Medicaid Enrollment Leads to More School Absenteeism: Empirical Evidence from National Health Interview Survey

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Medicaid is the government insurance program that provides health insurance to the poor. The effect of Medicaid eligibility on children's health is of great concern. The literature survey demonstrates that Medicaid eligibility largely increased the utilization of medical service. However, there are few studies evaluating the effect of Medicaid eligibility on children's health conditions. This paper use 'days of school missed due to illnesses or injury' as the measurement to illustrate the effect of Medicaid eligibility on children's health. Four econometric models are used to fully analyze the effect of Medicaid eligibility on children's health outcome. The four models are probit model, triprobit model, negative binomial model and endogenous negative binomial model. Medicaid eligibility and days of school missed due to illness or injury are positively correlated in all four models.

INTRODUCTION

Economists are very concerned by the take-up rate of Medicaid (Yelowitz, 1999). Without a significant take up rate, the Medicaid will not have a great effect on the health outcome of children. If an important segment of those taking up Medicaid coverage are simply families exchanging public insurance for private coverage (the "crowd out" phenomenon), and if Medicaid and private practitioners have similar motives in treating children, then there will not even be a policy effect on reported health, let along intrinsic health (Thorpe and Florence, 1998; Shore-Sheppard, 2005). It is unlikely that Medicaid take-up rate for children is 100%. There are mainly three reasons for this low take-up rate: welfare-stigma, lack of program awareness and the transition cost (Powers, 2002).

Although take-up rates in the Medicaid program have been fairly low, they were sufficiently large to significantly increase medical service utilization among newly eligible children (Currie and Gruber, 1996). Actually, Medicaid expansions have been effective in terms of enrollment. Between 1986 and 1994, there was a 71% increase in the number of children enrolled in the program and a 107% real increase in Medicaid spending for children (Thorpe and Florence, 1998).

The significant take-up rate results in a wide utilization of health facilities. There is a great amount of literature devoted to the increase of medical care utilization due to Medicaid enrollment. Some literature analyzes children's Medicaid by studying children's hospitalization and treatment intensity.

Hospitalization is an important issue for studying the utilization of Medicaid. Hospitalizations were responsible for $21.4 billion in charges in 2000, representing 4.5% of hospital charges and over 40% of total expenditures on children's health care services.

The estimate of Dafiny (2000) implies that the Medicaid expansions are associated with more, rather than fewer, hospitalization of children. The article finds that an increase in Medicaid eligibility of 10% is associated with an increase in the child hospitalization rate of 8.4%. This estimate is nearly identical to the estimate obtained by Currie and Gruber (1996) using 1984-1992 micro-data on children from the National Health Interview Survey.

Treatment intensity is another issue in studying Medical utilization. Dafiny (2000) points out that there will be more intensive treatments for those moving from an uninsured state to Medicaid, but less intensive treatments for those moving from private insurance to Medicaid. Medicaid expansions appear to be leading to shorter stays for children in the hospital on average, but more intensive treatment per day when hospitalized.

Aside from the research on the utilization of Medicaid, to my knowledge, there have been only very limited studies of the effect of Medicaid on the health status of children (Gruber and Yelowizt, 1999; Riportella-Muller, 1998; Banthin and Cohen, 1998; Joyce and Racine, 1999). Some of the studies demonstrate that children 'health improves due to Medicaid enrollment while the others support the opposite results. This lack of prior research on the effect of Medicaid eligibility on children's health and further their school absences leads to the birth of this paper.

METHODOLOGY AND HYPOTHESIS

Basically, Medicaid affects the demand for child health care 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. Thus, the net effect of Medicaid on the price of 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 (Edwards, 2000; Kaestner, Joyce, and Racine, 1999).

The empirical framework is based on the education production function:

$$SM_t = f(HS_t, HC_t, R_t) \qquad \text{Equation 1}$$

and the health production function:

$$HS_t = m(HC_t, R_t) \qquad \text{Equation 2}$$

Based on the above two production functions, I derive the following results:

$$\partial SM_t / \partial HC_t = \partial SM_t / \partial HC_t + \partial SM_t / \partial HS_t * \partial HS_t / \partial HC_t \qquad \text{Equation 3}$$

SM_t --- days of school missed due to illness or injury

HS_t ---child's health status

HC_t ---health care visits

R_t ---other random variables

As Medicaid eligibility increases, children will have more access to health care. Therefore, $\partial SM_t / \partial HC_t$ is positive, which means that the days of school missed due to illness or injury will increase in the short run due to more medical services.

