DOES PUBLICLY PROVIDED HEALTH INSURANCE IMPROVE THE HEALTH OF LOW-INCOME CHILDREN IN THE UNITED STATES?

Robert Kaestner
Theodore Joyce
Andrew Racine

Working Paper 6887
http://www.nber.org/papers/w6887

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
January 1999

The authors thank Lisa Dubay, Michael Grossman, Jeannette Rogowski, and seminar participatns at the Urban Institute of Medicine and Dentistry for their helpful suggestions. The views expressed here are those of the author and do not reflect those of the National Bureau of Economic Research.

Does Publicly Provided Health Insurance Improve
the Health of Low-Income Children in the United States?
Robert Kaestner, Theodore Joyce, and Andrew Racine
NBER Working Paper No. 6887
January 1999
JEL No. I12, I18

ABSTRACT

In this study we analyze the effect of Medicaid on children's heath. We examine the effect of Medicaid on a variety of health outcomes using two data sources: the National Health Interview Surveys (NHIS) and the Nationwide Inpatient Sample (NIS) of hospital discharges. Using the NHIS, we examine the effect of Medicaid participation on maternal ratings of child health and maternal reports of the number of bed days in the past year (i.e. morbidity). The NIS data was used to examine the effect of Medicaid program expansions on the incidence of ambulatory care sensitive (ACS) discharges. ACS discharges are known to be sensitive to medical intervention and are objective measures of children's health. The results of this paper provide at best weak support for the hypothesis that Medicaid improves the health of low-income children.

Robert Kaestner
NBER
50 East 42nd Street, 17th Floor
New York, NY 10017-5405
Robert_Kaestner@baruch.cuny.edu

Theodore Joyce
NBER
50 East 42nd Street, 17th Floor
New York, NY 10017-5405
Ted_Joyce@baruch.cuny.edu

Andrew Racine
NBER
50 East 42nd Street, 17th Floor
New York, NY 10017-5405
aracine@email.gc.cuny.edu

I. Introduction

Conventional wisdom holds that expansion of publicly provided health insurance is an effective means of improving the health of children from low-income families. The Balanced Budget Act of 1997 included a $24.3 billion block grant to states to extend health insurance coverage to uninsured children from families with incomes up to 200 percent of the federal poverty level. This most recent expansion in publicly provided health insurance comes on the heels of expansions in the traditional Medicaid program that began in the latter part of the 1980s and which continues to affect children today. Motivating this legislation is a belief that expanded health insurance coverage will increase utilization of medical services and improve the health of low-income children.

The Medicaid expansions have been effective in terms of enrollment. Between 1986 and 1994, there was a 71 percent increase in the number of children enrolled in the program and a 107 percent real increase in Medicaid spending for children. Overall, the expansions in Medicaid eligibility constitute the largest expansion of public health insurance coverage for children since the original introduction of the Medicaid program. Yet, there is surprisingly little empirical evidence of Medicaid's effectiveness in improving the health of children from poor and near-poor families. The majority of Medicaid related studies have focused on the relationship between Medicaid and health care utilization.[1] Implicit in this approach is the presumption that better access and increased utilization will improve health. However, there is only limited evidence to support this proposition. Findings from the RAND Health Insurance Experiment (RHIE), probably the most credible study to date of the effect of health insurance on health outcomes, provide little support for the hypothesis that increased utilization associated with greater health insurance coverage improves children's health (Newhouse 1993).

The purpose of this study is to provide evidence of the effect of Medicaid on children's health. A primary motivation for this study is the belief that the effectiveness of Medicaid should be evaluated not only by its effect on utilization, but also by its effect on children's health. As noted, relatively little is known about the effects of Medicaid on health outcomes. Remarkably, there is only one study of the effect of Medicaid on children's health,

[1] See the studies by Newachek et al. (1997), Long and Marquis (1996), Currie and Thomas (1995) and St. Peter et al. (1992) for more on the effect of Medicaid on health care utilization.

although several studies have examined the effect of Medicaid on birth outcomes. Findings from studies of Medicaid's affect on infant health are inconclusive, and more importantly, may not be applicable to child health. There is a growing literature suggesting that medical care (e.g., prenatal care) has a relatively minor effect on birth outcomes since the clinical scope of such an intervention is limited.[2] Thus, there is little direct evidence of the effect of Medicaid on children's health, and the important developmental consequences of child health and magnitude of the expenditures on Medicaid invite additional study.

In this study we undertake an extensive analysis of the effect of Medicaid on children's health. We examine the effect of Medicaid on a variety of health outcomes using two data sources. Specifically, we use a nationally representative sample of children from the National Health Interview Surveys (NHIS) to examine the effect of Medicaid participation on maternal ratings of child health and maternal reports of the number of bed days in the past year (i.e., morbidity). The advantage of the NHIS is that it is nationally representative and has been used in the past to study similar issues. Thus, we link our research to prior studies of the effect of Medicaid on health care utilization and health outcomes. We extend this line of research, however, by addressing several empirical weaknesses in past analyses. A unique contribution of our study is the analysis of hospital discharge data for a sample of hospitals in eleven states. We examine the effect of Medicaid program expansions on the incidence of ambulatory care sensitive (ACS) discharges. ACS discharges are known to be sensitive to medical intervention and are objective measures of children's health.

II. Review of Previous Research

Only one study has examined the effect of Medicaid on children's health. Currie and Gruber (1995, 1996) used individual-level data from the National Health Interview Surveys (NHIS) and state-level aggregate data on child mortality from vital statistics to test whether Medicaid eligibility affects child health. The authors found that being

[2] See Guyer (1990), Huntington and Connell (1994), and Alexander and Korenbrot (1995) for a discussion of the role of prenatal care in affecting infant health.

eligible for Medicaid had either no effect or a negative effect on a mother's evaluation of her child's health (e.g., activity limitations), but that greater Medicaid eligibility reduced child mortality, particularly for black children. The authors attribute the differences in results to the fact that the individual-level data contain only subjective measures of child health.

