have led to decreases in racial gaps in utilization and health, I re-estimate my models separately for black and non-black children. The utilization results are presented in Table 6. It is difficult to draw strong conclusions because the standard errors in 2SLS models are large and the estimates are not significantly different from each other for black and non-black children. Moreover, the relative magnitudes of point estimates change for the two different specifications of the 2SLS models.

The results on health outcomes are reported in Table 6. Although 2SLS estimates are again not statistically significant, taken at face value, the point estimates suggest that Medicaid coverage reduces the probability of being reported in poor or fair health among African-American children but not among white children.

VI. Conclusion

The implementation of a universal health-care plan in the United States is again at the center of politics before the presidential election. The uninsured are the focus of policy concern because health insurance is believed to contribute to better health by improving access to medical care. Literally, hundreds of studies show that the uninsured people have worse health outcomes than do the insured. Only a handful of these studies, however, are able to ascertain a *causal* relationship between health insurance and health. Causation is difficult to establish because we never observe truly random variation in health insurance status. Instead, people who have health insurance and people who do not presumably differ in many ways.

In this paper, I study the effects of public insurance coverage on health care utilization and health by exploiting dramatic expansions of Medicaid eligibility in the late 1980s and early 1990s for low-income children. These expansions of Medicaid eligibility represent a natural experiment in which insurance coverage varies in a way that is plausibly considered exogenous. I try to utilize the fact that some states expanded Medicaid eligibility more than others did and they did so at different times. The basic idea is that by correlating the magnitude and timing of the eligibility expansions with the magnitude and timing of changes in health outcomes and utilization patterns, it is possible to find out whether there is any causal effect of Medicaid on health and health-care utilization of children.

The resulting instrumental variables (2SLS) models suggest that children covered by Medicaid utilize substantially more medical care. They are far less likely to go without a visit to a doctor in the previous year and they are much more likely to have visited a service provider in the last two weeks and more likely to be hospitalized. The fact that visits to a physician's office increase substantially more than visits to hospitals and visits to a physician's office is being the only site of care where IV estimation produces statistically significant results suggests that there may be some efficiency gains produced by the Medicaid expansions.

The results of this paper, however, provide no support for the hypothesis that Medicaid improves the health of low-income children. There are a few caveats to this finding. The first is that the health measures I use are subjective and more detailed and more objective measures of health are needed. Another explanation for the lack of positive health effect of Medicaid is that relating current child health to current insurance status may not be appropriate if health care does not have an immediate effect on child health. It is easy to imagine a situation where a previously uninsured child, who currently receives Medicaid, may be in poor health because the child's health had deteriorated during the period he was uninsured. Alternatively, we can examine whether there are long term benefits of health insurance. These can be quite substantial, especially among children since children obtain mostly preventive care, the effects of which can only be measured over the long run. Long-term health effect of Medicaid is a direction for future research.

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Appendix

Summary of Federal Legislation Related to Medicaid Coverage for Pregnant Women, Infants, and Children, 1984-1992.

Deficit Reconciliation Act (DEFRA) 1984: Effective October 1, 1984.

Required: States must extend Medicaid coverage to children born after September 30, 1983, if those children lived in families that were income-eligible for AFDC.

Omnibus Budget Reconciliation Act (OBRA) 1986. Effective: April 1987.

Optional: States may raise the income eligibility threshold above AFDC levels to as high as the federal poverty level for pregnant women, infants, and children up to 5 years of age, even if the principal earner is employed. (Children may be phased in gradually.)

Omnibus Budget Reconciliation Act (OBRA) 1987. Effective: July 1988.

Required: States must cover all children under age 7 born after 9/30/83 who meet income and resource standards for AFDC, regardless of family structure.
Optional: States may raise income thresholds for pregnant women and infants to 185% of the federal poverty level. States may cover children under age 2, 3, 4, or 5 who were born after 9/30/83 with incomes below the Federal poverty level.

Medicare Catastrophic Coverage Act (MCCA) 1988. Effective: July 1989.

