Health Insurance Transitions of SCHIP-Eligible Children in Response to Higher Public Premiums

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Abstract

SILVIYA NIKOLOVA: Health Insurance Transitions of SCHIP-Eligible Children in Response to Higher Public Premiums.
(Under the direction of Thomas Mroz.)

This is the first study to explore the impact of premium variation across individuals, states, and time on enrollment in the State Children's Health Insurance Program and their transitions to private insurance or uninsurance in response to higher premiums. With a sample of income-eligible children from the Medical Expenditure Panel Survey, I evaluate the effect of premium changes on public and private insurance enrollment and uninsurance using a wide array of methods: Regression-Discontinuity Design for the study of the within-state variations in premiums, cross-sectional analysis for evaluating the response using across-state variation in premiums, and difference-in-differences strategies that exploit temporal variations in premiums. The main regression-discontinuity estimates point to significant declines in public enrollment along with significant increases in private take-up and no change in the rate of uninsurance. The cross-sectional results support the finding that higher premiums are associated with statistically important decrease in public enrollment and increase in private. I find no evidence of increases in the rate of uninsurance as a result of public premium increases. These results are reinforced by the longitudinal findings. They indicate a statistically significant decline in public enrollment, significant increase in private and no change in uninsurance for children in the higher-income group in response to a per dollar increase in premium over the course of 2003 year.

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Chapter 1

Premium Increases and Disenrollment from SCHIP

1.1 The Problem

Concerns about the adequacy of health insurance coverage for children have expanded Medicaid from a program only for low-income families to a broader program for families who earn too much money to qualify for Medicaid, yet not enough to afford private insurance. The highly successful State Children's Health Insurance Program (SCHIP) was created by the Balanced Budget Act of 1997 which appropriated $24 billion over five years and $40 billion over ten years to help states expand health insurance coverage.

Like Medicaid, SCHIP is a partnership between federal and state governments. The programs are run by the individual states according to requirements set by the federal Centers for Medicare and Medicaid Services. The SCHIP law offers states three options for covering uninsured children. States can use SCHIP funds to cover children through Medicaid-independent children's health insurance programs (separate child health programs), expand coverage available under Medicaid (SCHIP Medicaid expansion programs), or combine both strategies (SCHIP combination programs). States with separate child health programs have more latitude than Medicaid programs. They have a great deal of flexibility in their cost-sharing and plan benefits structure, as well as in eligibility and enrollment matters. Flexibility is regulated at the federal level and state plans must receive approval prior to implementation.

Most SCHIP programs require enrollees to share in the cost of coverage or services. Oftentimes, a monthly premium is charged with co-payments (e.g., a beneficiary would pay a monthly charge regardless of utilization and a co-payment when a service is utilized). While the majority of separate programs require participants to pay a monthly premium, others allow participants to pay on a quarterly or annual basis. As of December 2003, twenty-six separate programs and nine Medicaid expansion programs charged premiums with those charging a premium having obtained special waivers to do so. As SCHIP programs are subject to the same financial pressures as private health insurance, eleven states increased premiums in 2003.

In this paper, I investigate the impact of premium increases on disenrollment from SCHIP. The analysis is based on a unique data set that combines 12 months of enrollment data from the nationally representative Medical Expenditure Panel Survey (MEPS) with information on eligibility rules and premium levels for all states and the District of Columbia (D.C.). The study employs a wide array of methods: Regression-Discontinuity Design for the study of the within-state variations in premiums, cross-sectional analysis for evaluating the response using across-state variation in premiums, and a difference-in-differences strategy that exploits temporal variations in premiums. The main regression-discontinuity estimates point to significant declines in enrollment in response to higher premiums. The cross-sectional results based on the two most homogeneous samples support the finding that higher premiums are associated with decrease in enrollment. These results are reinforced by the difference-in-differences findings. They indicate a statistically significant decline in public enrollment for children in the higher income group in response to a per dollar increase in premium over the course of one year.

The paper is structured in the following way. I start out with a brief introduction to the SCHIP program and a discussion of some earlier studies that spell out the importance of premium increases on disenrollment from SCHIP. Section 1.3 presents the economic model. Section 1.4 details the methodology. Section 2.5 describes the data and health insurance eligibility assignment procedure. Section 2.6 discusses the estimation results. Section 1.7 concludes.

1.2 Literature Review

The purpose of this section is twofold; namely the comparison of the different methods used in premium policy analysis and review of the results in previous literature. The section compares different methods that have been applied to the analysis of premium impacts and contrasts the ability of these methods to deal adequately with the consequences of endogeneity. The section also reviews earlier works that document the extent to which premium increases affect disenrollment from the SCHIP program.

The evaluation of the impact of premium increases on disenrollment needs to deal with "enrollment" endogeneity. Children who remain covered and those who do not may be very different with respect to their health, family resources, and preferences. Shenkman, for example, finds that following a premium change, the short-term enrollment duration for children with moderate to major chronic conditions is not affected, while for healthy children, it decreases. Studies that imperfectly control for factors that have the potential to impact the enrollment outcome, such as the health of the child as in Shenkman's research, may incorrectly estimate the effect of premium on coverage. Omitting a significant regressor from the regression equation may lead to biased estimates for the coefficients on the included variables.