It is noteworthy that Currie and Gruber (1996) found a significant effect in the aggregate data, but not the individual-level data since Medicaid affects only a fraction of the aggregate population. Random variation in aggregate child mortality will tend to obscure the effect of changes in Medicaid eligibility that affects only a small portion of the aggregate population. In addition, the reported estimates of Currie and Gruber (1996) are implausibly large. Currie and Gruber (1996) calculated that a ten-percentage point increase in the number of eligible children would increase the number of children who participate in Medicaid by 1,293,194 and reduce the number of child deaths by 727 (Currie and Gruber, 1996 p. 455). This implies a reduction of 5.6 deaths per 10,000 children, or a 147 percent decrease in child mortality among children affected by the Medicaid expansions. An effect of this magnitude is implausible given that sixty four percent of all deaths to children between the ages of one and fifteen are due to four causes—unintentional injuries, congenital anomalies, malignant neoplasms and homicide—that do not lend themselves to medical interventions (U.S. Department of Health and Human Services 1996).

There are two aspects of the Currie and Gruber (1995, 1996) study that are particularly important in the context of our study. First, 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 infrequent occurrence and the majority of child deaths are not medically preventable. In this paper, we use both objective and subjective measures of health. An advantage of the objective measures we employ, however, is that they are known to be sensitive to medical interventions. Specifically, we use hospital discharge data to construct measures of health defined by the incidence of ambulatory care sensitive (ACS) conditions resulting in hospital admission. Examples of ACS conditions relevant to children are asthma, pneumonia, convulsions and dehydration. ACS conditions are treatable in an ambulatory care setting and therefore should not result in hospitalization unless adequate care was not obtained.

A second aspect of the Currie and Gruber (1995, 1996) study is that they focus on the effect of Medicaid eligibility as opposed to Medicaid participation. One obvious reason for this choice is that information on participation was not uniformly available in the authors' data. A second argument for focusing on eligibility is that eligibility is an important instrument of public policy. Finally, eligibility is less likely to reflect behavioral outcomes and therefore less likely to be endogenous. There are, however, disadvantages associated with using eligibility. Estimates of the effect of Medicaid eligibility measure the effect of the "intention to treat", and not the effect of "treatment on the treated." The effect of "treatment on the treated," however, is a parameter of particular importance to policymakers that has not been previously estimated. We disagree with the often made argument that the only policy lever available is eligibility since policymakers can implement programs designed to enhance Medicaid enrollment without altering eligibility (e.g., presumptive eligibility), or can implement programs aimed at improving care without altering enrollment (e.g., Healthy Start). Therefore, knowledge of the effect of Medicaid participation on health is critical, as is knowledge of what determines participation. Studies that focus on the effect of Medicaid eligibility on health provide only indirect evidence about these two separate questions.

A second problem associated with using Medicaid eligibility is that eligibility is measured with significant error. For example, Currie and Gruber (1995) assign eligibility based on reported annual income in the past year, but actual Medicaid eligibility is determined based on a family's current monthly income. As a result, eligibility is often incorrectly assigned. Yazici (1997) shows that between 20 and 25 percent of a sample of low-income women in either the National Maternal and Infant Health Survey (NMIHS) or the Current Population Survey (CPS) reported that Medicaid covers them even though their annual income is greater than the eligibility threshold. This result suggests that measurement error associated with Medicaid eligibility is non-random. Eligibility among high-income families who are truly ineligible will be correctly assigned, as will eligibility among very low-income families who are truly eligible. In each case, measurement error in reported incomes will have little consequence for assignment because the (mis) reported income is so far above or below the eligibility threshold that it doesn't often affect the assignment. On the other hand, there is a significant probability that eligibility among near-poor families will be incorrectly assigned because of measurement error (Yazici 1997). 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. Measurement error in eligibility also eliminates the exogeneity advantage associated with eligibility, as noted by Currie and Gruber (1996), who use an instrumental variables procedure to address this problem.

In this study, we examine the effect of both Medicaid participation and eligibility on child health. While we would prefer to focus on the effects of participation, since this is a parameter that has not been previously estimated, data constraints force us to examine both eligibility and participation. The hospital discharge data we employ does not provide reliable information on health insurance status and only limited information about patient income that can be used to assign eligibility. Thus, in analyses that use these data we focus on eligibility. However, we also use selected years of the National Health Interview Survey (NHIS) that include information about Medicaid and health insurance participation. Therefore in analyses that use the NHIS we examine the effect of Medicaid participation on child health. We 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. Note that Currie and Gruber (1996) use a similar identification strategy and IV procedure to correct for measurement error and other statistical problems associated with Medicaid eligibility.

III. Analysis of the NHIS Data and the Effect of Medicaid Participation on Child Health

The first analysis we present uses data from the 1989 and 1992 National Health Interview Surveys. In this analysis we examine the effect of Medicaid participation and private health insurance coverage on the health of a nationally representative sample of low-income children between the ages of two and nine.

A. Empirical Model

Our empirical framework is motivated by Grossman's (1972) model of the demand for health. The key feature of the Grossman (1972) model is the recognition that health is a commodity that cannot be purchased, but is instead self-produced using a combination of market inputs such as medical care, and own time. Thus, embedded in this model is a health production function that describes the relationship between health inputs and health output (i.e., health status). The Grossman (1972) model can be applied to an analysis of child health by noting that child health outcomes are largely determined by the decisions of the family and that child health is an argument of the parents' utility function.

Child health at age k and time t is a function of past investments in medical care (M), other market inputs (Y), and parental time (L):

(1) $H_t = g(M_t, M_{t-1}, \ldots, M_{t-k}, Y_t, Y_{t-1}, \ldots, Y_{t-k}, L_t, L_{t-1}, \ldots, L_{t-k} : e, u)$.

Note that in equation (1), child health depends on the cumulative amount of inputs as well as the child's health endowment (e), and a production efficiency parameter (u). The demand function for child health that results from this model has the following general form:

(2) $H_t = g'(p_t, p_{t-1}, \ldots, p_{t-k}, w_t, w_{t-1}, \ldots, w_{t-k}, I_t, I_{t-1}, \ldots, I_{t-k} : e, u, q)$,

where p is the price of child health care services, w is the price of parental time input, I is family income, e is the child's health endowment, u is an efficiency parameter associated with the child health production function, and q is a taste parameter. Our empirical analysis focuses on estimating equation (2), or the parameters of the demand function for child health. The distinguishing aspect of the analysis of child health outcomes, as opposed to adult health, is the prominent role that parents play in determining child health.