However, in the long run, the child's health status will improve due to more medical visits; as a result, the child will have fewer days of school missed due to illness or injury: $\partial SM_t / \partial HS_t < 0$.

From $\partial HS_t / \partial HC_t > 0$ and $\partial SM_t / \partial HS_t < 0$,I have $\partial SM_t / \partial HS_t * \partial HS_t / \partial HC < 0$. As a result, $\partial SM_t / \partial HC_t + \partial SM_t / \partial HS_t * \partial HS_t / \partial HC >< 0$, the sign of Equation 3 is ambiguous depending on whether it is short run or long run effects.

Based on the above analysis, for my dataset[1], I obtain the hypothesis: in a short period, the eligibility of Medicaid will lead to an increase in days of school missed due to illness or injury due to more utilization of medical services. The hypothesis is expressed as the following:

∂Days of school missed due to illness or injury/∂Medicaid Eligibility >0.

DATA AND ESTIMATION STRATEGY

I draw data from NHIS (National Health Interview Survey), a large national sample. NHIS contains data on social and demographic characteristics of families. I use the data from the year 2005, the most recent survey available from NHIS. NHIS asks the following question, "During the past 12 months, about how many days did [the child] miss school because of illness or injury?" I used four separate files from NHIS which are “household,” “family,” “personal,” and “child.” I start by using the “household” component of NHIS which consists of basic demographic information. Following that, I link the “household” component to the “personal” component to create an accurate description of each household.

After restricting the sample to children between the ages of 5 to 19, the number of observations comes to 8333. By deleting the observations with missing information, there are 6844 observations left. Among these observations, 29% of the children have single mothers and 6% of the children have single fathers. The private insurance coverage among the sample children is about 70%. The average Medicaid eligibility is around 26% for children all over the United States. The Northeast region has the lowest Medicaid eligibility for children (16%), while the Southern region has the highest Medicaid eligibility for children (35%). (See Table 1 in Appendix)

The dependent variable is days of school missed due to children’s illnesses or injuries. The independent variable of concern is whether the children’s has Medicaid or not[2]. The estimation model for this study is the following:

$$S_{it} = \alpha + \delta_1 MC_{it} + \delta_2 P_{it} + \delta_3 I_{it} + \sum \delta_m X_{itm} + \varepsilon_{it} \quad [3] \qquad \text{Equation 4}$$

S_{it} ---children’s school attendance

MC_{it} ---a dummy variable indicating that the child is on Medicaid

P_{it} ---a dummy variable indicating that the child has private insurance

X_{itm} --- is a vector of other independent variables including race, gender, region, Hispanic (whether the children is Hispanic origin or not), race, mothers’ education, father’s education, whether both mother and father are in the household, the income level of the family.

Many of these independent variables are dummy variables. The independent variables are included to control for differences in the price of parental time, health production efficiency, and family preferences. The regression analysis identifies the effect of Medicaid eligibility on school attendance[4].

RESULTS

The Effect of Medicaid Eligibility on Days of School Missed in the Probit Model

I run a probit model to see the impact of Medicaid eligibility on days of school missed due to illness or injury. Table 2 depicts the marginal effects of Medicaid eligibility on days of school missed due to illness or injury. Based on the above hypothesis, I would expect that the days of school missed due to illness or injury will increase in the short run because of greater utilization of medical services. The marginal effect of a change in Medicaid eligibility on days of school missed due to illness or injury is 0.109. This means that if a child has a 0.8 probability of missing school, then Medicaid eligibility increases the probability by 0.109. The probability of one more school day missed rises by 13.6%. With a p-value of 0.000, this result is statistically significant. (See Table 2 in Appendix)

The Effect of Medicaid Eligibility on Days of School Missed Due to Illness or Injury in the Triprobit Model

Estimates of the effect of Medicaid on health status may be biased if unobserved factors that affect Medicaid participation also affect school absences. In Table 3, I use a triprobit model to eliminate the possible endogenous relationship among days of school missed, private insurance, and Medicaid eligibility.[5] In this model, I obtain the coefficient results rather than the marginal effect. The sign of the result does not change; it remains positive. This result indicates that children who have Medicaid are more likely to miss school[6]. With a p-value of 0.000, this effect is considered to be statistically significant. As previously mentioned in the literature review, the high take-up rate of Medicaid eligibility will lead to a high utilization of Medical services (Currie and Jonathan Gruber, 1996).Therefore, in the short run, it is not surprising that children will have more days of school missed due to illness or injury because of the higher utilization of medical care. (See Table 3 in Appendix)

The Effect of Medicaid Eligibility on Days of School Missed Due to Illness or Injury in the Negative Binomial Model[7]

Table 4 reports the results from the negative binomial model. The output looks very much the same as the probit model, but the interpretation is very different. The probit (triprobit) model explains whether Medicaid eligibility increases or decreases the probability that children will miss school. The coefficients of the negative binomial model explain whether children enrolled in Medicaid miss school more often comparing with children with no insurance. The negative binomial coefficient for Medicaid is 0.388.