Required: States must cover pregnant women and infants with incomes less than or equal to 75% of the poverty level (it was to move to 100% by the following year, but was superseded by OBRA 1989)
Optional: States may cover children up to 8 years of age with incomes less than or equal to 75% of the poverty level.

Family Support Act (FSA) 1988. Effective: October 1990.

Required: States must extend Medicaid coverage to eligible 2-parent families where the principal earner is unemployed.

Omnibus Budget Reconciliation Act (OBRA) 1989. Effective: April 1990.

Required: States must cover pregnant women and children under age 6 with family incomes up to 133% of the Federal poverty level.

Omnibus Budget Reconciliation Act (OBRA) 1990. Effective: July 1991

Required: States must cover children under age 19 who were born after 9/30/83 whose family income level is below 100% of the poverty level. States must continue benefits for pregnant women until 2 months after the end of pregnancy, and for infants through the first year of life.

Figure 1

Medicaid Eligibility and Coverage Trends for All Ages, NHIS 1984-1992

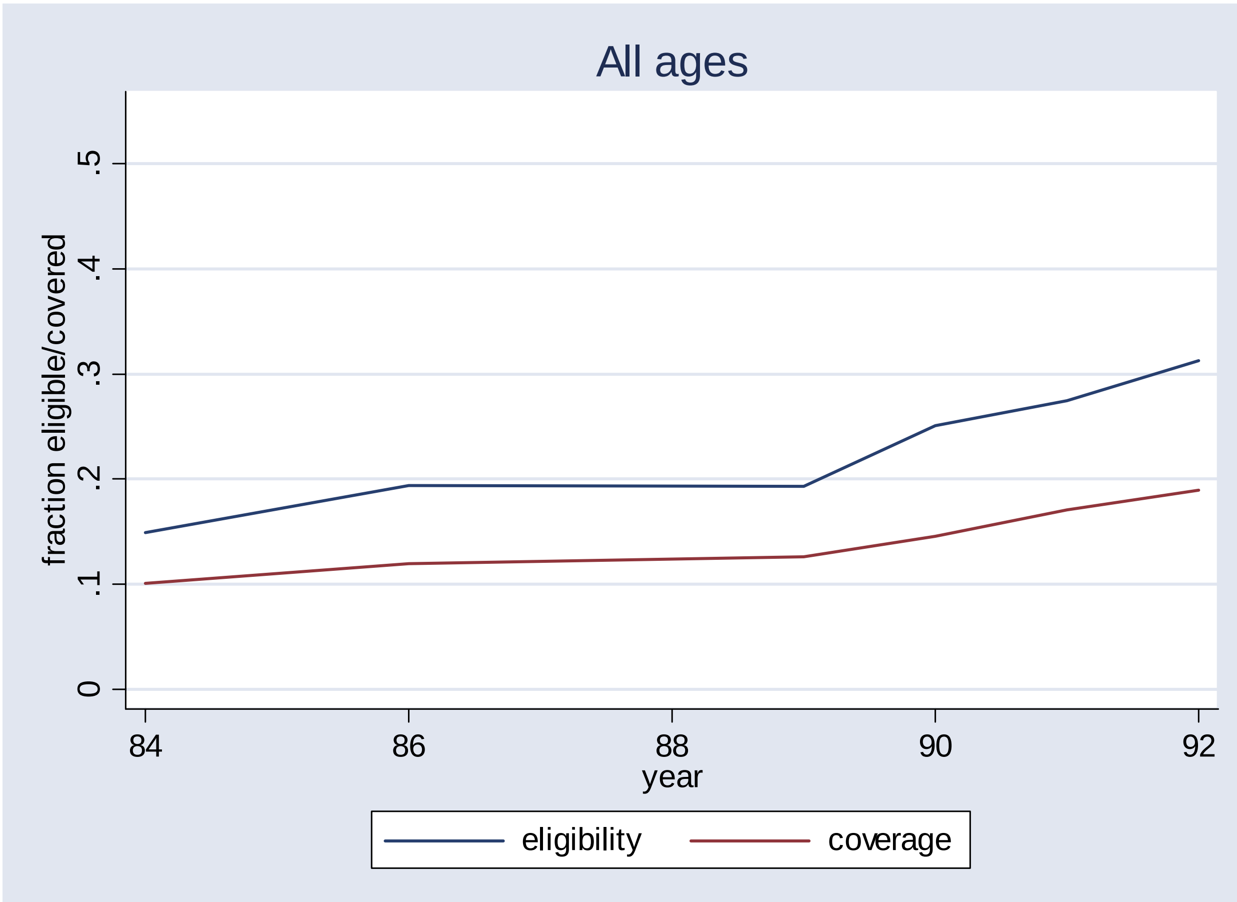

Figure 2

Medicaid Eligibility and Coverage Trends for Select Ages, NHIS 1984-1992

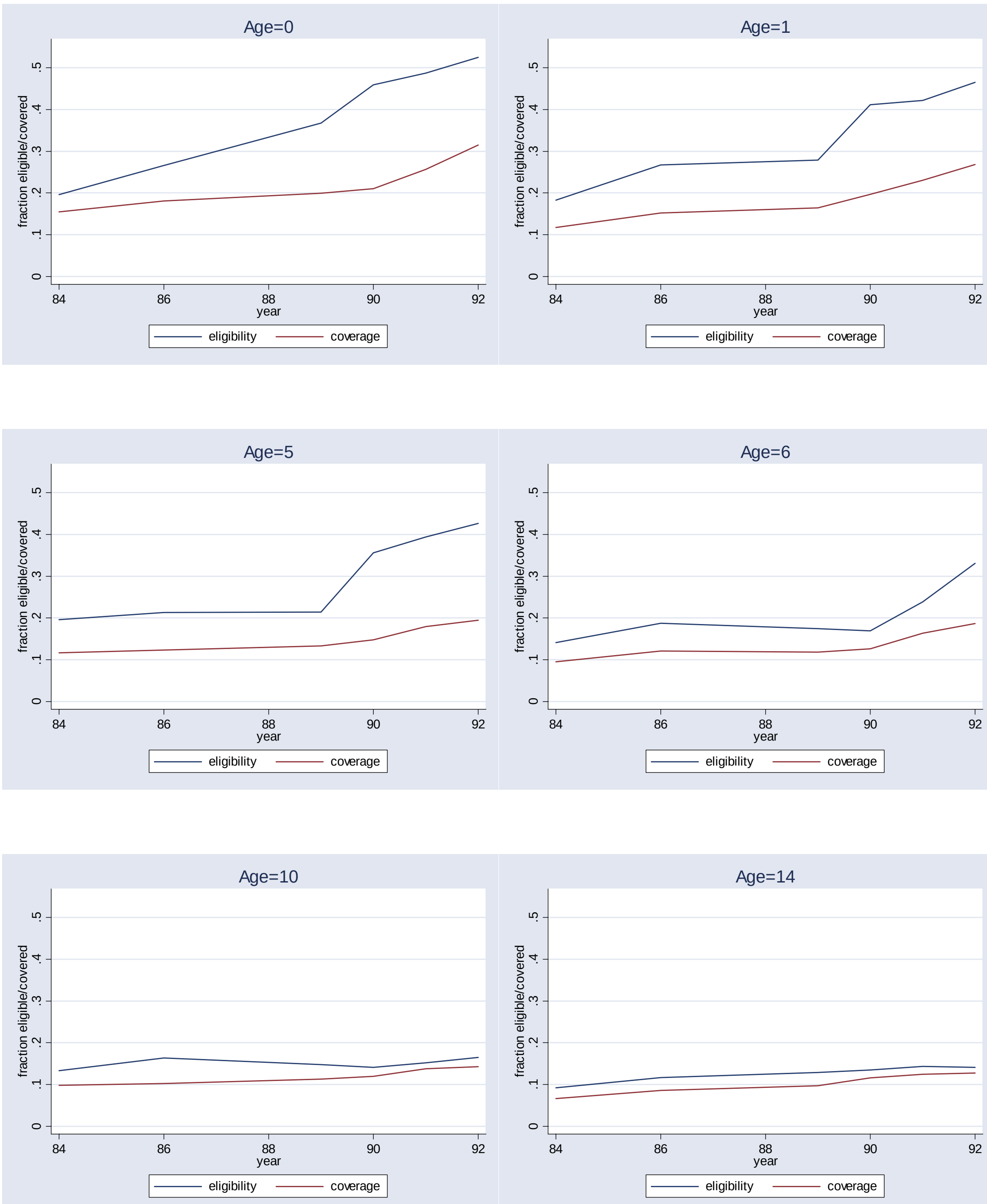

TABLE 1

NHIS SAMPLE MEANS