Medicaid and private insurance affects the demand for child health through its effect on the price of health care. Medicaid virtually eliminates out-of-pocket costs of care and insurance premium payments, but may increase time costs of care since access to providers may become limited.[3] Thus, the net effect of Medicaid on the price of

[3] Medicaid can decrease insurance costs even if insurance is received through employment. Implicit in this argument is that there is shifting of insurance costs to wages.

health care depends on which component of price is most affected. For most families that are eligible for Medicaid, it is likely that the elimination of out-of-pocket and insurance costs dominates, implying a lower price of health care. We assume that a decrease in the price of health care will improve child health because children will receive more health care services. Accordingly, our null hypothesis is that Medicaid participation, relative to being uninsured, improves the health of children.

We specify the following linear-in-parameters demand function for child health at time t and age k:

(3) $$H_{it} = a_i + d_1 MC_{it} + d_2 P_{it} + d_3 I_{it} + \sum_{m=4}^{M} d_m X_{itm} + e_{it} \quad ,$$

where H is a measure of child health status, MC is a dummy variable indicating that the child is on Medicaid, P is a dummy variable indicating that the child has private insurance, I is a measure of family income, and i and t index individuals and time respectively. X_m is a vector of other independent variables including race, sex and age of child, mother's education, mother's marital status, mother's health status and geographic area. These independent variables are included to control for differences in the price of parental time, health production efficiency and family preferences. Note that in this analysis we are focusing on the effect of Medicaid participation since we know the child's health insurance status.

One shortcoming of the equation (3) is that it assumes that current health depends only on current determinants of health. This specification may result in biased estimates if the effects of past child health-production inputs are important and prices or circumstances have changed in real terms. For example, 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 not because of a lack of current insurance, but because the child's health had deteriorated during the period he was uninsured. We address this issue by including a measure of past health status in the model to control for the effect of omitted past determinants of health. Past health is measured as the presence of a chronic health condition with onset at least one-year prior to the survey. This empirical strategy tests whether having public or private health insurance affects current health conditional on underlying health status. In other words, it tests whether current health insurance affects changes in the health stock. This is a limited test of the effect of health insurance on child health, but preferable to simply regressing measures of the **stock** of health on **current** health insurance status.

A second statistical problem associated with equation (3) is selection bias. Estimates of the effect of Medicaid on health status may be biased if unobserved factors that affect Medicaid participation also affect health status. A similar caveat applies to participation in a private health insurance plan. Families choose a type of insurance plan based on a variety of factors such as income, the level of risk aversion, and the child's health endowment. These same factors may also determine the child's health status. Researchers, however, only have access to a limited number of observable characteristics. Thus, any attempt to compare health status among children who differ by type of health care insurance must address this "selection" issue in order to separate the effect of insurance from the effect of unobservable factors. To address this problem, we use an instrumental variables (IV) procedure. The critical aspect of the IV procedure is finding instruments that are correlated with insurance status, but uncorrelated with children's health status. We use state-year-income interactions and child-year interactions as instruments. States differed in the timing, magnitude, implementation (e.g., presumed eligibility) and coverage (e.g., children below age six) of their expansions of the Medicaid program and this cross-sectional and time variation may be used to predict Medicaid participation. We allow the state-year interactions to have different effects by income (e.g., poor and near poor) to increase the explanatory power of our instrument set.

B. Data

The NHIS contains self-reported health measures and is a large national sample. In 1989 and 1992, the NHIS included a supplement on health insurance. Thus, for these two years, we can link information about child health to data on health insurance status. In addition to information about health and health insurance, the NHIS contains data on social and demographic characteristics of families. We limit the analysis to children between the ages of two and nine who come from families with incomes of less than $25,000.[4] The age restrictions coincide with the federally mandated guidelines, which by 1992 mandated that states provide publicly financed insurance for children up to age nine who come from families with incomes below the poverty line. We limit the sample on the basis of income because our interest is in estimating the effect of Medicaid participation on child health and Medicaid affects only poor and near-poor families. Including families from the upper part of the income distribution introduces unnecessary heterogeneity into the sample. Descriptive statistics for this sample are presented in the appendix.

It is fortuitous that the NHIS included health insurance supplements in the years 1989 and 1992. During this period, the Medicaid program was greatly expanded to cover higher income families and older children. This significant variation across states and over time in Medicaid program eligibility will enhance the efficacy of the instrumental variables procedure in which state-year-income interactions are used as instruments to predict Medicaid participation.

Health measures in the NHIS are less than perfect and consist of maternal reports of general health (excellent to poor) and morbidity (e.g., bed days) and the mother's inventory of her child's acute and chronic conditions. Ideally, an analysis of the effect of Medicaid on child health would focus on measures of health that reflect variation in health care such as the ambulatory care sensitive conditions noted previously. A review of the acute and chronic conditions inventoried by the NHIS reveals that few of them are preventable with medical care, although many are curable and better managed with medical care. Thus, we chose not to analyze indicators of the presence or number of acute or chronic conditions, and instead focus on the general measures of health and morbidity. In particular, we use the mother's rating of her child's health and the number of bed days in the past 12 months as dependent variables. Both of these measures are highly correlated with the presence of acute and chronic conditions. The assumption underlying the use of these health measures is that greater access to, and utilization of, medical care will improve the general health of children and reduce morbidity as measured by the number of bed days. It is important to note that we control for past health status of the child by including several dummy variables indicating the

[4] We impute income for families missing income information. We predict income using a regression model that includes all the right hand side variables used later in the analysis and a sample with complete information. We also include a dummy

presence of chronic conditions with onset at least one year prior to the interview. We include this variable in the model to control for the influence of past determinants of child health and the child's health endowment. In sum, we are measuring the effect of Medicaid and private insurance on the general health and morbidity of children conditional on their prior health status (health stock).

Another aspect of the health measures is that they are maternal self reports and may be poor measures of actual child health. This may decrease the precision of our parameter estimates, and under some conditions may result in biased estimates. In preliminary analyses, however, all of the child health measures in the NHIS were significantly correlated with the number of physician visits and other measures of utilization. This suggests that maternal reports of child health do in fact measure actual child health. In addition, all empirical analyses control for race, family income and a variety of maternal characteristics that may be correlated with any measurement error in maternal reports of child health.