Differences in coverage may also result from the fact that differences in the levels of and jumps in premiums across states are more likely the result of purposeful policy making than of a natural experiment, and thus adequate controls for the forces behind these levels and changes are needed. The New Hampshire SCHIP experience proves that, through careful design of the premium policy, it is possible to reach a high rate of health insurance coverage for children and, at the same time, to charge some of the highest premiums in the country. Another problem in SCHIP evaluation arises because true insurance status is not observed and must be assigned. Assignment error can result either because the assignment process fails to completely replicate the insurance assignment process or simply because the information on income has been misreported.

Several studies (Kappel, 2004; Mann and Artiga, 2004) examine month-to-month changes in SCHIP enrollment in states that increase their premiums and find a decrease in enrollment following the premium hike. Although these studies do not control for other factors that might impact on enrollment and they record trends that are strictly state-specific, these papers establish a relationship and provide an insight about possible dependence of the premium effect on income, child age, and timing.

There are also state-specific studies that explore the impact of premium increases in a regression setting using data from Florida (Shenkman et al., 2002; Shenkman, Herndon and Vogel, 2006); New Hampshire, Kansas, and Kentucky (Kenney, Allison, Costich, Marton and McFeeters, 2006); Arizona and Kentucky (Kenney, Costich, Marton and McFeeters, 2006), and Kentucky(Marton, 2006). All studies find that disenrollment increases following the premium hikes. The common approach to modeling the probability of enrollment is to use a Cox proportional hazard model with premium policy change as a time-varying covariate (i.e., the premium variable is a time-varying variable that takes the value zero before the premium increase and the value one after the premium increase). This model is designed for individual-state analysis, but can be easily modified to apply to the analysis of national data, for example, by including a variable for the premium level instead of a dummy into the regression equation. Comparing the same subjects' response before and after a policy intervention requires that the effect is registered quickly, before other factors vary. Otherwise, a control group is needed to absorb the "time effects". In the literature to date, only Marton (2006) has taken advantage of the treatment versus control relationship between two income categories in SCHIP. He compares the disenrollment probabilities obtained by the same model but applied to two different income groups. The author draws conclusions about the impact of premium increases on the duration of enrollment by comparing exit probabilities after the premium hike to the baseline probability for the group.

Only three studies, to the best of my knowledge, combine data on multiple states in examining the impact of the SCHIP premium on enrollment. The estimates based on national data affirm the single-state findings that higher premiums reduce enrollment. Kronebusch and Elbel (2004) simultaneously analyze the impact of various SCHIP policies that may influence enrollment. Hadley, Reschovsky, Cunningham, Dubay and Kenney (2006) and Kenney, Hadley and Blavin (2006) provide independent estimates of the effect of public insurance premium on SCHIP enrollment using a multinomial logit regression. This econometric approach controls for the costs of private insurance and the transitions between public and private insurance and "no insurance" following public premium increases. In addition, Hadley et al. (2006) introduce controls for the effect of two other policy variables: SCHIP waiting period and enrollment cap. The repeated-cross-sections nature of the data in these studies allows the use of controls for year effects and/or state-fixed effects. Although such models constitute an advance over those that look at premium impacts in a cross-section framework, they are sensitive to the inclusion of state-level variables, for example the rate of unemployment, that directly influence premium policy and enrollment.

In this paper I re-examine the effects of premium increases on disenrollment from SCHIP using several approaches. I use a simple Regression-Discontinuity (RD) model to examine enrollment decisions in the largest state in my data set making use of the specific features of the state's SCHIP program [1]. I also study the impact of the SCHIP premium on enrollment combining cross-sectional data on all states to estimate the average impact of premium increase on enrollment of children in the high-income SCHIP group. I employ a Difference-in-Differences specification to examine the impact of the temporal variation in premium.

1.3 SCHIP Enrollment Decision. Economic Model

In this section I present a one-period model of the SCHIP enrollment decision. The probability that a child becomes sick depends on the health stock at the beginning of the period. The family's decision problem can be described as having to make an optimal choice over a discrete set of insurance and non-insurance related characteristics. The decision to provide a SCHIP eligible child with health insurance is defined as a choice over the following set of coverage options: ($j = 1$) enroll in SCHIP, ($j = 2$) enroll in private health insurance, and ($j = 3$) be uninsured. The enrollment decision can be thought of as choosing the maximum over the value functions associated with each health insurance alternative. Given health insurance status, parents decide on the number of medical visits M, and on the amount of other health-related goods G.

The parents' utility depends upon their consumption of non-health related goods (Z)

[1] For convenience I will henceforth use the term "income group" when discussing a group of SCHIP children who belong to a state-specific income bracket.

and on the health stock of the child at the end of the period (H). If the child becomes sick during the period, the parents, conditional on insurance choice j, make optimizing decisions about medical care and other health-related goods. Medical treatment M and other child health-related goods G improve the health of the child. The level of the health stock decreases if more medical treatment is needed at the end of the period. The parents will choose some non-negative amount of other health goods regardless of whether the child is sick or well as the marginal utility with respect to Z increases steeply for low values of Z. Thus the end-of-period health stock could be smaller, larger, or the same as the initial health stock.

