

The effect of Medicaid on Children's Health: a Regression Discontinuity Approach

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Abstract

In this paper I estimate the impact of Medicaid on children's health care utilization and their subsequent health outcomes. I estimate the causal effects using a Regression Discontinuity (RD) design. I exploit the discontinuity generated by Medicaid's eligibility rule, based on family income, on program participation rates. In contrast with a standard regression discontinuity approach, here there are multiple eligibility thresholds that vary across states. This allows me to estimate heterogeneous effects of the program at different income thresholds. Using data from the Panel Study of Income Dynamics (PSID) and its Child Development Study (CDS) supplement, I find that the effects of Medicaid on measures of children's health are heterogeneous depending on the family income level. Negative impacts of Medicaid are generally observed for children of higher-income families —185 and 250% of the poverty line—, while generally null or positive effects are observed for poorer children —with family income lower than 185% of the poverty line. A possible explanation for the heterogeneous impacts is the differential effect of Medicaid on health care utilization. While I find that Medicaid increases the use of preventive medical care among children with low family income, no significant effects are observed among those with higher income. Also, if higher-income families are switching from a private health insurance that allowed them to access to better quality of health care than the public program, then Medicaid may have negative effects on children's health outcomes.

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1 Introduction

There is strong evidence showing the positive relationship between parental socioeconomic status and children’s health, leading to health inequalities in early childhood. To the extent that poor health affects the formation of human capital, it is then possible that health could play a key role in the intergenerational transmission of socioeconomic inequalities (Currie (2009), Almond and Currie (2010)). Currie (2009) suggests that children’s health inequalities may be partially explained by disparities in the access to health care services. The provision of public health insurance coverage to children of low-income families facilitates the access to medical care and, therefore, may help to break the link between socioeconomic status and health.

In this paper, I address the question of whether a public health insurance targeting poor children contributes to the improvement of their subsequent health outcomes. In particular, I study the contemporaneous and mid-term impacts of Medicaid, the US public health insurance program for low-income families, on children’s health care utilization and health outcomes.

I exploit the particular characteristics of Medicaid’s eligibility rules to identify the causal effects of the program on children’s outcomes. A child is eligible to receive Medicaid coverage if her family income is below a given threshold, defined as a percentage of the poverty line. This rule generates a discontinuity in the enrollment rates of children with family income close to the threshold, which allows me to implement a regression discontinuity (RD) design. Since enrollment into Medicaid is not mandatory, the RD design is denoted as “fuzzy” RD.

Eligibility criteria for the Medicaid program are set at the state level. Thus, the income threshold that determines eligibility varies across states. Moreover, the income thresholds may depend on the child’s age. The multiplicity of thresholds is advantageous for the external validity of the RD design I implement since the effects estimated are not restricted to the individuals located around a single income threshold, but they are averages of the effects across different thresholds. I quantify the effects of the program on children with different levels of family income, and check whether these effects are heterogeneous.

I use data from the Panel Study of Income Dynamics (PSID) and complement it with the Child Development Study (CDS) supplement, which provides rich information about children’s health and health care utilization as well as detailed information on socioeconomic characteristics of the family. The PSID data allows tracking of children’s Medicaid status at different ages through childhood.

Some studies have addressed the question of whether health insurance has a positive effect on children’s health. Among the studies using data on Medicaid the results are mixed. For example, Currie and Gruber (1996) find evidence that the expansions in Medicaid eligibility thresholds between 1984 and 1992 increased the utilization of medical care and reduced child mortality. In contrast, Currie et al. (2008) find that expansions in Medicaid eligibility thresholds from 1986 to 2005 had no effect on the health of children between 9 and 17 years old, as reported by their parents. Their estimates, however, suggest that expansions that affected children of ages between 2 and 4 are associated with better health by the time they are 9-17 years old.

This paper contributes to this literature in several ways. First, I analyze both the contemporaneous and the lagged effects of Medicaid on different measures of health. Since health is a stock, the effects of insurance coverage may be visible with a lag. The paper by Currie et al. (2008) is among the first to attempt estimating these lagged effects. However, in the cross sectional datasets they use, they must impute the family income and the state of residence of the child, since these variables are not observed during childhood. In contrast, I exploit the panel dimension of PSID data to match past eligibility with current health outcomes. Second, the identification strategy I propose allows the estimation of Medicaid effects that vary across different levels of income. Results show the importance of this disaggregation when drawing any conclusions about the effects of the program.

Results show that Medicaid enrollment rates are relatively low, consistent with previous findings (e.g. Currie and Gruber (1996)), and that they decrease with family income. Making a child eligible for Medicaid increases the likelihood that she will be enrolled in the program by 12 percentage points on average.

Moreover, I find that Medicaid eligibility increases the utilization of preventive medical care—measured by the probability of visiting a doctor for a routine check-up in the last 12 months—, by 12 percentage points, but only for children whose family income is lower than 185% of the poverty line. The effect is much larger for “compliers” —those who enroll in the program when it is available. According to LATE estimates, Medicaid increases compliers’ likelihood of visiting a doctor by 63 percentage points. I do not observe significant effects on utilization for children with family income between 185 and 250% of the poverty line.

In the short run, Medicaid’s effects on health are null or even negative. Even the medium run effects —1 to 3 years after being eligible— tend to be negative on average. When disaggregating

the results by income, however, I find that the average negative impact of Medicaid on children's outcomes is driven by its negative impact on the health of children in higher-income families. I show that the impact of Medicaid on the health of poorer children is relatively higher, and in some cases also positive.

One possible explanation for the heterogeneous effects of Medicaid on children with different levels of family income could be the heterogeneous impact of Medicaid on health care utilization. In fact, my findings indicate that only poorer children increase health care utilization, which in turn may positively affect their health in the mid-run.

A second reason why Medicaid's impact varies by family income is that while Medicaid may be the only option for poorest families to access health care, this may not be so for higher-income families, who, more likely, have enough resources to buy health insurance in the private market. Then, for poorer children enrolled in Medicaid, we may expect better health outcomes because for them the counterfactual situation is, more likely, being uninsured. However, for children of higher-income families enrolled in Medicaid, this is not necessarily the expected effect. These children were enrolled into Medicaid because the public insurance program allows their families to reduce the expenditures on health care.¹ But switching to the public system may have a cost in terms of the quality of care they have access to. The higher the family income, the better the quality of care they may be sacrificing when switching to Medicaid. In an independent and simultaneous work, Koch (2010) also finds evidence that supports this hypothesis. His results indicate that families with larger incomes have access to better insurance quality and that the quality of care received by children decreases as they become eligible for public health insurance. Hence, Medicaid coverage in this case may actually have a negative impact on children's health.

The remainder of the paper is organized as follows: Section 2 describes the Medicaid program; Section 3 presents the empirical strategy; Section 4 describes the data; Section 5 validates the regression discontinuity strategy; Section 6 presents the results; and section 7 presents a discussion of the results and concludes.

¹There is a large literature studying to what extent Medicaid expansions have lead eligible families to switch from the private to the public sector. This effect is known in the literature as "crowding-out" effect (Cutler and Gruber (1996), Lo Sasso and Buchmueller (2004), Card and Shore-Sheppard (2004), Ham and Shore-Sheppard (2005), Gruber and Simon (2007)).

2 Medicaid Program

The Medicaid program was introduced in the late 1960s as a health insurance component for state cash welfare programs targeting low-income single female head families. It is a state administered program and each state sets its own guidelines regarding eligibility and services, but subject to federal rules requiring minimum levels of coverage and services.

Medicaid eligibility for children was in its origins tied to the participation in the Aid for Families with Dependent Children (AFDC) program. Since the mid 1980s the linkage between AFDC coverage and eligibility for Medicaid has been gradually weakened, by eliminating the family structure requirements for young children and by allowing states to increase the income thresholds that determine eligibility. The increase in the thresholds was first a state option, but later minimum levels of coverage were imposed by federal mandates. By April 1990, states were required to offer coverage to all children under 6 years old in families with income up to 133% of the poverty line and, starting in July 1991, they were required to provide coverage to all children under age 19, who were born after September 1983 and lived in households with incomes below 100% of the poverty line. As a result, by the mid-1990s, most children in the US living in households with incomes below 100% of the poverty line, and all young children living in households with incomes below 133% of the poverty line were eligible for Medicaid.

In practice, most states opted to raise the income thresholds beyond 133% of the poverty level and some did further increases using own state funds. States also set different threshold levels for different age groups. In 1997, the Medicaid program for children was augmented by the Children's Health Insurance Program (CHIP), which provided extra funds to expand eligibility for children beyond the existing limits of Medicaid program. The CHIP program was implemented either by expanding the Medicaid program, or designing a new program, with features that mimic private health insurance.

The types of services that Medicaid must cover according to the federal rules include major services as outpatient and inpatient hospital services. Services such as prescription drugs or dental care are not mandatory, however all states in practice cover most of them. For the traditional Medicaid population these services are provided with little or no copayment required (Gruber and Simon, 2007).² In terms of the package of services covered, Medicaid tends to be more generous than many private insurance plans.