C. Results

Estimates of the effect of Medicaid on children's health are obtained by ordinary least squares (OLS) and two-stage least squares (2SLS) procedures. The instruments used in the 2SLS procedure are state-year-income interactions and age-year interactions. In all cases these instruments are significant predictors of insurance status with a partial F statistic always greater than two and as high as four. The two dependent variables are an indicator of whether the mother rated her child's health to be good or excellent and the number of bed days in the past 12 months. Explanatory variables include health insurance coverage, which we treat as endogenous in most cases, and the following: child characteristics—age, race, sex and prior health status as measured by the presence of chronic conditions; mother characteristics—age, education, marital status, and health status; family income in the past year; variables indicating residence in a central city or urban area; and year and state dummy variables. Since the dependent variables are not true continuous measures, standard errors have been calculated using White's (1980) correction. All models are estimated separately by two race/ethnicity groups defined as follows. Group 1 consists of

variable in all model indicating that income was predicted.

white, non-Hispanic children and group 2 consists of black, non-Hispanic and Hispanic children. We combined black, non-Hispanic children and Hispanic children to insure sample sizes sufficient to yield reasonable statistical power.

Table 1 lists the estimates of the effect of Medicaid and private insurance coverage on child health. The estimates in the top half of Table 1 pertain to the sample of white (non-Hispanic) children and the estimates in the bottom half are associated with the sample of black (non-Hispanic) and Hispanic children. We begin the discussion with the results associated with Medicaid coverage for the sample of white children. For this group of children, Medicaid appears to have few health benefits. Mother's of children covered by Medicaid rate their child's health as the same or slightly worse than do mothers of uninsured children and children covered by Medicaid have about the same or slightly more number of bed days in the past 12 months than do uninsured children. The 2SLS estimate of the effect of Medicaid on the number of bed days, however, is large and negative, but insignificant ($p> 0.05$).[5] The standard error of this 2SLS estimate is large enough to prevent rejection of the exogeneity of Medicaid participation, even though the numerical difference between the OLS and 2SLS estimate is large. In general, the OLS estimates provide no evidence to suggest that Medicaid coverage improves the contemporaneous health or incidence of morbidity of low-income white children. The 2SLS estimates, however, suggest that Medicaid improves children's health, but the imprecision of these estimates raises questions about their reliability.

The last two columns of Table 1 list estimates of the effect of Medicaid and private insurance on the number of physician visits in the last year. For this outcome, Medicaid coverage for white children is associated with an increase in the number of physician visits relative to that of uninsured children. The OLS estimate indicates that children covered by Medicaid had approximately one1.7 more visits to the doctor in the last year than did uninsured children. This is a relatively large effect since the mean number of visits for white children is approximately three. The 2SLS estimate is positive, smaller than the OLS estimate and insignificant. Again, the imprecision of the 2SLS estimate prevents a rejection of the exogeneity hypothesis.

The estimates of the effect of private insurance coverage indicate that for white children, private insurance coverage has a slight positive effect on general health status, but no effect on morbidity as measured by bed days. With regard to the measure of health status, only the 2SLS estimate is statistically significant, but the imprecision of the estimate indicates that it is not statistically different from the OLS estimate. In the case of the number of bed days, however, none of the estimates associated with private insurance are statistically significant for the sample of white children. Private insurance is also associated with an increase in the number of visits to the doctor, but this result is less robust since the OLS and 2SLS estimates have different signs. The OLS estimate indicates that private insurance coverage increases visits to the doctor while the 2SLS estimate suggests the opposite. The 2SLS estimate, however, is imprecisely measured and there is little reason to expect that private insurance should lower utilization relative to being uninsured. Again, a test of the exogeneity of insurance status could not reject the null hypothesis.

An interesting finding in Table 1 is that uninsured white children tend to be healthier than are children covered by either Medicaid or private insurance. This result is derived from a comparison of the estimates obtained from models that do and do not control for prior health status. When prior health status is added to the model, estimates of the effect of insurance coverage are reduced in absolute value (move toward zero) in three out of four cases. For example, the effect of Medicaid coverage on the number of bed days is reduced by 39 percent and is no longer significant when prior health status is added to the model. This result is reasonable given behavioral decisions related to purchasing insurance since there is an incentive for parents to obtain health insurance when their child is in poor health. This result also illustrates the inappropriateness of relating current health stock to current insurance status.

The results for black (non-Hispanic) and Hispanic children are somewhat different than they were for white children. Both Medicaid and private insurance coverage are associated with better maternal ratings of child health. The magnitude of the estimates is relatively small, approximately three to four percentage points (or five percent) in most cases and statistically significant in five out of six instances. There is also some evidence that Medicaid coverage is associated with a larger number of bed days in the past 12 months for black and Hispanic children, although the 2SLS estimate is imprecisely estimated. There is no evidence, however, that either Medicaid or private

[5] Throughout the discussion of the results, we use p=0.05 to differentiate between significant and not significant results.

insurance coverage decreases the number of bed days of black and Hispanic children. In regard to utilization, the estimates in the last two columns indicate that Medicaid and private insurance are associated with a greater number of physician visits in the last year for black and Hispanic children. The estimates associated with private insurance, however, are never statistically significant. Finally, a comparison of estimates from models that do and do not control for prior health status indicates little difference between the estimates. This suggests that there is little difference in prior health status among black and Hispanic children by insurance status.

IV. Analysis of Hospital Discharge Data and the Effect of Medicaid Eligibility on Child Health

A potential weakness of the previous analysis was the limited measures of health available in the NHIS. In particular, the NHIS lacked measures of health that unambiguously reflect variation in medical care utilization. It is precisely this variation in access and utilization of medical care that motivated policymakers to provide publicly financed health insurance to low-income families. To address this point we use data on hospital discharges from a sample of 544 hospitals in 11 states to test whether the incidence of ambulatory care sensitive discharges among low-income children, the target group of the Medicaid expansions, decreased relative to the incidence of ACS discharges among high-income children. ACS discharges are the result of hospital admissions that could have been avoided with better primary outpatient care (Millman 1993). Expansion of publicly provided insurance is expected to improve access to primary care and reduce the number of ACS discharges.

A. Empirical Model

Our hypothesis is that insurance coverage for children, either public or private, lowers the price of medical care and stimulates utilization. As a consequence of increased access and utilization, child health improves. In particular, more extensive health insurance coverage of a population should result in a decrease in health outcomes that are for the most part non-stochastic and responsive to medical intervention. Accordingly, we examine changes in the incidence of ambulatory care sensitive (ACS) discharges between 1988 and 1992 for low-income and high-income children. The expectation is that if the Medicaid expansions were effective, there should be a relative decrease in the incidence of ACS discharges for low-income as compared to high-income children. Health insurance coverage of low-income children should have become more widespread as a result of the Medicaid expansions and resulted in a relative improvement in health.