	All	Covered by Medicaid
Number of Observations	145357	21162
Fraction covered	0.146	1.000
	(0.001)	
Health-care Utilization		
No doctor's visits last 12 months	0.188	0.140
	(0.001)	(0.002)
Doctor's visit last 2 weeks	0.132	0.160
	(0.001)	(0.003)
Any hospitalization last 12 months	0.035	0.061
	(0.000)	(0.002)
Visit to doctor's office last 2 weeks	0.087	0.089
	(0.001)	(0.002)
Visit to ER or hospital clinic last 2 weeks	0.017	0.033
	(0.000)	(0.001)
Visit to other site of care last 2 weeks	0.012	0.026
	(0.000)	(0.001)
Health Measures		
Reported to be in fair or poor health	0.027	0.062
	(0.000)	(0.002)
Bad days greater than 7 last 12 months	0.080	0.095
	(0.001)	(0.002)
Any activity limitation	5.17	9.23
	(0.059)	(0.079)
Individual Characteristics		
Male	0.513	0.504
	(0.001)	(0.003)
Black	0.176	0.418
	(0.001)	(0.003)
Hispanic	0.128	0.203
	(0.001)	(0.003)
Age	6.883	5.855
	(0.011)	(0.030)
Central City	0.310	0.524
	(0.001)	(0.003)
Rural	0.247	0.215
	(0.001)	(0.003)

TABLE 1, Continued

NHIS SAMPLE MEANS

	All	Covered by Medicaid
Family Characteristics		
Mom is high school dropout	0.186	0.448
	(0.001)	(0.003)
Mom has some college	0.382	0.125
	(0.001)	(0.002)
Child is oldest	0.539	0.466
	(0.001)	(0.003)
Number of siblings	1.313	1.722
	(0.003)	(0.009)
Male head present	0.779	0.393
	(0.001)	(0.003)