A health production process generates the end-of-period health stock of the child which is dependent upon medical services received M, other child health-related goods G, initial health stock $\overline{H}$, and health shock μ. Formally, the health of a child is $H^{\mu}(M, G, \overline{H})$. For expositional convenience μ is assumed to take on only two values referred to as sick or well. The marginal product of health inputs differs for sick and well children. It is straightforward to extend the model to different types of illness with the marginal productivity of the inputs depending on the health shock realization. Figure 1.1 shows a plausible relation between the stock of health and medical treatment. The slope of the curve in the figure at any point gives the marginal product of medical visits. Health stock increases at a decreasing rate and reaches its upper limit as the number of medical visits becomes equal to or larger than M_{max}. Other health goods improve child's health and an increase in G leads to an increase in the health stock for any level of necessary medical treatment needed for a sick child to recover.

$$\lim_{G \to 0} \frac{dH}{dG} \to \infty \tag{1.1}$$

The probability of sickness π_s depends on the health stock at the beginning of the period $\overline{H}$. Note that the probability of being sick does not depend on the current choice of inputs M and G.

$$\pi_s(\overline{H}) = 1 - \pi_w(\overline{H}) \tag{1.2}$$

where π_w is the probability of being well.

Given health insurance coverage j and health shock μ of the child, sick or healthy, the parents choose how many medical visits to make and how much of other child-health related goods to buy. It is assumed that $M_{max} = 0$ for healthy children. Let the variable α reflect the exogenous proportion of the total value of medical care for which an insured individual is responsible, $\alpha \in [0, 1]$. The product αC denotes the out-of-pocket expenditures of a medical visit, which reflects the total price C of a visit. Thus, $\alpha = 0$ implies no out-of-pocket payment by the consumer and $\alpha = 1$ implies full out-of-pocket expenditures by the consumer. If an individual is uninsured, then he always faces the full price of medical treatment. Premium P depends on the insurance coverage type as well with $P^3 = 0$ if the parents opt to have the child uninsured. To the extent that copayments and premiums vary with j, the utility maximizing amounts of M, G, and Z under each health state will depend on the insurance choice.

Depending on the health state, the parents face two different budget constraints:

$$Z^j = \begin{cases} Y - P^j - p_g G_w^j & \text{if the child is well} \\ Y - P^j - M^j \alpha^j C - p_g G^j & \text{if the child is sick} \end{cases} \tag{1.3}$$

where Z is consumption of non-health related goods, the variable Y denotes family income. The model assumes that the price of other health goods p_g and the price of the non-health related goods p_z are exogenous. Further, p_z is normalized to \$1.

The parents solve two optimization problems for each insurance coverage. When the child is sick:

$$\max_{Z_s^j, M_s^j, G_s^j} \quad U(Z_s^j, H^s(M_s^j, G_s^j, \overline{H}))$$
$$\text{s.t.} \quad Z^j = Y - P^j - M^j \alpha^j C - p_g G^j$$

Let $(Z_s^{j^*}, M_s^{j^*}, G_s^{j^*})$ denote the optimal choice of non-health related goods, medical services, and other child health-related goods for insurance j when the child is sick. The value function for insurance j with a sick child is

$$V^{j,s}(Y, p_z, p_g, \alpha^j, C, P^j) \equiv U(Z_s^{j^*}, H^s(M_s^{j^*}, G_s^{j^*}, \overline{H}))$$

When the child is well the family's optimization problem for insurance j is

$$\max_{Z_w^j, G_w^j} \quad U(Z_w^j, H^w(G_w^j, \overline{H}))$$
$$\text{s.t.} \quad Z^j = Y - P^j - p_g G_w^j$$

Analogously, $(Z_w^{j^*}, M_w^{j^*}, G_w^{j^*})$ are the optimal consumption choice of non-health related goods, medical services and other child health-related goods for insurance j when the child is well. The value function for insurance j when the child is well is:

$$V^{j,w}(Y, p_z, p_g, P^j) \equiv U(Z_w^{j^*}, H_w(G_w^{j^*}, \overline{H}))$$

Thus, for each insurance choice, prior to knowing whether their child is sick or not, the parents have the following expected value function:

$$EV^j = (1 - \pi_w) V^{j,s}(Y, p_z, p_g, \alpha^j, C, P^j) + \pi_w V^{j,w}(Y, p_z, p_g, P^j)$$

The parents choose the insurance alternative j associated with the maximum expected value function.

Insurance policies are assumed to differ only in their premium and copayment structure.Further, in the case of SCHIP and private insurance coverage, it is assumed that there are no copayments. Thus, a higher expected value is associated with a lower-premium insurance. The choice between being insured or uninsured depends on the difference between expected value functions associated with these two choices.