We use a simple difference-in-differences (DD) estimator to obtain the effect of Medicaid eligibility. The logic underlying the DD procedure is illustrated in Table 2.

Table 2
Incidence of ACS Discharges Before and After Medicaid Expansions

	After Expansion of Medicaid Eligibility (1992)	Before Expansion of Medicaid Eligibility (1988)	Difference
Treatment Group	A	B	A-B
Control Group	C	D	C-D
Difference-in-Differences (DD)			(A-B)-(C-D)

Table 2 shows the incidence of ACS discharges for various groups of children in our sample before (1988) and after (1992) expansion of Medicaid eligibility. In Table 2, the difference (A-B) measures the effect of Medicaid eligibility expansions and unmeasured factors that affect ACS discharges among the treatment group of children—those children whose eligibility is affected by the Medicaid expansions. The difference (C-D) measures the effect of unmeasured factors on the incidence of ACS conditions among the control group of children—those children whose eligibility is unaffected by the Medicaid expansions. The difference-in-differences, [(A-B)-(C-D)], measures the effect of changes in Medicaid eligibility on the incidence of ACS conditions among children in the treatment group. A critical assumption underlying the DD analysis is that unmeasured, time-varying factors that affect the incidence of ACS conditions have the same effect on treatment and control group members. If this is not the case, then DD estimates are biased.[6]

[6] This problem is not unique to the DD analysis: all non-experimental studies require controls for time-varying factors that affect the outcome of interest and which may be correlated with a right hand side variable of interest.

There are two practical challenges that we had to confront to implement the DD procedure. The first was how to define treatment and control groups. There is no information about a child's family income in the discharge data that could be used to assign eligibility. The only information about income available in the data is the median family income of the child's zip code of residence. Therefore, we defined two treatment groups and one control group based on the median family income of the child's zip code of residence. The two treatment groups are children from zip code areas with the following median family incomes: less than $25,000 and $25-30,000.[7] The control group is children from zip code areas with median family incomes of $35,000 or more. Obviously, these working definitions will not replicate true treatment and control groups and there will be some contamination—controls (i.e., not affected by Medicaid expansions) in the treatment group and treatments in the control group. This contamination problem will lead to biased DD estimates. One important result, however, is that the DD estimate using the contaminated treatment and control groups will have the same sign as the true DD estimate as long as the share of treatments in the control group is smaller than the share of treatments in the treatment group.[8] The Medicaid expansions affected relatively a small part of the income distribution and therefore we expect the share of treatments in the control group to be quite small. Thus, the DD estimate biased by contamination will still have the same sign as the true DD estimate.

The second empirical problem is that we do not know the true denominator to use to define incidence of ACS conditions. Ideally, we would like to use the relevant population as the denominator, but we have no way of calculating the correct population. The correct population would be the number of children in the catchment area of the 544 hospitals in our sample, but this information is unavailable. To address this issue, we use the number of non-ACS discharges and the number of births in our sample of hospitals to calculate incidence of ACS discharges. Non-ACS discharges are primarily the result of stochastic health outcomes and the number of occurrences should reflect the underlying population of children in the relevant geographic area. The number of births is also expected to reflect

[7] Median family income in a patients zip code was measured in four intervals: 0-25,000, 25-30,000, 30-35,000 and 35,000 or more.

the underlying population of children.

Difference-in-differences estimates can also be obtained using OLS regression methods. The advantage of using a regression procedure is that we can include other variables in the model and obtain more precise DD estimates. Also, since our data are based on the discharges of 544 hospitals, a regression framework facilitates the inclusion of hospital specific controls that may confound estimates. The regression analog to the Table 2 is

$$(4)\quad ACS_{ijt} = a_i + Xb + d_1 treat_1 + d_2 treat_2 + d_3 year_{1992} + d_4 (treat_1 \; x \; year_{1992}) + d_5 (treat_2 \; x \; year_{1992}) + n_{ijt}\,.$$

The parameter estimates of interest are δ_4 and δ_5, which measure the effect of the Medicaid eligibility expansions on poor and near-poor children (i.e., treatment groups 1 and 2) relative to non-poor children. Equation (4) includes hospital specific intercepts (α_i) and a vector (X) of control variables such as age and sex of child.

B. Data

The hospital discharge data come from the Agency for Health Care Policy and Research (AHCPR), which makes available to researchers a database of a sample of discharges from all non-federal, short-term, general and other specialty hospitals in 11 states for the period 1988 to 1993.[9] These data, referred to as the Nationwide Inpatient Sample (NIS) contain basic information about every discharge from a 20 percent sample of hospitals including; the age and race of the patient, state of residence, median income of the patient's zip code of residence, hospital characteristics, and the principal and secondary diagnoses. We limit the sample to 544 hospitals that were present in both the 1988 and 1992 NIS database.

Using the diagnostic codes contained in the NIS, we follow the definitions used by Billings et al. (1991, 1993) and a recent Institute of Medicine (Millman 1993) study to develop measures of ambulatory care sensitive

---

[8] The biased DD estimate is (a-b) [(A-B)-(C-D)], where a is the share of treatments in the treatment group and b is the share of treatments in the control group. The bias can be substantial depending on the values of a and b. For example, if a=.7 and b=.2 then the biased DD estimate is half as large as the true DD estimate.

(ACS) discharges. There are 27 ACS discharges defined by Billings et al. (1991), although several do not pertain to children. The most common ACS discharges observed for children are convulsions, asthma, dehydration and pneumonia. ACS discharges are the result of hospital admissions that could have been avoided with better primary outpatient care (Millman 1993). Expansion of publicly provided insurance is expected to improve access to primary care and reduce the number of ACS discharges.

C. Results

The difference-in-differences estimates were obtained by ordinary least squares. All estimates were obtained separately for children ages two to six and children ages seven to nine. Federal mandates required that states cover children up to age six from families with incomes below 133 percent of the federal poverty line, but for older children the minimum threshold was the poverty line. Thus, the expansions affected a greater number of younger than older children. This fact should be reflected in our DD estimates since the contamination problem and resulting downward bias of the DD estimates is greater the fewer number of children affected by changes in the law. Therefore, we expect to find more significant results for the younger children than for the older children. Similar reasoning suggests that we would expect to find stronger effects for children in Treatment Group 1 than in Treatment Group 2 since more of the children in treatment Group 1 are expected to be affected by the Medicaid expansions. We did not obtain separate estimates by race because information on race was not well reported in the data.