²In states that have CHIP, the copayments are allowed to be higher for those above 150% of the poverty line.

States also determine the rules to reimburse health care providers. In most cases, Medicaid’s reimbursement is lower than the obtained from private insurance, which may induce some physicians to reject Medicaid patients or to lower the quality of the service provided.³

3 Identification

3.1 Contemporaneous effects

The main objective is to estimate a simple model of the causal effect of Medicaid coverage on children’s health care utilization and health outcomes:

$$y_i = \alpha + \beta M_i + u_i \tag{1}$$

where M_i indicates whether the child received Medicaid coverage. A simple OLS regression of equation 1 would yield a biased estimate. Medicaid coverage is an endogenous variable, because the access to this type of coverage is correlated with family income. Even after controlling for family income, there exists the problem of selection, because taking Medicaid is not mandatory. Among eligibles, the decision to take Medicaid may be correlated with other unobserved characteristics that are correlated with the outcomes of interest.

In order to identify the effect of interest, I exploit the rule of assignment into Medicaid to implement a Regression Discontinuity (RD) design. The RD design is a quasi-experimental design with the defining characteristic that the probability of receiving treatment changes discontinuously as a function of the variable that determines eligibility (Hahn et al. (2001)).⁴

The intuition behind the RD is the following. Under the assumption that families have imperfect control of their income –which in the RD jargon is called the assignment or forcing variable– the variation in eligibility status will be as good as randomization in the neighborhood of the threshold, approximating a randomized experiment. This implies that children’s

³For example, Decker (2007) finds that higher Medicaid fees increase the number of private physicians, especially in medical and surgical specialties, who see Medicaid patients. She also finds that higher fees also lead to visit times with physicians that are more comparable to visit times with private pay patients. Another paper by Cunningham and OMalley (2009) finds that not only reimbursement fees matters, but also delays in reimbursement. They find evidence that Medicaid reimbursement time affects physicians’ willingness to accept Medicaid patients.

⁴For a comprehensive discussion of the RD design and its application in economics see Imbens and Lemieux (2008), van der Klaauw (2002), and (Lee and Lemieux, 2010)

observable and unobservable characteristics should have the same distribution just above and just below the threshold. Making the additional assumption that the outcome is a smooth function of income, the causal effect of being assigned into treatment –being eligible for Medicaid– can be identified by comparing the average outcome of children just below the income threshold (“treatment group”) with children just above it (“control group”). Any difference observed between these two groups can be attributed to the *availability* of treatment –being eligible to Medicaid– for treatment group members. This difference would identify an average treatment effect only in the case of perfect compliance, that is, the probability of *receiving* the treatment –being enrolled into Medicaid– is equal one for eligible individuals and zero for non-eligibles.⁵

Under imperfect compliance, which is the case in my dataset because enrolling into Medicaid is not mandatory, the comparison of outcomes of eligible and non eligible individuals close to the threshold does not identify the average treatment effect, but the average effect of assignment into treatment or the *intent to treat effect* (ITT) at the threshold.⁶ The ITT effects, however, could be significantly lower in absolute value than the effect the program for those who are actually covered by Medicaid. I can still estimate β implementing a “fuzzy” RD design under the assumptions that the probability of treatment – having Medicaid coverage– is discontinuous at the threshold, the association between the outcome variable and income is smooth, and persons close to the threshold are similar in baseline (pre-treatment) characteristics.

As shown by Hahn et al. (2001), the treatment effect can be recovered by dividing the “jump” in the relationship between the outcome and eligibility –the ITT at the threshold– by the fraction of individuals induced to take Medicaid at the threshold:

$$\beta = \frac{\lim_{z \rightarrow z_0^-} E[y_i | z_i = z] - \lim_{z \rightarrow z_0^+} E[y_i | z_i = z]}{\lim_{z \rightarrow z_0^-} E[M_i | z_i = z] - \lim_{z \rightarrow z_0^+} E[M_i | z_i = z]} \quad (2)$$

where z_i is the family income and z_0 is the eligibility threshold.

Hahn et al. (2001) were the first to show the connection between how the treatment effect is defined in the fuzzy RD design and the “Wald” estimation of the treatment effect in an instrumental variables setting. They suggest estimating the treatment effect in the fuzzy RD

⁵This would mean that M_i is equal to and indicator of eligibility status, El_i , that takes the value one when the child is eligible for Medicaid.

⁶For instance, studies like Currie and Gruber (1996) and Currie et al. (2008), although using different identification strategies than in this paper, identify the intent to treat effects of Medicaid on children who where newly eligible to receive Medicaid benefits with the Medicaid expansion.

setting using two-stage least-squares (TSLS). Furthermore, they also pointed out that equation 2 can be interpreted as a *Local Average Treatment Effect* (LATE) at the threshold under the same assumptions as in Imbens and Angrist (1994). Under these assumptions, the LATE is defined as the average effect of treatment on eligible individuals at the threshold who receive the treatment if and only if they are assigned to it. These individuals are called the “*compliers*”.

Given that Medicaid is a state administered program, and that each state sets its own eligibility threshold, there are multiple thresholds. Assuming that treatment effects are different for different thresholds, the estimates obtained using a sample that pools all states reflects an average of LATE’s at each threshold.

I implement a parametric RD strategy that controls for a flexible function of income as proposed by van der Klaauw (2002), in order to retain observations that are not necessarily close to threshold. This flexible function of income controls for variation coming from income differences far from the threshold. I also include flexible functions of other variables that determine eligibility (family size, and child age) and I follow a similar functional specification as in Carneiro and Ginja (2009).

First I estimate the following equation:

$$y_i = \alpha + \theta Eli_i + f_g(z_{it}; \gamma_g) + u_i \quad (3)$$

where Eli_i is a dummy variable that takes the value one if the child is eligible for Medicaid, $f_g(z_{it}; \gamma_g)$ is a flexible function of income –second-order polynomials in my baseline estimations– and other determinants of eligibility. The parameter θ is the ITT effect of Medicaid. The periods for which I observe the outcomes are t=1997, 2002, 2007, as I explain in section 4.

I also implement the Fuzzy RD parametrically –using polynomial regression– and estimate β by 2SLS, where I instrument the treatment dummy M_i with Eligibility, Eli_i . The two equation system is:

$$y_i = \alpha + \beta M_i + k_{2g}(z_i; \alpha_{2g}) + u_i \quad (4)$$

$$M_i = \pi_0 + \pi_1 Eli_i + k_{1g}(z_i; \alpha_{1g}) + v_i \quad (5)$$

where $k_{1g}(\cdot)$ and $k_{2g}(\cdot)$ are polynomials of order g of z_i (family income, child's age and family size), and u_i and v_i are unobserved error components. Since the model is exactly identified, 2SLS estimates or β are numerically identical to the ratio of the reduced form coefficients θ/π_1 , provided the same order of polynomial is used for $k_1(\cdot)$ and $k_2(\cdot)$ (Lee and Lemieux, 2010). In all the baseline estimates I use second order polynomials.

3.2 Lagged effects

In order to identify mid-run effects of Medicaid, I should account for the possibility of multitreatment. Children may have multiple opportunities to be assigned to treatment during their childhood. Therefore, the dynamic dimensions of the effects of the Medicaid Program are twofold: 1) the effects of being assigned to treatment or receiving treatment in a given period t may be visible—in terms of health outcomes—with some lag, 2) current assignment to treatment may affect participation in the program in subsequent periods, which in turn may have a cumulative effect on health.

Then, the marginal effect of making a child randomly eligible for Medicaid in a period $t - \tau$ on health outcomes in period t would reflect a cumulative effect which is the sum of: 1) a direct effect on health outcomes τ years later, if it were possible to prohibit her from being assigned to treatment in any other subsequent period; 2) an indirect effect on health outcomes through the effects on subsequent participation in the program. The total effect or *mid-run ITT effect* Medicaid eligibility on subsequent health is the effect of exogenously making a child eligible in a given period, without controlling for the family behavior in subsequent years. Following Cellini et al. (2010) the ITT parameter is:⁷

$$\theta_{\tau}^{ITT} = \frac{\mathbf{d}y_{it}}{\mathbf{d}El_{i,t-\tau}} = \frac{\partial y_{it}}{\partial M_{i,t-\tau}} \times \frac{\partial M_{i,t-\tau}}{\partial El_{i,t-\tau}} + \sum_{h=1}^{\tau} \left(\frac{\partial y_{it}}{\partial M_{i,t-\tau+h}} \times \frac{\partial M_{i,t-\tau+h}}{\partial El_{i,t-\tau}} \right) \quad (6)$$

where $El_{i,t-\tau}$ is a dummy variable that takes the value one if the child was eligible for Medicaid in the year $t - \tau$; $\frac{\partial y_{it}}{\partial M_{i,t-\tau}}$ is the direct effect of Medicaid in period $t - \tau$ under the assumption that the child would not have access to Medicaid in the subsequent years.⁸

⁷The main difference with Cellini et al. (2010) is that in their paper they have a “sharp” RD design, that is, being eligible is equivalent to receiving the treatment.