An extensive body of literature (see Shenkman, Herndon and Vogel, 2006; Marton, 2006) has established the importance of the SCHIP premium on the decision to enroll in the program. A usual problem that arises in the evaluation of the premium effect is the lack of information on all factors that influence the enrollment decision, many of which are unobserved by the researcher. The most important information that is typically missing is the cost of the coverage options that a family has. The missing data include the out-of-pocket expenditures for treatment if the child is uninsured and premiums for the health plans that are available to and chosen by the family. I define gain as the difference between the expected value function associated with the SCHIP plan and the value function associated with the most preferred option other than SCHIP. Thus, for child i the decision to enroll in public coverage is determined by the positive gain from choosing SCHIP coverage over the next best alternative insurance option.

$$EN_i^* = EV_i^1 - \max(EV_i^2, EV_i^3) \tag{1.4}$$

Following Van der Klaauw (2002), who models the choice to enroll in college as a function of discretionary aid offered, I specify the utility associated with SCHIP choice as a linear function of the premium and an unobserved component capturing all other factors. Let P denote the SCHIP premium and P^A denote the premium fee associated with the "most preferred" alternative. Then, for a child i the enrollment decision can be defined as

$$EN_i^* = \tau_i + \delta(P_i - P_i^A) + v_i \tag{1.5}$$

where the unobserved random component v_i measures all other individual differences in expected utility associated with alternative choice options and τ_i is a person-specific intercept. The larger the value of EN^*, the larger the probability that a child will enroll in the SCHIP program.

Thus, the SCHIP enrollment decision depends on the SCHIP premium amount as well as on the premium payment requested for participation in the "most preferred" option. As mentioned above, information on private premiums are not available to the researcher. With P_i^A unobserved, the utility difference can be written as

$$EN_i^* = \tau_i + \delta P_i + \varepsilon_i \tag{1.6}$$

where $\varepsilon_i = \delta P_i^A + v_i$. Generally, one would expect premium payments for other coverage options and the payment for SCHIP to be correlated since they all depend on the same set of family and child characteristics, for example family income. Therefore, P_i and ε_i are likely to be correlated.

With $EN_i = 1$ if $EN_i^* > 0$ and $EN_i = 0$ otherwise, the probability that the child will be enrolled in SCHIP is given by:

$$\begin{aligned} Pr(EN_i^* = 1) &= Pr(\delta P_i + \varepsilon_i > 0) \\ Pr(EN_i^* = 0) &= 1 - Pr(EN_i^* = 1) \end{aligned} \tag{1.7}$$

The enrollment decision could be described by a linear probability model specification for Eqn. 1.7:

$$EN_i = \beta + \alpha P_i + u_i \tag{1.8}$$

where u_i like ε_i is expected to be correlated with P_i because of omitted variables. Because of omitted variables problems, when evaluating the effect of premium on enrollment the former cannot be considered exogenous with respect to the enrollment decision. Section 1.4 addresses the different approaches of dealing with the endogeneity issue.

1.4 Methodology

The goal of an evaluation is to measure the effect of a variation in premium across families, states, and over time on SCHIP insurance coverage. The purpose of this section is to provide the theoretical underpinnings for the evaluation analysis later in the paper. The estimation problem, irrespective of the dimensionality of the change, arises because SCHIP-eligible children, depending on their family income, can be assigned only to one income group with a fixed premium. No family is observed paying both low and high premiums at the same time. Thus we do not know what would have been the coverage status of the child had the child not been placed, for example, in the "treatment" group that requires a high premium.

To identify and estimate the treatment effect of interest, one must, instead, rely on comparison between the outcomes of two groups, a treatment ($d = 1$) and a control ($d = 0$), which are as similar as possible in characteristics other than the treatment itself (Hahn, Todd and Van der Klaauw, 2001). Estimating the effect of premium on SCHIP enrollment utilizes knowledge of discontinuities in the income group assignment rule and of changes in premium levels over time. SCHIP eligible children can be divided into two groups on the basis of the interval a calculated family income index fell into. These intervals are determined by a state-specific income score $\overline{I}$[2]. Children with household income I at or above $\overline{I}$ are referred to as being in the treatment group and children with income I below $\overline{I}$ are referred to as being in the control group.

The actual decision rule for assigning SCHIP eligible children to income groups varies across states and therefore is difficult to characterize by a simple formula. However, within each state, the assignment rule is fairly simple and easy to implement. One such rule, adopted by the largest state in my data set referred to as state X, says that children based on their family income are assigned to the following two groups: children with family income below 150 percent of the federal poverty line fall into the low income group while children with income at or above 150 of the federal poverty line and below 250 are assigned to the high income group.

The premiums differ by income group with higher premiums for higher-income families. However, within an income group, the premium payment is fixed. In the case of state X, parents pay a premium of \$7 per month for the SCHIP insurance coverage of a child assigned to the low income group and \$9 for a child when in the high income group. Thus, the premium payment as a function of I will contain jump at the cutoff between the first and second income intervals.

Because of the discontinuity in the amount of premium charged as a function of family income measure, the assignment mechanism conforms to that of the Regression-Discontinuity Design. If everyone just above the income cutoff was assigned to the treatment group, the RD design is referred to as sharp. If there are other factors that place into the control group children who, on the basis of their family income, are to

[2]Although there can be up to three income cutoffs in a certain state, because of sample size restrictions, I estimate the premium effect focusing on the intervals below and above the first income cutoff.

be assigned to the treatment, the RD setup is fuzzy.

I focus on the theoretic and econometric considerations under the sharp design, as there are no data on the decision to enroll in SCHIP. All children with $I \geq \overline{I}$ are assigned to the treatment group if they are observed to be covered by public insurance. Respectively, children with $I < \overline{I}$ are assigned to the control. Thus, as incomes crosses the eligibility threshold $\overline{I}$, the treatment status steps from 0 to 1. That is, the "reconstructed" treatment status depends deterministically on whether family income I is above the cutoff value $\overline{I}$.