Table 3 contains the DD estimates of the effect of the Medicaid expansions on the incidence of ACS discharges. The top panel contains the estimates that were obtained using the number of non-ACS conditions to calculate incidence. The bottom panel contains the estimates based on incidence that was calculated using the number of births. There are six measures of ACS discharges: all non-asthma ACS conditions, asthma, pneumonia, dehydration, convulsion and severe eye, nose and throat conditions. For the sample of young children, pneumonia, dehydration, convulsions and eye, nose and throat conditions make up 78 percent of all non-asthma ACS discharges. A similar figure for older children is 63 percent. For each outcome, incidence was calculated separately using the

[9] The states are AZ, CA, CO, FL, IA, IL, MA, NJ, PA, WA, and WI.

either non-ACS discharges or births as the denominator. For example, the analysis of pneumonia included only non-ACS discharges (or births) and discharges for pneumonia.

Among the sample of young children, the Medicaid expansions appear to have decreased the incidence of ACS discharges, particularly for children in Treatment Group 1. Ignoring estimates pertaining to asthma, nine out of ten DD estimates of the effect of the expansions on ACS discharges in Table 3 are negative for children in Treatment Group 1. Six of the ten estimates are statistically significant ($p<0.05$). Remember that these DD estimates are biased downward, so the lack of statistical significance may simply reflect this bias. For young children in Treatment Group 2, six of the ten estimates are negative and three are statistically significant. The stronger evidence of a Medicaid effect for children in Treatment Group 1 than for children in Treatment Group 2 is consistent with the hypothesis that more children in Treatment Group 1 were affected by the expansions than in Treatment Group 2. Evidence that this in fact may be the case is presented in Yazici and Kaestner (1998) who show that Medicaid participation among children always eligible for Medicaid increased as much as Medicaid participation among newly eligible children. Thus, children in Treatment Group 1 affected by Medicaid include those who were always eligible for Medicaid and children newly eligible because of the expansions.

It is difficult to discuss the magnitude of the estimates since they are in all likelihood downward biased. For young children in Treatment Group 1, most of the significant estimates indicate reductions in ACS discharges of between 10 and 20 percent. While these effects may seem modest, they may obscure some very large effects. For example, if we assume that 30 percent of the children in Treatment Group 1 were affected by the Medicaid expansions and five percent of children in the control group were affected, the DD estimates in Table 3 are only 25 percent of the true estimates. Under these circumstance the true effect of the Medicaid expansions may be to decrease ACS discharges by 40 to 80 percent among children affected by the expansions.

The effect of the Medicaid expansions on the incidence of asthma related hospital discharges is positive and in most cases statistically significant for the sample of young children. This result is surprising since hospital admission for asthma can be avoided with proper primary care and home treatment. One explanation for this result is that home treatment for asthma is relatively complex. A recent study of this issue found that parents of low-income children with asthma did not have faith in the efficacy or safety of asthma medications and failed to administer the medications on a daily basis as required to prevent serious episodes (Wasilewski et al. 1996).

The DD estimates pertaining to older children are less consistent. For older children in Treatment Group 1, seven of the ten estimates are negative, but none are statistically significant. For older children in Treatment Group 2, eight of the ten DD estimates are negative and two are statistically significant. Again, it is important to note that we would expect the contamination problem and downward bias to be a bigger problem in the older children's sample since fewer of these children were affected by the Medicaid expansions. Thus, the preponderance of negative DD estimates is an important finding. The inconsistent aspect of the results, however, is that the estimates are larger (more negative) and more often significant for children in Treatment Group 2 than for children in Treatment Group 1. This is the opposite of what would be expected if, as hypothesized, fewer children in Treatment Group 2 were affected by the expansions than in Treatment Group 1.

Asthma related discharges among older children declined for those children in Treatment Group 2, but not for children I Treatment Group 1. Again, this is a surprising result since we expect the Medicaid expansions to have a greater effect on children in Treatment Group 1 than in Treatment Group 2. More importantly, there was no evidence that the Medicaid expansions decreased the incidence of asthma among younger children were expected to have been the most affected group of children.

VI. Conclusion

In this paper, we have examined the effect of health insurance coverage on low-income children's health. The paper was motivated by an absence of prior research on the effect of insurance on children's health and dissatisfaction with the practice of evaluating the merits of health insurance solely on the basis of its effect on utilization. We have focused on publicly provided insurance because of its public policy relevance.

The results of this analysis were mixed. In the analysis of the NHIS data, Medicaid and private insurance were associated with better maternal ratings of low-income black and Hispanic children's health, but had no effect on the general health status of white children. In fact, among low-income white children, Medicaid was associated with slightly worse health, although the 2SLS estimate was positive, but not statistically significant. In regard to morbidity, there was little credible evidence that Medicaid and private insurance reduced the number of bed days in the past 12 months. Among low-income black and Hispanic children, Medicaid was associated with a greater number of bed days in the past 12 months. Again, 2SLS estimates of the effect of Medicaid on the number of bed days suggest a more positive health effect for low-income white children, but their imprecision make then less than reliable.

The inconsistent nature of the results associated with the NHIS sample makes it difficult to draw firm conclusions. While there was some evidence that Medicaid and private insurance improved health, it was not robust. For example, Medicaid was associated with better maternal ratings of child health among black and Hispanic children, but among white children, Medicaid had either a slight negative effect or no effect on maternal ratings of her child's health. It is not obvious what mechanism would cause this result. Perhaps Medicaid provides greater access to care for poor black and Hispanic children than it does for white children, but this hypothesis is only conjecture at this point and in need of further testing. Similarly, there was no evidence that Medicaid or private insurance affected morbidity as measured by the number of bed days. This is inconsistent with the hypothesis that Medicaid and private insurance increase access to primary care that can provide better management and quicker cures of many acute and chronic conditions. One alternative hypothesis is that bed days is an input into better health and that greater access to primary care results in more bed days as physicians recommend greater rest or require more bed days as a part of treatment.