⁸Health outcomes in period t can be written as a function of the history of eligibility status $y_{it} = \sum_{\tau=0}^T \delta_{\tau} El_{i,t-\tau} + u_i$. Each of the partial effects δ_{τ} capture the direct effects of Medicaid eligibility on sub-

I implement an RD design similar Cellini et al. (2010) to estimate the θ_{τ}^{ITT} parameters. I regress the outcomes in period t on eligibility status $t - \tau$, controlling for flexible functions of family income and family characteristics in $t - \tau$ but not for any subsequent income or other characteristics:

$$y_{it} = \alpha + \theta_{\tau} \text{Eli}_{i,t-\tau} + f_g(z_{i,t-\tau}; \gamma_{\tau}) + u_{it} \quad (7)$$

where f_g is a polynomial of order g . As in previous specifications the baseline estimate controls for second-order polynomials of income and other variables that determine eligibility, such as age and family size.

4 Data

I use the data from the Child Development Study (CDS), a supplementary study to the Panel Study of Income Dynamics (PSID). The CDS gathers information of a nationally representative sample of children between 1 and 12 years old by 1997 and collects health care utilization and health outcomes, obtained from the child's primary caregiver, as well as characteristics such as age and race of the child. Data for this cohort of children were collected in three waves: 1997, 2002, and 2007. Information on family income, Medicaid coverage, and family characteristics is provided in the PSID dataset. I use the three CDS waves-matched with PSID data as repeated cross-sections, and I restrict the sample to children between 5 and 18 years old. I keep only those children for whom I can follow back their eligibility and Medicaid status up to 5 years before the outcomes are observed.

First, I assign Medicaid eligibility status of each child in the survey on a yearly basis. To impute eligibility I need to compare the annual family income with the annualized income threshold that determines eligibility. The family income is reported in each wave of PSID and it always refers to the previous calendar year. I compute the income threshold that corresponds to each child, z_{oit} , according to the following formula:

$$z_{oit} = PL_t(\text{family size}_{it}) \times k_t(\text{state}_{it}, \text{age}_{it}) \quad (8)$$

sequent outcomes. Cellini et al. (2010) propose a methodology to estimate also these partial effects.

where PL_t is the poverty threshold in period t and $k_t(.)$ is the state-age specific factor of adjustment in period t . I use the annualized official poverty threshold which is provided in the PSID data file for each family.⁹ I get the information of state-age-year specific adjustment factors from various reports of the National Governors' Association. All income measures are expressed in 2000 dollars. A child is eligible for Medicaid in period t if his family income is below the income threshold, $Eli_{it} = \mathbf{1}\{\text{income}_{it} \leq z_{oit}\}$.

I use three types of outcome variables: preventive health care utilization, objective measures of health, and subjective measures of health. The measure of preventive health care utilization is a variable that indicates whether the child had visited a doctor at least once in the last 12 months for a routine health check-up. This measure is generally used to capture the utilization of medical resources for preventive purposes. Other measures of health care utilization, such as the number of hospitalizations, may confound access and morbidity, as pointed out by Currie and Gruber (1996). An absence of a doctor visits for a regular check-up, however, better reflects an "access" problem. Preventive medical care may help to improve and maintain the health stock of the child, hence it is an important measure to look at.

For an objective measure of the child health I use the Body Mass Index (BMI).¹⁰ A child's weight status is determined based on an age and sex-specific percentile for BMI rather than by the BMI categories used for adults, because children's body composition varies as they age and varies between boys and girls. The CDS dataset provides indicators of the child's obesity and overweight status, based on the Centers for Disease Control and Prevention (CDC) growth charts.¹¹ Hence, a child is classified as obese if her BMI is at or above the 95th percentile of the BMI distribution of children of the same age and sex. A child is overweight if her BMI is at or above the 85th percentile but below the 95th percentile. Medicaid coverage may facilitate and increase the contact with physicians, which in turn increases the likelihood that children's weight status is monitored. Physicians recommendations about the quality of the diet and the adequate level of physical activity the child might do, may be critical inputs to improve poorer children's health status.

Additionally, I use two subjective health measures, both reported by the child's caregiver:

⁹See Grieger et al. (2009) for further details on the measures of family income and poverty thresholds in PSID.

¹⁰Although it is not completely "objective", since during the interview, the primary caregiver reports the weight of the child, and the interviewer measures his or her height

¹¹Each of the CDC BMI-for-age gender specific charts contains a series of curved lines indicating specific percentiles. See the CDC Growth Charts for children at: <http://www.cdc.gov/growthcharts>.

an indicator of whether the child has an excellent health status and a dummy of whether the child missed more than five days of school due to illness during the last 12 months. The first measure reflects the caregiver’s perception about the child’s overall health status. I interpret any deviation from excellent health as reflecting some health problem. The second measure links child’s health status and school attendance, thus, it captures some aspect of how health may affect her human capital formation. A better health status allows to prevent illnesses and to be in better health for not missing school days.

One drawback of using subjective health measures is that they are difficult to interpret. Currie and Gruber (1996) argue that these measures may capture two possible effects. If the public insurance coverage leads individuals to increase the contacts with the medical system, then there could be a “true” effect on child health, resulting in better child’s health reports. The increased contacts with physicians, however, may also affect parents’ perception about the health of the child. Parents may learn about health conditions the child already had but, because they did not contact physicians so frequently before having the public insurance coverage, they were not aware of them. Also, if targeted children are switching from a private insurance to the public, parent’s reports may be sensitive to perceived changes in the quality of health care they have access with the public insurance relative to the private. Thus, these measures should be interpreted with caution.

Samples I restrict the sample to children for whom I observe all the outcomes of interest in at least one of the three CDS waves. I pool the three years treating them as repeated cross sections.¹² Each outcome is matched with eligibility and Medicaid status up to 5 years before the outcomes is observed.

The objective is to analyze the effect of making someone randomly eligible in a given year, on his outcomes τ years latter. I look at effects up to 5 years later, thus τ takes values from 0 to 5. I center the periods in the year t when outcomes are observed ($t = 1997, 2002, 2007$). To estimate both the contemporaneous effect and each of the lagged effects of Medicaid –which I do in separate regressions– I define a specific sample according to the following criteria. In each sample, I keep those children whose family income in the period $t - \tau$ was close to the eligibility threshold of that period. Because of the small sample sizes I would get by restricting the analysis only to observations in a tight neighborhood of the threshold, I focus on an implementation of the

¹²All estimations control for year effects.

RD strategy that retains observations that may be far from it. The parametric RD estimation I implement uses a flexible function of income to absorb the variation coming from non-close income levels. The baseline estimates are based on samples of individuals whose family income, in the respective year eligibility is analyzed, is within a distance of ± 50 thousand dollars from the income threshold.

The means describing the main characteristics of the sample are presented in the table 1.¹³ Columns 1 and 2 present descriptive statistics for the full sample. Columns 3 to 8 present the same descriptives but for three subsamples, defined by the level of Medicaid generosity in each state: the first subsample is composed of children living in states where the generosity of Medicaid coverage is relatively low –the eligibility thresholds are less than 185% of the poverty line; the second subsample keeps children living in states with middle level of generosity –the eligibility thresholds are between 185 and 250% of the poverty line; and finally, the third subsample is composed by children living in states with relatively high levels of generosity –the eligibility thresholds are above 250% of the poverty line.

From columns 1 and 2, it is clear that Medicaid eligibles are more disadvantaged than non-eligibles in several dimensions. They have not only lower family income –by definition of eligible– but also they are likely to be minorities, to live in a female-headed family, and to live with a less educated head of household. They are worse off in terms of health outcomes; however they are more likely to have visited a doctor for a check up in the last 12 months. The same picture emerges if I split the sample according to the different levels of Medicaid’s coverage generosity. In the 3 groups, eligible children are always more disadvantaged in terms of socioeconomic characteristics, they also tend to have worse health outcomes and to use more preventative health care services, with the exception of states with higher levels of Medicaid generosity, where utilization is higher for non-eligibles.

About 53% of eligible children are actually enrolled in Medicaid, although enrollment is heterogeneous depending on family income level.¹⁴ The incentives to enroll in Medicaid decreases

¹³These descriptive statistics corresponds to the sample selected to analyze the contemporaneous effects of Medicaid. That is, it is restricted to children whose annual family income is within a distance of ± 50 thousand dollars in period t , for $t=1997$, 2002, and 2007.