1.4.1 Sharp Regression Discontinuity Design

In the SCHIP program children are assigned to treatment and control groups solely on the basis of an observed continuous income variable I. Thus, the assignment makes the two income groups very different at least in terms of their average income values. This is in sharp contrast with pure randomization

Despite no randomization taking place, the premium effect on enrollment y can be identified and estimated within the framework of a RD design using a sample of individuals within a very small interval around the income cutoff where the I value is practically the same. The essential nonparametric identification requirement in RD is for borderline (or threshold) randomization: those subjects near the income threshold are likely to be similar in all observable and unobservable aspects except the premium level. A standard regression model representation of the evaluation problem with the sharp regression-discontinuity design is

$$y_{di} = \alpha_i + \beta_d d_i + u_{di} \tag{1.9}$$

where $d = 1$ if the child is assigned to the treatment group. Oftentimes the modest number of data points just below and just above the cutoff motivates the exploration for premium effects on enrollment by looking at wider intervals around the income cutoff point. Considering a narrow interval around the threshold is likely to produce a bias in the effect estimate as the observations entering the estimation are heterogeneous in income. The inclusion of a smooth function g(I) which is continuous at the income cutoff addresses this income dependence issue. In the case of the RD design it is often assumed that the "true" functional form of I can be approximated by some known polynomial. The model for the observed SCHIP enrollment is specified

$$y_{di} = \alpha_i + \beta_d d_i + g(I_i) + u_{di} \tag{1.10}$$

where u_0 is the unobserved error term for those below the cutoff and u_1 for those above.

Note that Eqn. 1.10 can be rewritten

$$y_i = \alpha_i + \beta_d d_i + g(I_i) + u_i \tag{1.11}$$

where $u_i \equiv (1 - d_i)u_{0i} + d_i u_{1i}$ is a composite error term.

Under the above assumption that individuals near the income cutoff share the same observable and unobservable characteristics except the treatment, we can claim that the limiting conditional expectation of the error term given income from above and from below the threshold is the same or that

$$\lim_{I \downarrow \overline{I}} E(u|I) = \lim_{I \uparrow \overline{I}} E(u|I) \tag{1.12}$$

By definition of u_0 and u_1, the term on the left is $\lim_{I \downarrow \overline{I}} E(u_1|I)$ and the term on the right is $\lim_{I \uparrow \overline{I}} E(u_0|I)$.

By definition of y_{0i} and y_{1i} the difference in outcomes for the two treatment groups is

$$y_{1i} - y_{0i} = \beta_d + u_{1i} - u_{0i} \tag{1.13}$$

Asymptotically, the difference between the mean enrollment outcomes for children on each side of the cutoff is

$$\beta_d + \lim_{I \to \overline{I}} E(u_1 - u_0 | I) \tag{1.14}$$

As explained above the limiting conditional expectations of the error terms on either side of the cutoff are the same. Thus β_d is the treatment effect. As illustrated in Figure 1.2, β_d can be estimated as the difference between two linear, regression lines at the cutoff point, which in this case equals the difference in the intercepts of the regression lines.

McCrary and Royer (2006) present a succinct comparison of the two procedures for estimating treatment effects using the RD approach. One procedure uses global polynomial estimators (see, for example, the references in Card and Lee (2006)). However, Hahn, Todd and Van der Klaauw (2001) support estimation with local linear regression, a nonparametric smoother studied in detail in the statistics literature and known to exhibit good boundary properties.

Using the local Ordinary Least Squares (OLS) approach of Hahn, Todd and Van der Klaauw (2001) I minimize

$$\sum_{i \in \mathcal{J}} (y_i - \alpha_i - \beta_d d_i - g(I_i))^2 \tag{1.15}$$

where $\mathcal{J}$ denotes the subsample such that $\overline{I} - h < I_i < \overline{I} + h$ and h is the bandwidth. In this notation, the parameter β_d measures the discontinuity in the expected enrollment for individuals on both sides of the income cutoff between two income groups, or the vertical distance at $I_i = \overline{I}$. The bandwidth around the cutoff determines the share of the sample included in the analysis, with smaller bandwidths producing less biased estimates with higher standard errors.

1.4.2 Cross-Sectional Model

To see how the premium effect can be identified and estimated when data on multiple states are combined, notice that the premium levels for the low-income and high-income groups, in general, differ not only within the state, a feature explored so far in the study, but also across states. Since state X is relatively larger in size compared to the entire sample, I do the following: first, I combine data on states with two income groups excluding state X. Defining the sample in this way is equivalent to splitting all available data into two distinct groups and running separate regressions for each of them. Second, I check the robustness of results by combining state X and all other states in one sample.