Mom is respondent	0.302	0.699
	(0.001)	(0.003)
Other female relatives present	0.026	0.042
	(0.000)	(0.001)
Other male relatives present	0.024	0.028
	(0.000)	(0.001)
Family income<$10,000	0.090	0.363
	(0.001)	(0.003)
$10,000<income<$20,000	0.141	0.356
	(0.001)	(0.003)
$20,000<income<$30,000	0.131	0.149
	(0.001)	(0.002)
$30,000<income<$40,000	0.119	0.055
	(0.001)	(0.002)
$40,000<income<$50,000	0.105	0.029
	(0.001)	(0.001)
Family income> $50,000	0.413	0.047
	(0.001)	(0.001)

Author's own tabulation of the NHIS data. Standard errors are given in parentheses.

TABLE 2

TAKE-UP OF MEDICAID ELIGIBILITY

LINEAR PROBABILTY MODELS: COEFFICIENTS *100

Dependent Variable: Medicaid Coverage

	(1) OLS	(2) 2SLS
Medicaid Eligibility	20.99	18.76
	(0.274)	(0.015)
Male	-0.26	-0.27
	(0.148)	(0.148)
Black	8.80	8.84
	(0.228)	(0.230)
Hispanic	-1.12	-1.02
	(0.256)	(0.264)
Mom is high school dropout	7.17	7.29
	(0.217)	(0.233)
Mom has some college	-1.32	-1.32
	(0.173)	(0.173)
income<$10,000	32.64	34.76
	(0.407)	(1.438)
$10,000<income<$20,000	20.03	21.31
	(0.303)	(0.884)
$20,000<income<$30,000	7.13	7.90
	(0.269)	(0.569)
$30,000<income<$40,000	2.10	2.55
	(0.261)	(0.392)
$40,000<income<$50,000	1.65	1.89
	(0.263)	(0.303)
Central City	3.52	3.54
	(0.190)	(0.191)
Rural	0.13	0.12
	(0.210)	(0.210)
R^2	0.3642	
Number of Observations	145357	145357