¹⁴Notice that among non-eligibles there are individuals with Medicaid coverage. This happens because there may be timing problems in the reports of individuals eligibility and Medicaid coverage. Also, income fluctuations during the year can make an individual eligible for Medicaid but using their annual income I classify them as non-eligible. Approximately 10% of the non-eligibles in the full sample report having Medicaid, although this percentage rise up to a 20% for the subgroup of individuals just below the eligibility threshold, as will be showed in section 5.

with income, as can be observed by comparing eligible children in states with increasing levels of Medicaid generosity. The take-up rate is 61% in states with modest Medicaid coverage generosity, where eligibles' average family income is 12.1 thousand dollars per year; this proportion falls to 53% in states with middle level generosity and where eligibles' average income is 21.4 thousand dollars; and it is even lower –35%– in states with the most generous coverage, where eligibles' average income is 33,6 thousand dollars. The incentives to enroll in Medicaid may decline with income because, as income rises, the family's financial constraint is less binding, which allows them to acquire an alternative source of coverage in private markets.

Table 1: Descriptive Statistics

	Pooling all Thresholds		Thresholds<185		Thresholds [185,250]		Thresholds>250	
	Eligible	Non-Eligible	Eligible	Non-Eligible	Eligible	Non-Eligible	Eligible	Non-Eligible
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Measures								
Visited a doctor at least once in last 12 months	0.75	0.68	0.70	0.62	0.76	0.71	0.74	0.77
Obese (over 95 percentile BMI dist.)	0.24	0.19	0.23	0.19	0.24	0.20	0.28	0.17
Overweight (85-95 percentile BMI dist.)	0.15	0.15	0.15	0.15	0.15	0.16	0.14	0.18
Obese + Overweight	0.39	0.35	0.38	0.34	0.39	0.36	0.42	0.35
More than 5 days of school missed	0.12	0.12	0.18	0.12	0.10	0.13	0.12	0.11
Health Excellent	0.39	0.54	0.27	0.47	0.42	0.58	0.47	0.62
Insurance Coverage								
Medicaid Coverage	0.53	0.09	0.61	0.12	0.53	0.07	0.35	0.05
Private Insurance	0.32	0.81	0.21	0.77	0.32	0.82	0.58	0.90
Family and Child Characteristics								
Family Income (2000 dollars)	20,438	53,349	12,101	44,120	21,352	58,124	33,641	78,361
	(12,481)	(18,574)	(7,325)	(15,010)	(11,076)	(16,290)	(15,220)	(20,573)
Income Cutoff (eligibility threshold)	35,768	30,898	22,465	21,315	37,260	35,681	56,647	58,971
	(13,557)	(12,832)	(6,755)	(5,993)	(9,339)	(8,384)	(13,475)	(14,546)
Income threshold as % of poverty line	200.65	174.30	123.68	120.02	205.67	201.91	341.23	331.43
	(66.33)	(61.07)	(24.56)	(24.62)	(18.05)	(16.45)	(46.78)	(41.84)
Metropolitan Area	0.67	0.60	0.76	0.60	0.64	0.57	0.61	0.80
Rural Area	0.15	0.16	0.11	0.14	0.15	0.20	0.20	0.09
	0.35	0.37	0.31	0.35	0.36	0.40	0.40	0.28
Family Size	4.20	4.09	4.30	4.09	4.24	4.08	3.75	4.08
	(1.35)	(1.13)	(1.34)	(1.07)	(1.38)	(1.19)	(1.16)	(1.16)
Education (yrs.) of the Head of the Household	11.84	12.92	11.91	12.66	11.69	12.97	12.55	14.10
	(2.29)	(2.04)	(1.84)	(2.01)	(2.47)	(2.00)	(1.98)	(2.13)
Female Head	0.61	0.23	0.68	0.27	0.60	0.21	0.46	0.16
Child Age	11.20	10.97	9.41	9.57	11.82	12.09	11.74	12.30
	(3.17)	(3.28)	(3.18)	(2.96)	(2.93)	(3.05)	(2.95)	(3.26)
Male	0.52	0.50	0.49	0.50	0.52	0.51	0.58	0.52
Black	0.61	0.35	0.73	0.45	0.61	0.29	0.37	0.30
Hispanic	0.06	0.03	0.00	0.01	0.09	0.04	0.00	0.00
Birth Weight (kg)	3.20	3.36	3.17	3.34	3.19	3.37	3.30	3.38
	(0.69)	(0.64)	(0.72)	(0.65)	(0.67)	(0.64)	(0.71)	(0.60)
Mother Age at Child's Birth	25.16	27.02	25.22	26.61	25.06	27.21	25.63	27.94
	(6.01)	(5.37)	(5.97)	(5.14)	(6.12)	(5.55)	(5.49)	(5.29)
N	1,127	1,668	284	700	713	835	130	105

Observations are always restricted to children whose family income is at a distance of $\pm$ 50 thousand dollars from the threshold in years 1997, 2002 or 2007.

5 Validity of RD design: robustness analysis

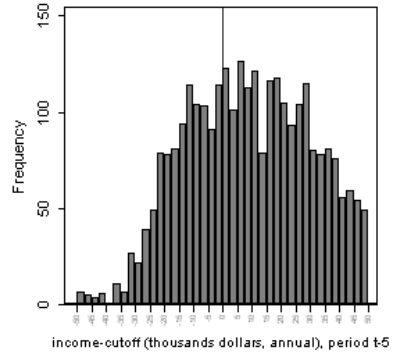
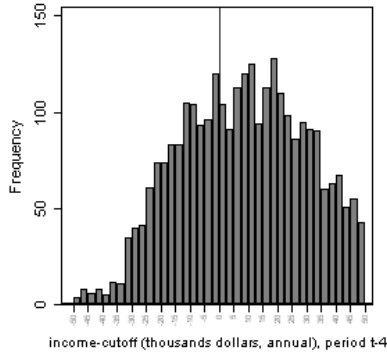
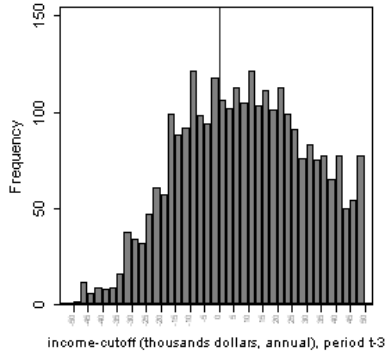
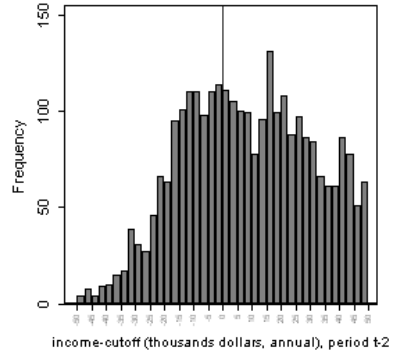
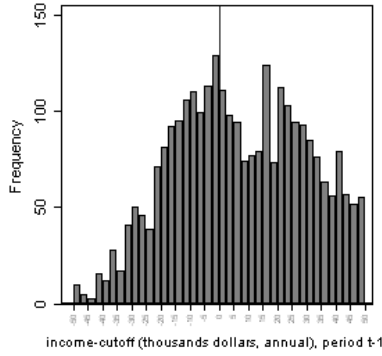
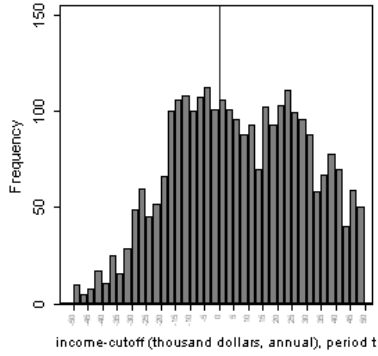
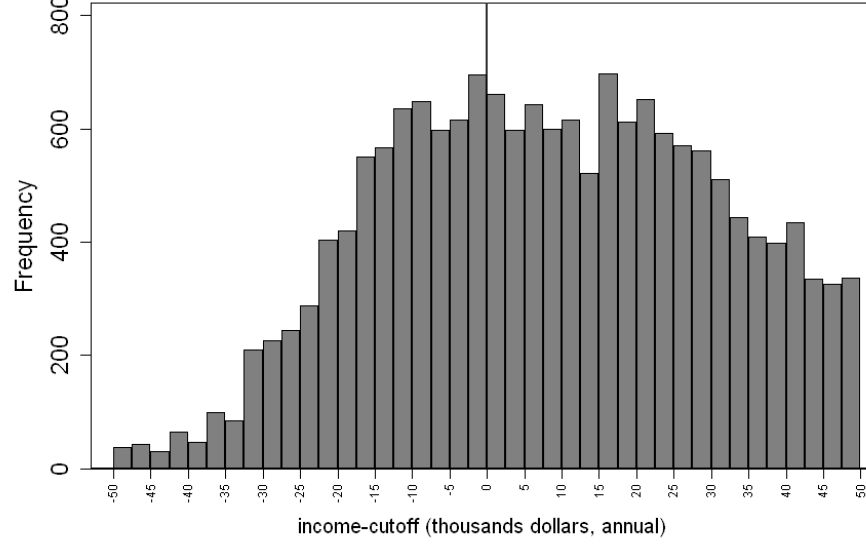
The empirical strategy is based on the assumption that eligibility to receive Medicaid coverage is as good as randomly assigned in the neighborhood of the income thresholds. This implies that individuals at either side of the threshold are similar both in observed and unobserved characteristics. Additionally, for the validity of the design, it should be observed a jump in the probability of participation at the threshold, and no signs of manipulation of the forcing variable. A first step in the analysis, therefore, involves testing these identification assumptions.