This positive coefficient indicates that Medicaid eligibility will increase child's number of days of school missed by 0.388. The p-value is very small (0.000) which suggests that the result is statistically significant. The alpha coefficient value is shown at the bottom of the table. If the alpha coefficient is zero, then the model would be better estimated using an ordinary poisson regression model. Below the coefficient estimation is a likelihood ratio test that tests if alpha equals zero. In this example, the associated chi-squared value is 16000, which is much larger than zero. The alpha test strongly suggests that the negative binomial model is better than the poisson regression model for this set of data. (See Table 4 in Appendix)

The Effect of Medicaid Eligibility on Days of School Missed Due to Illness or Injury in the Endogenous Negative Binomial Model

In order to control for the possible endogeneity of insurance status and school days missed in negative binomial regression, the fourth empirical model I use is the endogenous negative binomial model[8]. In this case, the coefficient is 0.407, which is again positive[9]. This means that Medicaid eligibility will increase children's number of days of school missed due to illness or injury. With the p-value of 0.000, the result is statistically significant. (See Table 5 in Appendix)

In short, by using four different models, I find that Medicaid eligibility has a positive effect on days of school missed due to illness or injury. The probit models demonstrate that Medicaid eligibility increases the probability that a child will miss school by a large percentage (13.6%)[10]. The negative binomial indicates that if a child is enrolled in Medicaid, then his school absences will be 0.388 days more than children with no insurance[11]. The triprobit and endogenous negative binomial models also indicate that Medicaid eligibility increases the probability and the number of children's days of school missed due to illness or injury[12]. The p-value are significant in all the above four tests. These estimates suggest that my findings are robust to alternative econometric approaches. This result is consistent with the hypothesis that Medicaid eligibility lowers the cost of medical service, and increases medical utilization. Consequently, days of school missed due to illness or injury will increase due to more medical utilization.

CONCLUSIONS

There are few studies about the effect of Medicaid on children's health status and their school attendance. In this paper, I used four models to analyze the effect of Medicaid on children's days of school missed. I find the following interesting result: the effect of Medicaid eligibility on days of school missed due to illness or injury is positive and significant in all four experiments. This means that Medicaid enrollment increases both the probability and the number of school days missed.

The positive correlation between Medicaid and days of school missed due to illness or injury complies with the several former studies. Joyce and Racine (1999) find that mothers of children covered by Medicaid rate their children's health as the same or slightly worse than do mothers of uninsured children. Also, they find that children covered by Medicaid have about the same or slightly more numbers of sick days in the past 12 months than do uninsured children. Currie and Gruber (1996) also demonstrate that being eligible for Medicaid had either no effect or a negative effect on a mother's evaluation of her child's health.

DISCUSSION

People may wonder why Medicaid has not improved children's health status so that the school attendance will drop. There are several possible reasons:

First, increased eligibility does not increase the efficiency with which medical care is delivered, so it will diminish the effect of Medicaid utilization on children's health conditions. Currie and Gruber (1996) demonstrate that physicians do not treat publicly insured patients because Medicaid reimburses at rates far below private fee levels; also, public insurance is concentrated in areas that are underserved by physicians.

Second, I wonder how long it takes for Medicaid to actually improve the health of children. It is possible that the increase in the utilization of Medicaid will not necessarily improve children's health. As pointed out by Currie and Gruber (1996), Medicaid usage mainly concentrated on the area of acute care which may have little health benefit. It is possible that if future research uses longitudinal dataset to follow each child in the long run, it may find out that children's absences will decrease in the long run.