Standard errors are in parentheses. All regressions also include an intercept, a full set of age, state, and year dummies

In the 2SLS model Medicaid eligibility is instrumented using simulated eligibility

Simulated eligibility is calculated using CPS, and matched to individulas by state, year, and age.

TABLE 3
UTILIZATION OF MEDICAL CARE AND MEDICAID

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	No visit last 12 months				Any visit last 2 weeks				Hospitalization last 12 months			
Medicaid coverage	-0.106*	-0.511+	-0.046*	-0.394+	0.057*	0.433+	0.033*	0.323**	0.029*	0.292**	0.029*	0.206**
	(0.006)	(0.302)	(0.005)	(0.222)	(0.004)	(0.223)	(0.004)	(0.154)	(0.003)	(0.135)	(0.002)	(0.089)
Male	-0.001	-0.002	-0.002	-0.004	0.010*	0.010*	0.010*	0.011*	0.009*	0.009*	0.009*	0.009*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Black	0.043*	0.067*	0.060*	0.153**	-0.042*	-0.064*	-0.050*	-0.128*	-0.007*	-0.022*	-0.008*	-0.055**
	(0.005)	(0.018)	(0.006)	(0.059)	(0.003)	(0.014)	(0.003)	(0.042)	(0.002)	(0.008)	(0.002)	(0.024)
Hispanic	0.016*	0.013+	0.062*	0.106*	-0.011*	-0.009+	-0.032*	-0.069*	0.001	0.002	-0.002	-0.024**
	(0.006)	(0.007)	(0.007)	(0.029)	(0.003)	(0.005)	(0.004)	(0.020)	(0.002)	(0.003)	(0.002)	(0.012)
Central city residence	-0.005	0.009			-0.002	-0.015+			-0.002+	-0.011**		
	(0.004)	(0.011)			(0.003)	(0.008)			(0.001)	(0.005)		
Rural residence	0.026*	0.029*			-0.011*	-0.014*			0.007*	0.006*		
	(0.004)	(0.005)			(0.003)	(0.003)			(0.002)	(0.002)		
Mom is high school dropout	0.031*	0.062*			-0.017*	-0.046*			0.001	-0.021**		
	(0.004)	(0.023)			(0.003)	(0.017)			(0.001)	(0.010)		
Mom has some college	-0.031*	-0.041*			0.012*	0.022*			-0.002	0.005		
	(0.003)	(0.008)			(0.003)	(0.006)			(0.001)	(0.004)		
Child is oldest	-0.021*	-0.014**			0.011*	0.004			-0.001	-0.006**		
	(0.002)	(0.006)			(0.002)	(0.005)			(0.001)	(0.003)		
Number of siblings	0.018*	0.030*			-0.010*	-0.021*			-0.002*	-0.010**		
	(0.002)	(0.009)			(0.001)	(0.007)			(0.001)	(0.004)		
Father present	0.023*	-0.027			-0.012**	0.035			0.001	0.033+		
	(0.006)	(0.039)			(0.005)	(0.029)			(0.003)	(0.017)		
Respondent is mother	0.012	0.071			0.005	-0.05			-0.007	-0.046**		
	(0.011)	(0.046)			(0.007)	(0.035)			(0.005)	(0.021)		
Respondent is father	0.024**	0.074+			0.002	-0.044			-0.011+	-0.043**		