To check the validity of the design I perform a series of robustness analyses, as proposed by Imbens and Lemieux (2008) and Lee and Lemieux (2010). First, I inspect the histogram of the family income –the assignment variable– to check whether individuals have imprecise control over it. A spike to the left of the threshold may indicate that families may be manipulating their income to fall below the eligibility threshold. Second, I estimate the enrollment equation to check whether the eligibility rule induces a discontinuity in Medicaid participation at the threshold. Finally, I examine whether baseline covariates (variables that should not be affected by the program as well as individual characteristics not taken into account to participate) are balanced on either side of the threshold. I run falsification tests to check whether the discontinuity in eligibility status affects these variables.

5.1 Manipulation of the assignment variable

Figure 1 presents the distribution of family income, pooling all observations for the period 1994 to 2007. Given that there are multiple thresholds, income is normalized by subtracting the corresponding eligibility threshold. A negative difference indicates that the child is eligible for Medicaid. I calculate the number of observations within bins of 2.5 thousand dollars width. An accumulation of observations below the normalized threshold (equal to zero) may be an indication of income manipulation. At first sight it does not seem that families manipulate their income in order to be below the threshold.

Figure 1: Distribution of the Family Income. Years 1994-2007.



5.2 Discontinuity in the probability of participating in Medicaid

As I discussed in section 3, an RD analysis can still identify treatment effects despite imperfect compliance, as long as the eligibility rule generates a jump in the participation rate at the threshold. I check this assumption first with a graphical analysis and then by a regression analysis.

Figure 2 plots the proportion of children who are enrolled in Medicaid over family income. This proportion is calculated within family income bins of 2 thousand dollars width. We can observe that at the threshold –which in this graph is normalized to 0– the probability of participation has a discontinuity of about 10 percentage points.

Figure 2: Participation decision

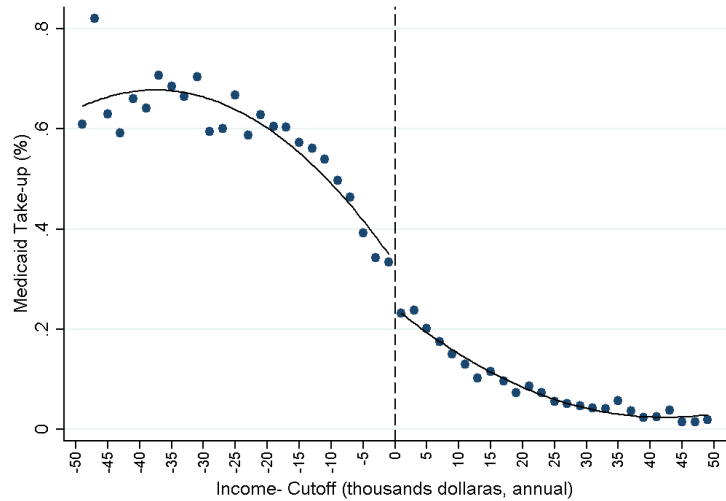


Table 2 reports the results of the parametric estimate of the participation equation specified as:

$$M_{i,t-\tau} = \pi_0 + \pi_1 Eli_{i,t-\tau} + k_{1g}(z_{i,t-\tau}; \alpha_{1g}) + u_{i,t-\tau} \quad (9)$$

where $Eli_{i,t-\tau}$ is the eligibility indicator in period $t - \tau$ and $M_{i,t-\tau}$ is Medicaid enrollment status in the same period, for $\tau = 0, \dots, 5$. Each row of table 2 reports the participation equation for different subsamples, according to the period in which eligibility is analyzed. The first column reports the estimated jump in the probability of participation at the threshold, for a sample that pools all states, that is, all possible thresholds. Making a child with family income at the threshold eligible for Medicaid increases the probability of enrollment between about 12

and 18 percentage points, depending on the period analyzed.

Columns 2 to 4 of table 2 report the estimates for this jump, but for subsamples that consider different levels of thresholds, to check whether the incentives to participate into Medicaid vary across families with different income levels. The results show that families with income at thresholds below 250% of the poverty level are responsive to eligibility into Medicaid, although participation decreases with income.

In contrast, for families at thresholds above 250% of the poverty line, I don't find that making a child eligible for Medicaid increases the chances that she receives coverage. This means that higher-income families, even when they are targeted by Medicaid in states with more generous coverage, may not find it beneficial to enroll their children in Medicaid because they have other options available. In terms of the fuzzy RD design, this mean that the condition that the probability of participation jumps at the threshold is not satisfied, hence I cannot perform any analysis on this subgroup.

Table 2: Participation Equation. Dep. var: Medicaid Coverage in period $t - \tau$.

	Pooling all Thresholds (1)	Thresholds <185 (2)	Thresholds [185,250] (3)	Thresholds >250 (4)
Eli _t	0.119*** (0.034)	0.184*** (0.065)	0.130*** (0.047)	-0.044 (0.074)
Eli _{t-1}	0.167*** (0.031)	0.297*** (0.057)	0.147*** (0.044)	-0.068 (0.092)
Eli _{t-2}	0.138*** (0.031)	0.214*** (0.054)	0.129*** (0.047)	-0.163 (0.106)
Eli _{t-3}	0.134*** (0.032)	0.175*** (0.048)	0.094* (0.053)	-0.013 (0.085)
Eli _{t-4}	0.135*** (0.032)	0.205*** (0.053)	0.123** (0.049)	0.018 (0.074)
Eli _{t-5}	0.182*** (0.033)	0.275*** (0.049)	0.185*** (0.057)	0.171 (0.124)

Each entry comes from a separate linear probability model like equation 5.
All regressions include the determinants of Medicaid eligibility (log income, age, and family size, and its squares), year and state dummies.
Standard errors (in parenthesis) are robust to heteroskedasticity and are clustered at the family level. All samples are restricted to observations with family income levels within a distance of ± 50 thousand dollars from the threshold.

5.3 Falsification test: balance of individual characteristics on either side of the thresholds

The third type of robustness analysis consist on checking whether the children characteristics are “locally” balanced. To check for this, I run regressions of the form:

$$y_i = \alpha + \beta E_i + k_{2g}(z_i; \alpha_{2g}) + u_i \quad (10)$$

where the outcomes y_i are child and family characteristics that are not taken into account at the moment of determining eligibility. Also pre-treatment variables which should not be affected by eligibility status, such as child’s birth weight or mother’s age at child’s birth, are considered. The indicator E_i is the eligibility status in any period $t - \tau$. The only variable that seems to have a discontinuous jump at the threshold, is the variable Hispanic. Hispanic children represent a small fraction of the sample and are not likely to drive the results.

Table 3: Falsification tests: Balance of covariates on either side of the thresholds. Pooling all thresholds.

Dep. Var:	Eli_t	Eli_{t-1}	Period Eligible			
			Eli_{t-2}	Eli_{t-3}	Eli_{t-4}	Eli_{t-5}
Gender	0.054 (0.036)	0.071** (0.035)	0.031 (0.035)	-0.040 (0.034)	0.037 (0.033)	0.074** (0.034)
Black	0.021 (0.030)	0.013 (0.029)	0.014 (0.029)	-0.020 (0.032)	0.011 (0.029)	-0.004 (0.029)
Hispanic	0.026** (0.012)	0.036*** (0.013)	0.043*** (0.015)	0.036** (0.015)	0.030** (0.014)	0.034** (0.015)
Metropolitan Area	0.041 (0.036)	0.038 (0.036)	0.017 (0.034)	-0.015 (0.037)	0.015 (0.034)	0.023 (0.035)
Rural Area	-0.043 (0.029)	-0.038 (0.031)	-0.030 (0.026)	-0.034 (0.027)	-0.040 (0.025)	-0.024 (0.027)
Education (yrs.) of the Head of the Household	0.013 (0.165)	-0.075 (0.170)	-0.096 (0.175)	-0.235 (0.178)	-0.074 (0.173)	-0.328* (0.171)
Birth Weight (kg)	-0.012 (0.049)	-0.033 (0.054)	-0.014 (0.050)	-0.001 (0.051)	-0.096** (0.048)	-0.062 (0.051)
Mother Age at child’s birth	0.353 (0.425)	0.504* (0.432)	0.748 (0.412)	0.182 (0.438)	0.003 (0.437)	-0.348 (0.466)

Each entry comes from a separate regression, $y_i = \gamma_0 + \gamma_\tau Eli_{i,t-\tau} + f_g(z_{it}; \gamma_\tau) + u_{it}$, where the dependent variable is replaced by children and family characteristics, and pre-treatment covariates.