The analysis of the effect of the Medicaid expansions on ambulatory care sensitive discharges provided the most consistent evidence that Medicaid has a positive effect on children's health. Many researchers would suggest that these results are more credible than those obtained using the NHIS since they were obtained using more objective measures of health. We tend to agree with this proposition and we find relatively robust evidence that the Medicaid expansions decreased the incidence of ambulatory care sensitive discharges among young children in low-income families. Nine of ten estimates of the effect of the Medicaid expansions on ACS discharges were negative and six were statistically significant for this group of children. The magnitude of the results was relatively large, on the order of 10 to 20 percent. As argued above, these estimates are downward biased and may obscure even larger effects. A caveat, however, is warranted since there were several anomalous results associated with the analysis of ACS discharges. For example, the Medicaid expansions had a larger effect for older children in Treatment Group 2 than for older children in Treatment Group 1, and the expansions appeared to decrease the incidence of asthma only for older children in Treatment Group 2.

In conclusion, we believe the results of this paper provide at best weak support for the hypothesis that Medicaid improves the health of low-income children. The absence of stronger evidence may be due to a variety of factors. One explanation of these results is that uninsured children may be receiving adequate health care. Parents of uninsured children in poor and near-poor families may be paying for essential and effective health care out-of-pocket, or these children may receive the necessary care at hospitals and clinics that treat the uninsured free of charge. In fact, children covered by private insurance may face the most expensive health care if there are significant co-payments associated with their insurance plan. This explanation, however, is not compelling in light of the evidence presented in this paper and others that showed that health insurance increased utilization. A second explanation of our findings is that our measures of child health do not adequately reflect the benefits of having Medicaid or private insurance. Health insurance may have very specific effects on child health that are manifest only in regard to certain types of child illnesses. We addressed this issue by examining the effects of the Medicaid expansions on ambulatory care sensitive discharges, which are known to be responsive to medical care. Indeed, it was this analysis that found the most consistent evidence of a positive health effect of Medicaid, although there were several anomalous results that raises questions about the robustness of such a finding.

We also believe, rather strongly, that there needs to be a refocus of research priorities away from studies that examine the relationship between health insurance and health care utilization if the goal is to evaluate what programs are effective at improving the health of low-income children. The proposition that health insurance is the cure for adverse health outcomes among poor and near-poor children has not been adequately demonstrated. There needs to be additional research that examines directly the relationship between health insurance status and health outcomes. Too much prior research has been content with showing that health care utilization increases with insurance coverage and then assuming that health also improves health. The federal government has recently allocated $24.3 billion for the expansion of publicly provided health insurance, ostensibly to improve the health of low-income children. It is remarkable that there is so little empirical evidence to support such a large expenditure. It is important that future research address this gap in our knowledge. We hope that our study motivates additional research in this area.

References

Alexander, G. and C. Korenbrot. 1995. "The Role of Prenatal Care in Preventing Low Birth Weight." The Future of Children 5(1):103-120.

Billings, J., Zeitel L., Lukomnik J., Carey T., Blank A., and L. Newman. 1993. "Impact of Socioeconomic Status on Hospital Use in New York City." Health Affairs 12(2): 162-173.

Billings, J., Anderson G., and L. Newman. 1996. "Recent Findings on Preventable Hospitalizations." Health Affairs 15(3): 239-249.

Currie, J., and J. Gruber. 1995. "Health Insurance Eligibility, Utilization of Medical Care, and Child Health." NBER Working Paper #5052, Cambridge, MA: National Bureau of Economic Research, Inc..

Currie, J., and J. Gruber. 1996. "Health Insurance Eligibility, Utilization of Medical Care, and Child Health." Quarterly Journal of Economics 445: 431-466.

Currie, J. and D. Thomas. 1995. "Medical Care for Children: Public Insurance, Private Insurance, and Racial Differences in Utilization." Journal of Human Resources 30: 135-162.

Grossman, M. 1972. "The Demand for Health: A Theoretical and Empirical Investigation." National Bureau of Economic Research Occasional Paper No: 119.

Guyer, B. 1990. "Medicaid and Prenatal Care: Necessary but Not Sufficient." Journal of the American Medical Association 264:2264-2265.

Huntington, J. and F. A. Connell. 1994. "For Every Dollar Spent - The Cost Savings Argument for Prenatal Care." New England Journal of Medicine 331:1303-1307.

Long, S. and S. Marquis. 1996. "Reconsidering the Effect." Health Services Research 30: 791-808.

Millman, M. 1993. Access to Health Care in America. Washington, DC: National Academy Press.

Newacheck, P.W., et al. 1998. "Health Insurance and Access to Primary Care for Children." The New England Journal of Medicine 338(8):513-519.

Newhouse, J. P. 1993. Free for All: Lessons from the RAND Health Insurance Experiment. Cambridge, MA: Harvard University Press.

St. Peter, R. F., et al. 1992. "Access to Care for Poor Children." Journal of American Medical Association 267: 2760-2764.

White, H. 1980. "A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test For Heteroskedasticity." Econometrica 48: 817-830.

Wasilewski et al. 1996. "Factors Associated with Emergency Department Visits by Children with Asthma: Implications for Health Education." American Journal of Public Health. 86(10):1410-1415.

Yazici, E. 1997. "Consequences of the Medicaid Expansions on Three Outcomes." New York, NY: CUNY Graduate Center. Unpublished Dissertation.

Yazici, E. and R. Kaestner 1998. "Medicaid Expansions and Crowding Out of Private Health Insurance." New York, NY: Baruch College. Unpublished Manuscript.