In the multiple state specification I assume that people around the state-specific cutoffs should be the same in their observable (income) and unobservable characteristics. As a first step to specifying a multiple-state regression equation for the impact of premium, I define a regression equation for state 1 which is one of the states with two SCHIP income groups. In the individual-state regression specification variable J_1 is a dummy that controls for the impact of the higher-income group premium on public insurance enrollment. The estimate of the constant θ_1 captures the impact of state-specific factors affecting the enrollment of the lower income group one of which is premium. The state 1 regression equation is specified as

$$y_{i1} = \theta_1 + \beta_1 J_1 + g(I_{i1}) + u_{i1} \tag{1.16}$$

Analogously, the regression equation for state 2 is

$$y_{i2} = \theta_2 + \beta_2 J_2 + g(I_{i2}) + u_{i2} \tag{1.17}$$

Combining across-state data by imposing linear and constant premium effects as well as constant income effects across states, the two-state regression model representation is

$$\underset{i \in \mathcal{J}_1 \bigcup \mathcal{J}_2}{y_{is}} = \theta_1 * \mathbf{1}(i \in 1) + \theta_2 * \mathbf{1}(i \in 2) + \beta \sum_{s=1}^{2} J_s + g(I_i) + u_{is} \tag{1.18}$$

where J_s is the magnitude of the premium jump above the point of discontinuity for state s. The estimate of β captures the impact of a \$1 variation in the premium increase on enrollment of children whose family income is at or above the state income cutoff. Because we assume constant premium effects across states, the effect estimate β is the same for state 1 and state 2. θ_1 and θ_2 are state dummies controlling respectively for the impact of state 1 and state 2 specific factors. These are factors that impact the low-income group probability of enrollment with the low premium fee being one of them. $\mathcal{J}_1 \bigcup \mathcal{J}_2$ denotes the subsamples from both states used in the analysis such that, for state 1, $\overline{I}_1 - h < I_{i1} < \overline{I}_1 + h$, $\overline{I}_1$ is state 1 specific income cutoff; for state 2, $\overline{I}_2 - h < I_{i2} < \overline{I}_2 + h$ with $\overline{I}_2$ the income cutoff. h is the bandwidth around cutoff.

Including multiple states in the evaluation of across-state premium variation modifies the two-state regression specification as follows:

$$\underset{i \in \bigcup \mathcal{J}_s}{y_{is}} = \sum_{s=1}^{S} \theta_s * \mathbf{1}(i \in s) + \beta \sum_{s=1}^{S} J_s + g(I_{is}) + u_{is} \tag{1.19}$$

Recall that the underlying assumption for the cross-sectional regression specification is that the premium increase effect is linear and proportional for all states. The β estimate is interpreted as the effect of a \$1 variation in the jump in premium on enrollment of children whose family income places them just above the cutoff. While the high-income groups are constrained to differ only in their premiums, the inclusion of state specific dummies allows the control groups to differ across states regardless of the income cutoff value for the jump in the premium.

1.4.3 Difference-in-Differences Design

Related to RD is "before-after" (BA) design, where the discontinuity takes place in the time dimension. Here, the control response comes from the period before the treatment, whereas the treatment response comes from the period after the treatment. To identify the impact of premium on enrollment, I can compare child participation in the SCHIP before and after the month of the premium change ($\bar{t}$), with t denoting months, $d_t = 1[t \geq \bar{t}]$. For BA design to be effective the break should be defined clearly and the effect should be measured soon after the premium change before other covariates change. This is analogous to the borderline randomization of RD, where in a small temporal neighborhood, the period just before the treatment should be compared to the period just after the treatment, because other changes are unlikely to take place over the short term.

SCHIP families that fail to pay their premiums will lose insurance coverage. Frequently, however, families that renege on their current payments are provided with a grace period[3] before their children become disenrolled, and the length varies by state. This implies that the outcome of interest may take place gradually over time which makes it difficult to separate the treatment effect from the "time effect" due to other factors that vary over the same period.

[3]A grace period is a specified period of time during which children can continue to access services after the payment due date. This allows families who fall behind in paying their premiums time to catch up on past payments before their children lose coverage.

The existence of grace periods with varying length in the SCHIP program motivates the use of "Difference-in-Differences" (DD) method. The advantage of DD over the BA approach is that there is a control group which incurs the time effect but not the treatment effect. Using the control group, the treatment can be identified even if the treatment takes place gradually. In a DD, the treatment is given only to a certain group of individuals, and those left out constitute the control group. In contrast, in BA (and RD), everybody gets the treatment without exception. Hence, there is no contemporary control group in BA. Only the treatment group's past before the treatment is available as a control group. In addtion, the DD parameter estimates will vary depending on the length of the time period considered.

To explore the temporal variation created by premium changes over time, I compare the SCHIP programme enrollment of children for states with two income groups[4]. Widening the window around the time cutoff shifts the identification from a local regression-discontinuity to a global difference-in-differences one, including only observations that are close to the state income cutoff. Let y_{it} be a (0,1) insurance outcome for the SCHIP coverage. As in RD evaluation, in each state the high-income group is selected as the"treatment" ($d = 1$) and the high- and low-income group are assumed to differ only in their premium fees. Thus, presuming the high and low income groups are similar in some state-specific unobserved aspects, then by choosing the low-income group as the control in each state these unobserved aspects are controlled for. I also define a binary time variable t that takes a value of either 0 or 1 depending on whether the child is observed before or after the premium change. The variable V is just the premium level which varies over time and by income group. This leads to:

$$y_{it} = \alpha + \beta d + \gamma t + \delta V_{it} + \beta_z' \mathbf{z}_{it} + \varepsilon_{it} \qquad (1.20)$$

[4]As explained earlier, the multiple-state sample does not include state X.