Each regression includes log of income, age, and family size, and its squares, as well as year and state dummies.

Standard errors are robust to heteroskedasticity and clustered at the family level.

All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in the period in which eligibility is analyzed.

6 Results

6.1 Contemporaneous effects on utilization and health

The models for utilization of preventive medical care are presented in table 4. All models reported in this table are linear probability models that control for flexible functions of income, child age, and family size. The first column reports estimates for the full sample, which pools all the eligibility thresholds. The effects reported in this column are thus average effects across thresholds. OLS estimates show a positive correlation between having Medicaid coverage and health care utilization. The intention to treat estimate in the third row shows that making a child eligible for Medicaid slightly increase health care utilization by 4.4 percentage points; the IV estimate, however, indicates that the average effect for the subpopulation of compliers –those who, made eligible for Medicaid, would enroll into the program– rises to 35 percentage points. These estimates are, however, not statistically significant.

In columns 2 and 3, I do the same estimation, but dividing the sample in two subgroups, according to the thresholds levels: states with thresholds under 185% of poverty line, and states with thresholds between 185 and 250%. I do not estimate the effects for thresholds above 250% of the poverty line, because I showed that Medicaid eligibility does not predict participation for individuals in the neighborhood of these thresholds. Medicaid eligibility induces a 12 percentage points increase in utilization for poorer children, with an average effect of 63 percentage points increase for compliers. For relatively richer children, there is not a statistically significant impact of Medicaid eligibility on utilization. Also the sign of the point estimates are negative.

The results for the contemporaneous effects of Medicaid on children’s health are presented in table 5. Panel A of the table presents the ITT estimates, while Panel B shows the IV estimates, which are the LATE estimates. The first two outcomes are the objective measures of health - Obese and Overweight. These measures should not be contaminated from effects of “perception” due to an increase in physician contacts or to a change in health care quality associated with access to Medicaid. The other two measures are subjective health outcomes.

Table 4: Medicaid and Utilization of Health Care. Children between 5 and 18 years old.
Dep. Var.: The child has visited a doctor for a routine health check-up in the last 12 months.

	Pooling all Thresholds (1)	Thresholds <185 (2)	Thresholds [185,250] (3)
Outcome equation			
Medicaid Coefficient			
OLS	0.122*** (0.024)	0.118*** (0.043)	0.115*** (0.030)
IV-RD	0.350 (0.256)	0.632 (0.396)	-0.076 (0.335)
Intention to treat			
Eligibility Coefficient	0.044 (0.032)	0.117* (0.063)	-0.010 (0.044)
Participation Equation (First stage)			
Eligibility Coefficient	0.126*** (0.034)	0.184*** (0.065)	0.133*** (0.046)
N	2795	984	1548

All regressions include the determinants of Medicaid eligibility: log income, age, and family size, and its squares. Year and state dummies are included. Standard errors (in parenthesis) are robust to heteroskedasticity and are clustered at the family level.

Each sample is restricted to observations with family income levels within a distance of ± 50 thousand dollars from the threshold. In the IV-RD regressions eligibility instruments for Medicaid coverage.

The likelihood of being in excellent health status, as reported by child's caregiver, is the only outcome that seems to be affected by Medicaid. Being made eligible for Medicaid causes a 8.8 percentage point drop in the probability of reporting excellent health, with a negative treatment effect for compliers of as much as a 70 percentage points drop. This negative impact is mainly driven by the negative and significant effect of Medicaid on the relatively richer children.

Table 5: Medicaid and Health outcomes. Contemporaneous effects.
Children between 5 and 18 years old.

Dep. Var.:	Pooling All Thresholds (1)	Thresholds <185 (2)	Thresholds [185-250] (3)
A. ITT			
Obese	-0.027 (0.030)	-0.067 (0.054)	-0.002 (0.041)
Overweight	0.035 (0.024)	0.060 (0.047)	0.015 (0.033)
Days school missed (> 5) due to illness	-0.014 (0.022)	-0.019 (0.047)	-0.031 (0.030)
Health Excellent	-0.088** (0.035)	-0.086 (0.064)	-0.125** (0.050)
B. IV-RD			
Obese	-0.217 (0.249)	-0.363 (0.323)	-0.017 (0.311)
Overweight	0.277 (0.206)	0.326 (0.269)	0.116 (0.256)
Days school missed (> 5) due to illness	-0.110 (0.180)	-0.104 (0.258)	-0.232 (0.245)
Health Excellent	-0.698** (0.336)	-0.467 (0.386)	-0.938** (0.508)
N	2795	984	1548

Each entry comes from a separate regression. All regressions include the determinants of Medicaid eligibility: log income, age, and family size, and its squares. Year and state dummies are included. Standard errors (in parenthesis) are robust to heteroskedasticity and clustered at the family level. Each sample is restricted to observations with family income levels within a distance of ± 50 thousand dollars from the threshold. In the IV-RD regressions eligibility instruments for Medicaid coverage.

6.2 Lagged effects on health

The finding that Medicaid eligibility and coverage have no statistically significant contemporaneous effect over health - with the only exception of a negative effect on the parent's evaluation of child's health-, may reflect the fact that health is a stock, and the effects of health insurance coverage on this health stock may be observed with some lag.

Table 6 reports the IIT estimates, which capture the effect of making a child randomly eligible for Medicaid in a given period, on outcomes after τ periods, for a sample that pools all income thresholds. Remember that the ITT estimate identifies the effects of eligibility in one moment of time on future outcomes, without controlling for behavioral changes in the period between assignment and when outcomes are measured. Thus, IIT estimates reflect accumulated effects.

The results in table 6 suggest that Medicaid eligibility neither induced, on average, better outcomes in the medium (1 to 3 year after) or in the long run (4 and 5 years after). Moreover, in the medium term, some health measures seems to be negatively affected by Medicaid eligibility. In particular, being made eligible for Medicaid increases the probability of being obese by 8.5 percentage points and decreases the probability of having excellent health by 8.4 percentage points, after two years. Being made eligible for Medicaid increases the probability of being obese by 5.4 percentage points after three years. On average, Medicaid does not have a significant effect on the probability of missing more than 5 days of school days due to illness. Eligibility seems to have almost no effects on any of the measures considered after 4 or 5 years.

Table 6: Lagged Medicaid Eligibility and Children’s Health. Lagged Intent to Treat (ITT) Effects. Children between 5 and 18 years old. All thresholds.

Time elapsed	Average Age when eligible (1)	Average threshold when eligible (2)	Objective Measures		Subjective Measures	
			Obese (3)	Overweight (4)	School days Missed (>5) (5)	Excellent health (6)
0 years (θ_0)	11.1	184.9	-0.027 (0.030)	0.035 (0.024)	-0.014 (0.022)	-0.088** (0.035)
1 years (θ_1)	10.0	184.8	-0.006 (0.027)	0.018 (0.023)	0.021 (0.022)	-0.061* (0.034)
2 years (θ_2)	9.0	174.7	0.085*** (0.029)	-0.009 (0.023)	0.006 (0.024)	-0.084** (0.037)
3 years (θ_3)	8.0	166.8	0.054* (0.030)	-0.033 (0.024)	-0.005 (0.023)	-0.060 (0.038)
4 years (θ_4)	7.0	168.3	0.033 (0.029)	0.025 (0.024)	-0.022 (0.020)	0.007 (0.036)
5 years (θ_5)	6.0	156.2	0.034 (0.029)	0.001 (0.025)	-0.011 (0.021)	-0.022 (0.038)

Each entry comes from a separate regression, $y_{it} = \alpha + \theta_\tau \text{Elig}_{i,t-\tau} + f_g(z_{i,t-\tau}; \gamma_\tau) + u_{it}$. Regressions controls for log of income, age, and family size, and its squares in period $t - \tau$, as well as year and state dummies. Standard errors are robust to heteroskedasticity and clustered at the family level. All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in period $t - \tau$. Columns 2 and 3 report the average children’s age and the average threshold in period $t - \tau$.

6.3 Heterogeneous lagged effects

In order to investigate whether the lagged effects are heterogeneous across different thresholds, I split again the sample into two income subgroups: thresholds below 185% of the poverty line, and thresholds between 185 and 250%.¹⁵ Results are shown in tables 7 to 9. I also disaggregate effects by ages: 5 to 11, and 12 to 18-years old subgroups.

The comparison between the two income subgroups, shows a good deal of heterogeneity of the impact of Medicaid depending of children’s family income level, as well as a differentials effect for children of different age groups. This heterogeneity highlights the importance of doing this disaggregation to draw any conclusions about the lagged effects of Medicaid.