TABLE 3, Continued

UTILIZATION OF MEDICAL CARE AND MEDICAID

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	No visit last 12 months				Any visit last 2 weeks				Hospitalization last 12 months			
male relative present	0.037*	0.023+			-0.016*	-0.003			-0.008**	0.002		
	(0.008)	(0.013)			(0.005)	(0.010)			(0.003)	(0.007)		
female relative present	0.008	0.005			-0.01	-0.007			-0.001	0.002		
	(0.008)	(0.009)			(0.006)	(0.007)			(0.003)	(0.004)		
0<family income<10K	0.091*	0.267**			-0.031*	-0.195**			-0.002	-0.116**		
	(0.006)	(0.133)			(0.005)	(0.098)			(0.003)	(0.059)		
10K<family income<20K	0.071*	0.177**			-0.025*	-0.122**			-0.002	-0.071+		
	(0.005)	(0.080)			(0.004)	(0.060)			(0.002)	(0.036)		
20K<family income<30K	0.060*	0.105*			-0.018*	-0.061**			-0.002	-0.031+		
	(0.005)	(0.035)			(0.003)	(0.026)			(0.002)	(0.016)		
30K<family income<40K	0.035*	0.054*			-0.016*	-0.033*			0.002	-0.01		
	(0.004)	(0.015)			(0.003)	(0.011)			(0.002)	(0.007)		
40K<family income<50K	0.028*	0.039*			-0.009**	-0.019*			0.004**	-0.003		
	(0.004)	(0.009)			(0.004)	(0.007)			(0.002)	(0.004)		
Full Controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No
Observations	145357											

+ significant at 10%; ** significant at 5%; * significant at 1%

Standard errors in parentheses. They are clustered by state. All regressions also include an intercept, dummy variables for each state, year,

and single year of age, season dummies, interactions between year and year of age dummies and interactions between year of age and state dummies.

In 2SLS models Medicaid coverage is instrumented using simulated eligibility calculated from CPS, and matched to individuals by state, year, and age.

TABLE 4

SITE OF MEDICAL CARE AND MEDICAID

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	Doctor's office				ER or hospital outpatient clinic				Other site			
Medicaid coverage	0.033**	0.415*	0.007**	0.262*	0.013**	0.087	0.017*	0.076	0.010**	-0.108	0.013*	-0.066
	(0.003)	(0.207)	(0.003)	(0.133)	(0.001)	(0.076)	(0.001)	(0.055)	(0.001)	(0.081)	(0.001)	(0.056)
Mean of dependent variable	0.087	0.087	0.087	0.087	0.017	0.017	0.017	0.017	0.012	0.012	0.012	0.012
# Observations	145357	145357	145357	145357	145357	145357	145357	145357	145357	145357	145357	145357
Full controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No

+ significant at 10%; ** significant at 5%; * significant at 1%

Standard errors in parentheses. They are clustered by state.

All regressions also include all the corresponding variables listed in Table III, as well as an intercept, dummy variables for each state, year,

and, single year of age, season dummies, interactions between year and year of age dummies and interactions between year of age and state dummies.

In 2SLS models Medicaid coverage is instrumented using simulated eligibility calculated from CPS, and matched to individuals by state, year, and age.

TABLE 5

HEALTH MEASURES AND MEDICAID

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	Reported to be in poor or fair health				Bad days greater than 7 last 12 months				Any activity limitation			
Medicaid coverage	0.020**	-0.009	0.037*	0.019	0.027**	0.197	0.028*	0.159	0.047**	0.163	0.058**	0.140
	(0.001)	(0.123)	(0.002)	(0.082)	(0.003)	(0.167)	(0.003)	(0.121)	(0.004)	(0.146)	(0.004)	(0.102)
Mean of dependent variable	0.027	0.027	0.027	0.027	0.080	0.080	0.080	0.080	0.052	0.052	0.052	0.052
# Observations	145357	145357	145357	145357	145357	145357	145357	145357	145357	145357	145357	145357
Full controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No

+ significant at 10%; ** significant at 5%; * significant at 1%

Standard errors in parentheses. They are clustered by state.