The DD regression specification implies that for the average child the lower income group enrollment in SCHIP in the period before the premium change $t = 0$ is:

$$y_{00} = \widehat{\alpha} + \widehat{\delta} * V_{00} + \widehat{\beta}_z' \overline{z} \tag{1.21}$$

The public insurance enrollment of low-income group children in the post-change period $t = 1$ is given by:

$$y_{01} = \widehat{\alpha} + \widehat{\gamma} + \widehat{\delta} * V_{01} + \widehat{\beta}_z' \overline{z} \tag{1.22}$$

According to Eqn. 1.20 the higher-income group enrollment at $t = 0$ is:

$$y_{10} = \widehat{\alpha} + \widehat{\beta} + \widehat{\delta} * V_{10} + \widehat{\beta}_z' \overline{z} \tag{1.23}$$

Finally, the SCHIP enrollment of the higher-income group in the period after the change is given by:

$$y_{11} = \widehat{\alpha} + \widehat{\beta} + \widehat{\gamma} + \widehat{\delta} * V_{11} + \widehat{\beta}_z' \overline{z} \tag{1.24}$$

From these simple, group specific models it is straightforward to see that the estimate of α captures the probability of enrollment for the lower income group at $t = 0$ after controlling for the effect of the premium. $\widehat{\beta}$ is the difference between the lower income group enrollment rates in the two periods after controlling for the change in premium. The estimate of γ gives the change in SCHIP enrollment in response to other time-varying factors besides the change in the premium. The estimate of the premium variable coefficient δ supposedly captures the effect of the difference in changes in premium for the two groups on the probability of enrollment after correcting for group and time effects. **z** is a set of other variables including: linear and nonlinear functions of family income, a child health indicator, and the age of the child. The **z** variables can vary over time and, therefore, impact on the treatment and control groups differently pre- and post-treatment. By controlling for the **z** variables, we make the condition of equal time change for both groups plausible. In addition, the composition of the treatment and control group must remain stable over the examined period.

I build the multiple-state regression equation by first defining a regression specification for State 1 only, which is one of the states with two SCHIP income groups. Let y_{it} be a (0,1) insurance outcome. The treatment dummy d indexes by 1 all children in the higher-income group for all states. The time dummy is 1 for all observations in the period following the month of the premium increase. The variable V is the level of premium which is time-, group-, and state-varying.

$$y_{it1} = \alpha_1 + \beta_1 d_1 + \gamma_1 t_1 + \delta_1 V_{it1} + \beta'_{z1}\mathbf{z}_{it1} + \varepsilon_{it1} \tag{1.25}$$

The regression equation for State 2 is

$$y_{it2} = \alpha_2 + \beta_2 d_2 + \gamma_2 t_2 + \delta_2 V_{it2} + \beta'_{z2}\mathbf{z}_{it2} + \varepsilon_{it2} \tag{1.26}$$

Combining data on state 1 and state 2 the two-state regression representation becomes

$$\begin{aligned} \underset{i \in \mathcal{J}_1 \bigcup \mathcal{J}_2}{y_{its}} &= (\alpha_1 + \beta_1 d_1 + \gamma_1 t_1 + \delta_1 V_{it1} + \beta'_{z1}\mathbf{z}_{it1} + \varepsilon_{it1}) * \mathbf{1}(i \in s = 1) \\ &+ (\alpha_2 + \beta_2 d_2 + \gamma_2 t_2 + \delta_2 V_{it2} + \beta'_{z2}\mathbf{z}_{it2} + \varepsilon_{it2}) * \mathbf{1}(i \in s = 1) \end{aligned} \tag{1.27}$$

Assuming constant premium-, treatment-, and time-effects across states, the multiple-state difference-in-difference specification becomes

$$\underset{i \in \bigcup \mathcal{J}_s}{y_{ist}} = \sum_{s=1}^{S} \alpha_s * \mathbf{1}(i \in s) + \beta d + \gamma t + \delta V_{ist} + \beta'_z \mathbf{z}_{ist} + u_{ist} \tag{1.28}$$

Unlike the individual-state specification (Eqn.1.20), the multiple-state specification should take into account states' heterogeneity. To control for it, in Eqn.2.14, I introduce a set of state dummies α_s. The specification also explicitly controls for the time-varying $\mathbf{z}$ variables that can impact on the outcome of interest. δ, the coefficient estimate of the premium variable V, captures the effect of a $1 change in the difference between the premium increases for the two group on the probability of enrollment. The high-income groups' probability of enrollment is constrained to be the same across states. The inclusion of state-specific dummies allows the control groups' enrollment to differ by state.