6.3.1 Objective health measures: obesity and overweight

Table 7 presents the lagged effects of Medicaid eligibility on measures of weight status, by level of income threshold and by age groups. Medicaid eligibility tends to have a negative impact

¹⁵Again, I drop the thresholds above 250% of the poverty line, because for this group I cannot find evidence that eligibility induces, at the threshold, an increase in Medicaid participation rates

for children in the the higher-income subgroup –185 and 250% of poverty line– in this health dimension, since it increases the probability of obesity by 7.8 and 9.4 percentage points, after 2 and 3 years, respectively (column 4, panel B). It also has a positive and significant effect on the probability of being overweight- a 8.3 percentage point increase- after 4 years. In contrast, for poorer children, the only negative effect of Medicaid is found 2 years later, as it increases the probability of obesity by 10 percentage points (column 1, panel B). The rest of the lagged effects estimated, both on obesity and overweight, are not statistically significant.

Interestingly, looking at different age subgroups I find that Medicaid eligibility has beneficial effects for poorer children aged 12-18. Being eligible for Medicaid reduces the likelihood of being overweight for this group by 14.5 percentage points after two years; however this effect is almost offset by with a rise in the probability of being obese, which increases by 11.3 percentage points, but the effect is not statistically significant (column 3). Moreover, for this subgroup, Medicaid eligibility systematically reduces both the probability of being obese or overweight after 4 and 5 years, although the point estimates are not statistically different from zero. For poorer children with ages between 5 and 11 (column 2), in contrast, the only statistically significant effect is an increase in the probability of being obese after 2 years of being eligible. For children of higher-income families, the negative impact of Medicaid eligibility on measures of obesity is driven by the negative impact it has on the subgroup of children between 5 and 11 years old (column 5).

Table 7: Lagged Medicaid Eligibility and Children’s Health. Lagged Intent to Treat (ITT) Effects on Objective Measures of Health, by level of Income Thresholds and by Age Group.

Time Elapsed	Thresholds<185%			Thresholds[185-250]%		
	5-18 years old (1)	5-11 years old (2)	12-18 years old (3)	5-18 years old (4)	5-11 years old (5)	12-18 years old (6)
A. Overweight						
0 years (θ_0)	0.060 (0.047)	0.070 (0.053)	-0.144 (0.107)	0.015 (0.033)	0.058 (0.047)	-0.087 (0.298)
1 years (θ_1)	-0.0001 (0.043)	0.021 (0.048)	-0.157 (0.101)	0.013 (0.032)	0.050 (0.043)	-0.022 (0.048)
2 years (θ_2)	-0.037 (0.039)	-0.018 (0.046)	-0.145* (0.080)	-0.015 (0.035)	0.015 (0.047)	-0.073 (0.052)
3 years (θ_3)	-0.041 (0.039)	-0.034 (0.046)	-0.062 (0.067)	-0.007 (0.038)	-0.003 (0.056)	-0.024 (0.057)
4 years (θ_4)	-0.006 (0.037)	0.002 (0.043)	-0.050 (0.071)	0.083** (0.040)	0.076 (0.062)	0.071 (0.051)
5 years (θ_5)	-0.012 (0.036)	0.011 (0.045)	-0.078 (0.065)	0.025 (0.046)	-0.015 (0.062)	0.089 (0.063)
B. Obesity						
0 years (θ_0)	-0.067 (0.054)	-0.027 (0.060)	-0.184 (0.121)	-0.002 (0.041)	-0.002 (0.053)	0.035 (0.069)
1 years (θ_1)	0.037 (0.052)	0.048 (0.056)	-0.001 (0.122)	-0.005 (0.038)	0.003 (0.049)	-0.005 (0.066)
2 years (θ_2)	0.101** (0.050)	0.103* (0.053)	0.113 (0.118)	0.078* (0.045)	0.126** (0.057)	0.028 (0.070)
3 years (θ_3)	-0.014 (0.045)	-0.024 (0.052)	0.015 (0.101)	0.094* (0.048)	0.124** (0.063)	0.050 (0.078)
4 years (θ_4)	0.039 (0.043)	0.080 (0.051)	-0.139 (0.085)	-0.005 (0.047)	0.019 (0.064)	0.015 (0.076)
5 years (θ_5)	0.034 (0.040)	0.028 (0.045)	-0.025 (0.080)	0.021 (0.054)	0.088 (0.068)	-0.019 (0.090)

Each entry comes from a separate regression, $y_{it} = \alpha + \theta_\tau Eli_{i,t-\tau} + f_g(z_{i,t-\tau}; \gamma_\tau) + u_{it}$. Regressions controls for log of income, age, and family size, and its squares in period $t - \tau$, as well as year and state dummies. Standard errors are robust to heteroskedasticity and clustered at the family level. All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in period $t - \tau$.

6.3.2 Subjective health measures

Medicaid also seems to have heterogeneous effects on each on the subjective health measures at different threshold levels.

Excellent Health. Table 8 reports the lagged effects of Medicaid on the probability of having excellent health. A negative and statistically significant effect —i.e. a reduction in the probability of having excellent health— is only observed for children in the higher-income

subgroup (column 4), and, within this income range, the effect is significant only for younger children (column 5). In contrast, for poorer children, the only statistically significant lagged effects of Medicaid on this measure are positive and statistically significant for children between 12 and 18 years old. For this subgroup, being eligible for Medicaid has a positive effect of about 20 percentage points in the probability of being in excellent health after 4 and 5 years (column 3).

Table 8: Lagged Medicaid Eligibility and Children's Health. Lagged Intent to Treat (ITT) Effects, by level of Income Thresholds and by Age Group. Dep. Var: The child has Excellent Health.

Time Elapsed	Thresholds <185%			Thresholds [185-250]%		
	5-18 years old (1)	5-11 years old (2)	12-18 years old (3)	5-18 years old (4)	5-11 years old (5)	12-18 years old (6)
0 years (θ_0)	-0.086 (0.064)	-0.081 (0.076)	-0.063 (0.134)	-0.125** (0.050)	-0.189*** (0.071)	-0.070 (0.077)
1 years (θ_1)	-0.042 (0.064)	-0.042 (0.072)	-0.074 (0.137)	-0.097** (0.048)	-0.118* (0.064)	-0.083 (0.074)
2 years (θ_2)	-0.045 (0.059)	-0.044 (0.068)	-0.026 (0.117)	-0.093* (0.054)	-0.208** (0.072)	0.032 (0.080)
3 years (θ_3)	-0.035 (0.055)	-0.079 (0.062)	0.100 (0.110)	-0.081 (0.063)	-0.160** (0.081)	0.031 (0.090)
4 years (θ_4)	0.057 (0.056)	0.018 (0.062)	0.193* (0.112)	-0.047 (0.064)	-0.034 (0.080)	-0.043 (0.093)
5 years (θ_5)	0.016 (0.050)	-0.047 (0.057)	0.214** (0.093)	-0.077 (0.074)	-0.080 (0.092)	-0.070 (0.111)

Each entry comes from a separate regression, $y_{it} = \alpha + \theta_\tau \text{El}_{i,t-\tau} + f_g(z_{i,t-\tau}; \gamma_\tau) + u_{it}$. Regressions controls for log of income, age, and family size, and its squares in period $t - \tau$, as well as year and state dummies. Standard errors are robust to heteroskedasticity and clustered at the family level. All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in period $t - \tau$.

More than 5 days of school days missed due to illness. Finally, table 9 presents the lagged effects of Medicaid eligibility on the probability of missing more than 5 days of school in year due to illness. The effects of Medicaid on this measure show a less clear pattern across income groups. On the one hand, for poorer children, eligibility increases this probability by 14.1 percentage points after 1 year, but the accumulated effect after 4 years is negative. That is, Medicaid reduces the probability of missing more than 5 days of school by 6.1 percentage points after 4 years (column 1). On the other hand, for richer children, Medicaid eligibility reduces this probability after 1 year by 4.5 percentage points (column 4). For both income groups, Medicaid eligibility improves children's health, measured by a reduction of school-days missed due to illness, some years later. In both cases, significant effects are observed only for younger

children, 5-11 years old (columns 2 and 5).

Table 9: Lagged Medicaid Eligibility and Children's Health. Lagged Intent to Treat (ITT) Effects, by level of Income Thresholds and by Age Group. Dep. Var: More the 5 days of school missed in the last 12 months due to illness.