All regressions also include all the corresponding variables listed in Table III, as well as an intercept, dummy variables for each state, year,

and, single year of age, season dummies, interactions between year and year of age dummies and interactions between year of age and state dummies.

In 2SLS models Medicaid coverage is instrumented using simulated eligibility calculated from CPS, and matched to individuals by state, year, and age.

TABLE 6

UTILIZATION OF MEDICAL CARE AND MEDICAID BY RACE

BLACK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	No visit last 12 months				Any visit last 2 weeks				Hospitalization last 12 months			
Medicaid coverage	-0.090**	-0.816	-0.053**	-0.344	0.035**	0.587	0.024**	0.283	0.010**	0.259	0.022**	0.122
	(0.006)	(0.917)	(0.009)	(0.360)	(0.005)	(0.637)	(0.005)	(0.238)	(0.003)	(0.371)	(0.003)	(0.141)
Mean of dependent variable	0.225	0.225	0.225	0.225	0.100	0.100	0.100	0.100	0.036	0.036	0.036	0.036
# Observations	25580	25580	25580	25580	25580	25580	25580	25580	25580	25580	25580	25580
Full controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No

NON-BLACK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Medicaid coverage	-0.108**	-0.507	-0.039**	-0.403	0.068**	0.474	0.038**	0.373	0.027**	0.338*	0.032**	0.269*
	(0.004)	(0.360)	(0.005)	(0.300)	(0.004)	(0.299)	(0.004)	(0.237)	(0.002)	(0.172)	(0.003)	(0.122)
Mean of dependent variable	0.180	0.180	0.180	0.180	0.138	0.138	0.138	0.138	0.035	0.035	0.035	0.035
# Observations	119777	119777	119777	119777	119777	119777	119777	119777	119777	119777	119777	119777
Full controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No

+ significant at 10%; ** significant at 5%; * significant at 1%

Standard errors in parentheses. They are clustered by state.

All regresions also include all the corresponding variables listed in Table III, as well as an intercept, dummy variables for each state, year,

and year of age, season dummies, interactions beetween year and year of age dummies and interactions between year of age and state dummies.

In 2SLS models medicaid coverage is instrumented using simulated eligibility calculated from CPS, and matched to individuals by state, year, and age.

TABLE 7

HEALTH MEASURES AND MEDICAID

BLACK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
Dependent variable	Reported to be in poor or fair health				Bad days greater than 7 last 12 months				Any activity limitation			
Medicaid coverage	0.014**	-0.123	0.033**	-0.008	0.018**	0.574	0.020**	0.277	0.038**	0.051	0.047**	0.060
	(0.003)	(0.415)	(0.004)	(0.175)	(0.005)	(0.592)	(0.004)	(0.206)	(0.005)	(0.361)	(0.004)	(0.158)
Mean of dependent variable	0.046	0.046	0.225	0.046	0.064	0.064	0.100	0.064	0.036	0.036	0.036	0.036
# Observations	25580	25580	25580	25580	25580	25580	25580	25580	25580	25580	25580	25580
Full controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No

NON-BLACK

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Medicaid coverage	0.023**	0.008	0.039**	0.018	0.030**	0.141	0.031**	0.135	0.052**	0.229	0.063**	0.184
	(0.002)	(0.139)	(0.003)	(0.098)	(0.004)	(0.221)	(0.004)	(0.182)	(0.005)	(0.218)	(0.005)	(0.163)
Mean of dependent variable	0.022	0.022	0.180	0.022	0.083	0.083	0.138	0.083	0.035	0.035	0.035	0.035
# Observations	119777	119777	119777	119777	119777	119777	119777	119777	119777	119777	119777	119777
Full controls	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No

+ significant at 10%; ** significant at 5%; * significant at 1%

Standard errors in parentheses. They are clustered by state.

All regressions also include all the corresponding variables listed in Table III, as well as an intercept, dummy variables for each state, year,

and single year of age, season dummies, interactions between year and year of age dummies and interactions between year of age and state dummies.

In 2SLS models Medicaid coverage is instrumented using simulated eligibility calculated from CPS, and matched to individuals by state, year, and age.