Table 1
Estimates of the Effect of Health Insurance on Low-Income Children's Health and Health Care Utilization
Children Age 2 to 9

Race/Ethnicity	Health Status Good or Excellent			Number of Bed Days Past 12 Months			Number of Physician Visits Past 12 Months	
White/Non-Hispanic (N=5911)	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	2SLS
Medicaid	-0.056 (0.016)	-0.048 (0.016)	0.028 (0.058)	0.785 (0.424)	0.476 (0.417)	-1.538 (1.203)	1.681 (0.243)	0.313 (1.205)
Private Insurance	0.012 (0.013)	0.015 (0.013)	0.130 (0.061)	0.523 (0.349)	0.358 (0.343)	-0.692 (0.996)	0.539 (0.199)	-1.323 (0.998)
Model Includes Prior Chronic Conditions	No	Yes	Yes	No	Yes	Yes	Yes	Yes
F-Stat. of Overid			1.483*			0.652		0.779
χ^2 Stat. of Exog.			4.792			2.339		5.532
Mean of Dependent Variable	0.775			3.043			3.227	
Black and Hispanic (N=6556)	OLS	OLS	2SLS	OLS	OLS	2SLS	OLS	2SLS
Medicaid	0.032 (0.014)	0.036 (0.014)	0.127 (0.059)	1.241 (0.306)	1.082 (0.302)	1.478 (1.937)	0.913 (0.149)	2.440 (1.943)
Private Insurance	0.034 (0.015)	0.034 (0.015)	0.036 (0.067)	0.008 (0.334)	-0.004 (0.329)	2.445 (2.663)	0.089 (0.162)	1.830 (2.666)
Model Includes Prior Chronic Conditions	No	Yes	Yes	No	Yes	Yes	Yes	Yes
F-Stat. of Overid			1.347*			0.697		1.880*
χ^2 Stat. of Exog.			3.448			3.117		8.733*
Mean of Dependent Variable	0.664			2.204			2.477	

Notes:
1. All models include the following variables: sex of child, age of child (11 categories), ethnicity (Hispanic), mother's education (4 categories), mother's age (5 categories), mother's marital status (3 categories), mother's health status (2 categories), family income (6 categories), indicator of predicted (missing) income, MSA location (3 categories), year and state dummy variables.
2. Prior chronic conditions are chronic conditions with onset at least one year prior to the interview. There are seven categorical variables indicating different types of prior chronic conditions.
3. The instruments for the two-stage least squares models include all variables listed in note 1 and: state-year-income interactions (294 categories) and child age-year interactions (22 categories).
4. In all models, the standard errors have been calculated using White's method and are in parentheses.

Table 3
Estimates of the Effect of Medicaid Expansions on the Incidence of Ambulatory Care Sensitive Discharges
Children Age 2 to 9

Age Group	Non-Asthma ACS	Asthma	Pneumonia	Dehydration	Convulsions	Eye, Nose and Throat
Age 2-6	Incidence Calculated Using Non-Ambulatory Care Sensitive Discharges in Denominator					
Treatment Group 1	-0.018 (0.007)	0.017 (0.006)	-0.005 (0.005)	-0.018 (0.006)	-0.007 (0.004)	0.003 (0.003)
Treatment Group 2	0.000 (0.008)	0.023 (0.007)	0.005 (0.006)	-0.003 (0.007)	0.003 (0.004)	0.001 (0.003)
Mean	0.347	0.167	0.111	0.179	0.041	0.028
N	95554	74880	70150	76044	65040	64180
Age 7-9						
Treatment Group 1	-0.001 (0.010)	-0.003 (0.008)	-0.005 (0.006)	0.005 (0.008)	-0.003 (0.004)	-0.005 (0.003)
Treatment Group 2	-0.010 (0.011)	-0.025 (0.009)	-0.009 (0.006)	0.005 (0.008)	-0.001 (0.004)	-0.009 (0.004)
Mean	0.233	0.114	0.049	0.095	0.019	0.015
N	35956	31111	28970	30449	28085	27987
Age 2-6	Incidence Calculated Using Births in Denominator					
Treatment Group 1	-0.0032 (0.0011)	0.0024 (0.0007)	-0.0013 (0.0006)	-0.0010 (0.0007)	-0.0010 (0.0003)	-0.0004 (0.0003)
Treatment Group 2	-0.0039 (0.0012)	0.0010 (0.0008)	-0.0008 (0.0006)	-0.0018 (0.0008)	-0.0002 (0.0004)	-0.0008 (0.0003)
Mean	0.0465	0.0180	0.0113	0.0197	0.0039	0.0026
N	713087	692413	687683	693577	682573	681713
Age 7-9						
Treatment Group 1	0.0002 (0.0006)	0.0003 (0.0004)	-0.0002 (0.0002)	0.0005 (0.0003)	-0.0002 (0.0001)	-0.0003 (0.0001)
Treatment Group 2	-0.0014 (0.0006)	-0.0014 (0.0004)	-0.0003 (0.0003)	0.0001 (0.0004)	-0.0001 (0.0002)	-0.0005 (0.0001)
Mean	0.0122	0.0052	0.0021	0.0042	0.0008	0.0006
N	688324	683479	681338	682817	680453	680355

Notes:
1. All estimates are adjusted for sex of child (female dummy variable) and hospital specific effects (hospital specific intercepts). Models that use non-ACS discharges to calculate the incidence of ACS discharges are also adjusted for age (4 age dummy variables).
2. Treatment Group 1 consists of children who live in zip code areas in which the median family income is less than $25,000. Treatment Group 2 consists of children who live in zip code areas in which the median family income is $25-30,000. The omitted group consists of children who live in zip code areas in which the median family income is $35,000 or more.
3. Standard errors are in parentheses.

Appendix Table 1
Means for Analysis Variables in NHIS Sample of Children Age 2 to 9

Variable	White (non-Hispanic) Children	Black (non-Hispanic) and Hispanic Children
Health Excellent or Good	0.775	0.664
Number of Bed Days Past 12 Months	3.043	2.204
Number of Physician Visits Past 12 Months	3.227	2.477
Medicaid Coverage	0.234	0.438
Private Insurance Coverage	0.519	0.278
Uninsured	0.247	0.284
Child's Age	5.398	5.367
Child's Hispanic		0.467
Mother's Age	30.925	31.739
Mother's Education		
11 or less Years of Completed Schooling	0.266	0.465
12 Years of Completed Schooling	0.496	0.392
13-15 Years of Completed Schooling	0.179	0.121
16 or more Years of Completed Schooling	0.059	0.022
Mother's Marital Status		
Married	0.711	0.465
Never Married	0.054	0.262
Separated/Divorced	0.235	0.273
Mother's Health Status Excellent or Good	0.602	0.475
Family Income		
0-4,999	0.059	0.157
5-6,999	0.091	0.139
7-10,999	0.109	0.168
11-14,999	0.156	0.183
15-19,999	0.298	0.216
20-24,999	0.288	0.137
Central City Residence	0.209	0.591
Urban Residence	0.395	0.261
Rural Residence	0.396	0.149
Year is 1992	0.480	0.577
Number of Observations	5911	6556