Time Elapsed	Thresholds <185%			Thresholds [185-250]%		
	5-18 years old (1)	5-11 years old (2)	12-18 years old (3)	5-18 years old (4)	5-11 years old (5)	12-18 years old (6)
0 years (θ_0)	-0.019 (0.047)	-0.003 (0.052)	-0.117 (0.136)	-0.031 (0.030)	-0.013 (0.044)	-0.006 (0.047)
1 years (θ_1)	0.141*** (0.048)	0.134*** (0.049)	0.133 (0.116)	-0.045* (0.027)	-0.048 (0.040)	-0.019 (0.039)
2 years (θ_2)	0.059 (0.037)	0.049 (0.041)	0.041 (0.083)	-0.057 (0.035)	-0.088* (0.049)	-0.019 (0.044)
3 years (θ_3)	0.002 (0.037)	-0.025 (0.043)	0.054 (0.065)	-0.006 (0.037)	-0.004 (0.048)	-0.034 (0.051)
4 years (θ_4)	-0.061* (0.035)	-0.092* (0.042)	-0.003 (0.066)	0.045 (0.035)	0.062 (0.049)	0.023 (0.052)
5 years (θ_5)	-0.041 (0.031)	-0.052 (0.038)	-0.012 (0.061)	0.008 (0.044)	0.004 (0.059)	0.017 (0.070)

Each entry comes from a separate regression, $y_{it} = \alpha + \theta_\tau \text{El}i_{i,t-\tau} + f_g(z_{i,t-\tau}; \gamma_\tau) + u_{it}$. Regressions controls for log of income, age, and family size, and its squares in period $t - \tau$, as well as year and state dummies. Standard errors are robust to heteroskedasticity and clustered at the family level. All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in period $t - \tau$.

7 Discussion and Conclusion

The main message from previous results is that Medicaid eligibility has heterogeneous lagged effects across different income thresholds and also for different age groups. Particularly, in terms of objective health measures, we saw that Medicaid eligibility has beneficial effects in reducing obesity and risk of overweight –the two objective health measures analyzed– for children with family income below 185% of the poverty line aged between 12 and 18 years old. However, I do not find significant effects for younger children in this income range, nor for children with family income between 185 and 250% of the poverty line. The heterogeneous effects of Medicaid on health care utilization across income groups may help to explain this pattern.

On the one hand, we saw that Medicaid coverage tends to increase poorer children’s - under 185% of poverty line- likelihood of visiting a doctor for a routine check up –which may include a weight check up. Given that the contact with doctors for preventive purposes increases, then the heterogeneous effects on measures of obesity and overweight for older and younger children in this income range, may be explained by how they and their families respond to physicians’ recommendations. One can imagine that in case of a child being obese or overweight, the physician may recommend improving the quality of the diet and increasing the time devoted to physical activity. For younger children, the effectiveness of these recommendations may depend more on parents rather than children’s decisions. If parents do not follow the recommendations, young children rarely will follow them by themselves. But, changing the diet and healthy behaviors of relatively poorer parents could be a difficult task, which may explain why no significant effects are observed for younger poorer children. However, older children may have greater control on their diet and physical activity, which may allow them to adapt better to physician’s recommendations. This, in turn, is reflected in a beneficial effect of Medicaid in reducing poorer older children’s obesity and overweight.

On the other hand, health care utilization analysis showed that children with family income between 185 and 250% of the poverty line do not increase the probability of visiting a doctor for a routine check-up in response to Medicaid coverage. Moreover, although not significant, the point estimate was negative. This negligible effect on utilization could be because many of these children had previous access to health care through private health insurance. Hence, the switch to the public system do not affect their contact with physicians. However, the quality of services provided by the public insurance may differ from the quality they received with the

private insurance. Indeed, if the quality of physicians who serve Medicaid patients is worse, this may be reflected in worse children's health outcomes, *relative* to the counterfactual situation of having private insurance. This explanation could be consistent with the finding that Medicaid eligibility induces worse results in terms of obesity and overweight for children in this range of income.

Also consistent with this story is the finding that Medicaid has a negative effect on the probability of having excellent health, according to parents' reports, only among children in the higher-income group. Again, higher-income families who enroll their children into Medicaid are more likely to have switched from private insurance when made eligible for the public insurance. These families may find the quality of services they receive with public coverage worse than quality they received with private coverage, hence their perception about their children's health may capture this effect and which is then reflected in a drop of the probability of reporting excellent health. This is less likely to have happened with poorer families, because they are more likely to be either uninsured or to have only basic private coverage if the Medicaid option is not available. This means that, in relative terms, higher-income families who take the public benefit are more likely to be scarifying a higher level of health care quality than poorer families.

Finally, another interesting finding is the effect of Medicaid on the probability of missing more than 5 days of school due to illness. The results indicate that Medicaid only affects children between 5 and 11 years old. For poorer children, Medicaid eligibility increases this probability after 1 year, but it reduces it after 4 periods. For children in higher income-families, the reduction occurs after 2 years of being eligible. This result suggests that at some point, Medicaid may contribute to the human capital formation of children, by allowing them to prevent illnesses and to be in better health to attend school.

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8 Appendix

Table 10: Falsification test: Balance of covariates on either side of the thresholds. Sample thresholds < 185 % of Poverty Line.

Dep. Var:	Eli _t	Eli _{t-1}	Period Eligible			
			Eli _{t-2}	Eli _{t-3}	Eli _{t-4}	Eli _{t-5}
Gender	-0.015 (0.070)	0.012 (0.065)	-0.032 (0.061)	-0.099* (0.052)	0.009 (0.053)	0.048 (0.046)
Black	0.086 (0.061)	-0.050 (0.060)	-0.056 (0.054)	-0.091* (0.047)	-0.009 (0.044)	0.012 (0.041)
Hispanic	-0.010 (0.011)	-0.018 (0.011)	-0.008 (0.012)	0.017 (0.012)	0.007 (0.012)	-0.008 (0.013)
Metropolitan Area	0.115* (0.065)	0.080 (0.063)	-0.030 (0.057)	-0.045 (0.055)	0.082 (0.051)	0.023 (0.050)
Rural Area	-0.120** (0.049)	0.012 (0.046)	0.033 (0.039)	0.001 (0.040)	-0.046 (0.036)	-0.007 (0.036)
Birth Weight	-0.022 (0.123)	-0.086 (0.110)	0.078 (0.093)	0.145* (0.075)	0.032 (0.076)	0.013 (0.067)
Education (yrs) of Head	0.491* (0.293)	0.110 (0.282)	0.368 (0.262)	0.007 (0.254)	0.220 (0.255)	-0.038 (0.207)
Mother Age at child'S birth	0.805 (0.793)	0.172 (0.760)	0.650 (0.676)	0.095 (0.623)	0.104 (0.631)	-0.495 (0.591)

Notes: Each entry comes from a separate regression, $y_i = \gamma_0 + \gamma_\tau Eli_{i,t-\tau} + f_g(z_{it}; \gamma_\tau) + u_{it}$, where individual and family characteristics, and pre-treatment covariates are the dependent variables in the regression. Each regression includes log of income, age, and family size, and its squares. Year and state dummies. Standard errors are robust to heteroskedasticity and clustered at the family level. All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in the period in which eligibility is analyzed.

Table 11: Falsification test: Balance of covariates on either side of the thresholds. Sample thresholds [185-250] % of Poverty Line.

Dep. Var:	Period Eligible					
	Eli _t	Eli _{t-1}	Eli _{t-2}	Eli _{t-3}	Eli _{t-4}	Eli _{t-5}
Gender	0.089* (0.050)	0.116** (0.048)	0.055 (0.052)	0.008 (0.056)	0.066 (0.060)	0.085 (0.074)
Black	0.034 (0.043)	0.039 (0.040)	0.039 (0.045)	0.032 (0.051)	0.005 (0.052)	0.004 (0.061)
Hispanic	0.026 (0.021)	0.061*** (0.021)	0.075*** (0.028)	0.045 (0.032)	0.055 (0.035)	0.022 (0.045)
Metropolitan Area	0.029 (0.056)	0.029 (0.054)	0.014 (0.054)	-0.029 (0.059)	-0.032 (0.065)	0.032 (0.067)
Rural Area	-0.054 (0.043)	-0.067 (0.044)	-0.073* (0.044)	-0.045 (0.033)	-0.050 (0.038)	-0.062 (0.052)
Education (yrs) of Head	-0.036 (0.251)	-0.187 (0.252)	-0.501* (0.274)	-0.333 (0.327)	-0.319 (0.308)	-0.330 (0.347)
Birth Weight	-0.048 (0.067)	-0.004 (0.069)	-0.008 (0.076)	-0.117 (0.081)	-0.324*** (0.084)	-0.210** (0.094)
Mother Age at child birth	0.187 0.616	0.840 0.621	0.785 0.637	0.954 0.782	0.549 0.845	-0.591 0.896

Notes: Each entry comes from a separate regression, $y_i = \gamma_0 + \gamma_\tau \text{Eli}_{i,t-\tau} + f_g(z_{it}; \gamma_\tau) + u_{it}$, where individual and family characteristics, and pre-treatment covariates are the dependent variables in the regression. Each regression includes log of income, age, and family size, and its squares. Year and state dummies. Standard errors are robust to heteroskedasticity and clustered at the family level. All samples are restricted to observations with family income within a distance of ± 50 thousand dollars from the threshold in the period in which eligibility is analyzed.