ENDNOTES

1. The dataset which I use for the paper is National Health Interview Survey, which is a one year cross sectional dataset. As a result, I apply the hypothesis for the short run effect of Medicaid enrollment on school absences.
2. In the paper, I also include the private insurance on the right hand of the equations. As a result, the treatment group is children who have Medicaid or private insurance, the control group is children who have no insurance. The estimation results compare the treatment effects with the control group.
3. "t" represents time, "i" represents each individual student.
4. In complement of the effect of Medicaid on school absences, the table 2, 3, 4, 5 also demonstrate the effect of private insurance on school absences. The effect of private insurance on school absences is similar to the effect of Medicaid on school absences.
5. It is possible that children who are in poor health conditions (originally have more school days missed) are more likely to enroll in Medicaid. Therefore there is two-way causality between Medicaid and school days missed. In this case, the triprobit model is applied to control for this simultaneity.
6. In a triprobit model, I cannot interpret what the coefficient (0.784) in quantity. However, I can at least say that Medicaid eligibility will increase the probability that a child will miss school.

7. One important feature of the data on school days missed is that it is skewed toward the left. The most common number of days missed is 3. Since the distribution of days of school missed due to illness or injury is far from normal, I could not use the OLS to analyze the results. The poisson regression is inappropriate in this case because the variance of the school days missed is much larger than the means (over-dispersed). As a result, I could not use the poisson regression. In this situation, negative binomial regression is the appropriate regression model.
8. It is possible that children who are in poor health conditions (originally have more school days missed) are more likely to enroll in Medicaid. Therefore there is two-way causality between Medicaid and school days missed. In this case, the endogeneous negative binomial model is applied to control for this simultaneity.
9. It is hard to give a quantitative explanation of the coefficients in the triprobit model, but the at least I could conclude that Medicaid eligibility and school absences are positively correlated.
10. The probit and triprobit model explains the increase of probability of children's school absences in related with Medicaid.
11. Note that 0.388 is a 10% increase of school absences for children who are enrolled in Medicaid since the average school absences for all children is only three days.
12. The negative binomial model and endogenous negative binomial model demonstrates the number of children's school absences in related with Medicaid. Although in the endogenous negative binomial model, it is hard to explain give a quantified explanation for the coefficients.

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APPENDIX

TABLE 1
DEFINITIONS AND DESCRIPTIVE STATISTICS

Variable	Definition	Means	SD
SCHDAYR1	Days missed due to illness/injury, past 12 month	3.44	5.67
MEDICAID	=1 if the individual has Medicaid =0 otherwise	0.26	0.30
PRIVATE	=1 if the individual has private insurance =0 otherwise	0.70	0.46
MALE	=1 if the individual is male =0 otherwise	0.52	0.50
Midwest	=1 if the individual lives in the Midwest region =0 otherwise	0.22	0.42
South	=1 if the individual lives in the South region =0 otherwise	0.35	0.48
West	=1 if the individual lives in the South region =0 otherwise	0.26	0.44
Northeast	=1 if the individual lives in the Northeast region =0 otherwise	0.16	0.37
Hispanic	=1 if the respondent reports origin as Hispanic/Latino =0 otherwise	0.27	0.45
White	=1 if the respondent reports race as white =0 otherwise	0.84	0.37
Black	=1 if the respondent reports race as black =0 otherwise	0.10	0.30
Others	=1 if the respondent reports race as others (Asian, multiple) =0 otherwise	0.06	0.24
MOM_C	=1 if the respondent's mother has some college =0 otherwise	0.30	0.46
DAD_C	=1 if the respondent's father has some college =0 otherwise	0.26	0.45
MOM_M	=1 if the respondent's mother has a college degree or above =0 otherwise	0.26	0.44
DAD_M	=1 if the respondent's father has college degree or above =0 otherwise	0.28	0.45
INCLESS1	=1 if the family's income is less than $10000 =0 otherwise	0.02	0.13
INCMORE1_2	=1 if the family's income is between $10000 and $20000 =0 otherwise	0.06	0.23
INCMORE3_5LESS4_5	=1 if the family's income is between $35000 and $45000 =0 otherwise	0.09	0.29
INCMORE4_5LESS5_5	=1 if the family's income is between $45000 and $50000 =0 otherwise	0.09	0.29
INCMORE5_5	=1 if the family's income is above $50000 =0 otherwise	0.55	0.50
SINGLEDAD	=1 if mother is not a household member=0 otherwise	0.06	0.24
SINGLEMOM	=1 if father is not a household member=0 otherwise	0.29	0.45
SCHDAYR2	LOG value of the school days missed	1.13	0.78
SCHDAYR3	=1 if school days missed is more than 3 days =0 otherwise	0.29	0.46

Note: SD represents standard deviations.
Means are calculated using 6844 respondents (age between 0 and 19) to the National Health Interview Survey in the year 2005.

TABLE 2
THE RESULTS OF PROBIT REGRESSION

SCHDAYR3	ME	SE	P>|z|
MEDICAID	0.109	0.018	0.000**
PRIVATE	0.028	0.016	0.077
MALE	0.006	0.011	0.589
South	-0.013	0.015	0.412
West	-0.007	0.017	0.682
Northeast	-0.013	0.018	0.484
Hispanic	-0.088	0.014	0.000**
White	0.088	0.025	0.001**
Black	-0.049	0.029	0.103
INCLESS1	0.179	0.040	0.000**
INCMORE1_2	0.086	0.032	0.006**
INCMORE2LESS3_5	0.070	0.028	0.011*
INCMORE3_5LESS4_5	-0.040	0.031	0.182
INCMORE4_5LESS5_5	0.029	0.031	0.352
INCMORE5_5	0.040	0.026	0.118
SINGLEDAD	0.015	0.024	0.522
SINGLEMUM	0.051	0.015	0.000**

Note: SE represents standard error, ME represents mean, and P represents p-value.
SCHDAYR3 is created as a binary variable indicate whether the student is absent or not.
** statistical significance at the 5% level.
* statistical significance at the 1% level.

TABLE 3
THE RESULTS OF TRIPROBIT REGRESSION

SCHDAYR3	Coef.	SE	P>|z|
MEDICAID	0.784	0.067	0.000**
PRIVATE	-0.966	0.096	0.000**
MALE	-0.005	0.029	0.851
South	-0.074	0.041	0.071
West	-0.038	0.042	0.370
Northeast	-0.064	0.046	0.169
Hispanic	-0.430	0.038	0.000**
White	0.262	0.064	0.000**
Black	-0.212	0.074	0.004**
INCLESS1	-0.170	0.080	0.032*
INCMORE1_2	-0.300	0.058	0.000**
INCMORE3_5LESS4_5	0.165	0.058	0.005**
INCMORE4_5LESS5_5	0.268	0.063	0.000**
INCMORE5_5	0.473	0.048	0.000**
SINGLEDAD	-0.030	0.037	0.416
SINGLEMUM	0.071	0.053	0.182

Note: Coef represents coefficient, SE represents standard error, and P represents p-value.
SCHDAYR3 is created as a binary variable indicate whether the student is absent or not.
** statistical significance at the 5% level.
* statistical significance at the 1% level.

TABLE 4
THE RESULTS OF NEGATIVE BINOMIAL REGRESSION

SCHDAYR1	Coef.	SE	P>|z|
MEDICAID	0.388	0.049	0.000**
PRIVATE	0.072	0.042	0.085
MALE	-0.039	0.030	0.193
South	-0.117	0.041	0.004**
West	-0.028	0.046	0.535
Northeast	-0.000	0.049	0.100
Hispanic	-0.205	0.038	0.000**
White	0.294	0.070	0.000**
Black	-0.076	0.079	0.337
INCLESS1	0.305	0.076	0.000**
INCMORE1_2	0.165	0.057	0.004**
INCMORE3_5LESS4_5	0.099	0.058	0.087
INCMORE4_5LESS5_5	0.036	0.060	0.550
INCMORE5_5	0.051	0.044	0.250
SINGLEDAD	-0.127	0.037	0.001**
SINGLEMUM	-0.048	0.057	0.392
Likelihood-ratio test of alpha=0:	chibar2(01)=1.6e+04	Prob>=chibar2=0.000	

Note: Coef represents coefficient, SE represents standard error, and P represents p-value.
** statistical significance at the 5% level.
* statistical significance at the 1% level.

TABLE 5
THE RESULTS OF ENDOGENOUS NEGATIVE BINOMIAL

SCHDAYR1	Coef.	SE	P>|z|
MEDICAID	0.407	0.054	0.000**
PRIVATE	0.420	0.072	0.000**
MALE	-0.017	0.031	0.572
South	-0.146	0.043	0.001**
West	-0.055	0.047	0.248
Northeast	-0.029	0.050	0.566
Hispanic	-0.321	0.040	0.000**
White	0.332	0.073	0.000**
Black	-0.090	0.082	0.272
INCLESS1	0.272	0.080	0.001**
INCMORE1_2	0.102	0.061	0.093
INCMORE3_5LESS4_5	0.109	0.060	0.068
INCMORE4_5LESS5_5	0.100	0.063	0.126
INCMORE5_5	0.176	0.047	0.000**
SINGLEDAD	-0.156	0.039	0.000**
SINGLEMUM	-0.005	0.059	0.932

Note: Coef represents coefficient, SE represents standard error, and P represents p-value.
** statistical significance at the 5% level.
* statistical significance at the 1% level.