1.5 Data and Assignment Method

1.5.1 Data

The data for the analysis come from the 2003 panel of the Medical Expenditure Panel Survey (MEPS). The MEPS provides information on a nationally representative sample of the non-institutionalized civilian population. It is sponsored by the Agency for Healthcare Research and Quality (AHRQ) and the National Center for Health Statistics (NCHS). The survey has an overlapping panel design, gathering two years of data for each household. MEPS is designed to produce nationally representative estimates for insurance coverage, medical expenditure, and a wide range of other health-related and socioeconomic characteristics. The data can also be used to support behavioral analysis that informs researchers and policymakers about how the characteristics of individuals and families, including their health insurance, affect medical care use and spending, as discussed in Cohen (1997). The MEPS cannot support the estimation of state-specific models for every state. However, in the context of a multivariate model, the effect of a state specific variable is identifiable when data on all states are used, as in Hudson, Selden and Banthin (2005)

I collected data on SCHIP premium schedules for all states and the District of Columbia. Premium information was obtained from websites maintained by the Centers for Medicare and Medicaid Services, the National Conference of State Legislatures, the American Academy of Pediatrics, and from several published sources by the Maternal and Child Health Policy Research Center (Fox, Levtov and McManus (2003), Fox and Limb (2004)). The constructed data set has information on premium payments, their frequency (monthly or annually), and the maximum premium amount that a family could pay. The premium data are merged to the 2003 full-year consolidated MEPS files at the state level. The analysis focuses on premium variation across individuals, states and over time in 2003.

The main focus is on the premiums and insurance status of children aged 18 and younger. Each state's premium information is used to assign the premium amount that the family unit will face to cover a given child for one month. I assess the extent to which the premium per child in a particular age/income/month/state group affects the enrollment decision. For states that have introduced a maximum total premium for families with multiple children, child-specific premiums were constructed by dividing the maximum premium by the number of children for which the cap becomes effective. If families were not subject to the family-level maximum, the child-specific premium was assigned. Enrollment decisions, however, are likely to be made at the family level. Family-level decision making will take into account the total number of children in a family unit and the possible decrease in total outlays on premiums because of the cap. Future work using information on families with only one child will likely provide a better understanding of family decision making regarding SCHIP enrollment.

In addition, every child that is income- and age-eligible for the SCHIP coverage at time t is assumed to be in one of three insurance states, namely: 1) SCHIP (public) coverage, 2) private health insurance, or 3) no insurance. A child may leave the SCHIP in order to take up insurance from another, private source, such as a parent's employer. A child eligible for the program can drop out of public insurance, without having any other form of health insurance and thus become uninsured. Although determining the share of disenrollment due to substituting with other insurance or losing public coverage when higher premiums are imposed is key to policy making, it is the beyond scope of the current paper and is addressed in Nikolova (2008). Defining the three insurance states between which SCHIP-eligible children can move is of research interest here. The sample for analysis is limited to children that have one of the three forms of insurance.

Eleven states increased their premiums in 2003. This feature of the data allows us to look at changes in enrollment over time. My sample for panel analysis includes children aged 18 and younger with positive full-year weights for 2003. The weight variable, when applied to the children who participated in that year, allows the researcher to obtain estimates of child-level changes in the health coverage variable[5]. I extracted a subset of children from the full-year population who were included in the survey at the very first day of 2003. To avoid drawing comparisons across children who entered the MEPS at different times during that year I also created a subset of children who were available for interview for all three rounds of data collection. In 2003, six states (Alabama, Colorado, North Carolina, Nevada, Texas, and Utah) charged annual premiums. Since one goal of this paper is to trace the monthly changes in enrollment following the premium increase, these states have been omitted from the panel and cross-sectional analysis.

Previous national studies of premiums that used repeated cross-sections of the March supplement to the Current Population Survey (CPS) imputed yearly measures of

[5]A person with a positive full-year weight for 2003 is a key in-scope person who responded for his or her entire period of 2003 eligibility. A person is considered as in-scope during a round if he or she is a member of the U.S. civilian, non-institutionalized population at some time during that round.

public insurance coverage for a number of consecutive years. The MEPS data set provides a definite advantage to studies that track changes in SCHIP/Medicaid enrollment with respect to precision of insurance status information. Information on the insurance coverage of each child is ascertained in the MEPS by asking: "Were you covered by Medicaid or SCHIP?" each month. However, because of grace periods, insurance coverage studies using the MEPS are susceptible to the timing of the enrollment response following a premium change. To circumvent the timing issue I compare the January and December enrollment outcomes of SCHIP eligible children. As no state has a grace period that would last until December this time span effectively captures the enrollment response in all states that chose to increase their premiums during the year. As mentioned in Hudson, Banthin and Selden (2004), the MEPS is widely regarded as providing more accurate and consistent public coverage estimates than the CPS, perhaps because the MEPS asks numerous detailed questions regarding the presence, source, and duration of coverage.

The MEPS includes information on children aged 18 and younger who are eligible for the first or second income group. Public insurance eligibility for each child is assigned as described below.

1.5.2 Assigning Program Eligibility

Assigning eligibility is pivotal to my analysis.[6] The health insurance coverage variable in the data only indicates that the person has Medicaid or SCHIP coverage. Whether the coverage is Medicaid or SCHIP is not directly observed and therefore must be assigned. To assign Medicaid/SCHIP elibility, I use data on family income, family structure, child age, and state-specific eligibility rules. In all cases, I have attempted

[6]The paper benefits from the experience and help of Julie Hudson and Jessica Banthin from the Division of Modeling and Simulation at the Center for Financing, Access and Cost Trends at the Agency for Healthcare Research and Quality.

to assign the rules as they would be applied to new applicants.

For the purpose of determining Medicaid or SCHIP eligibility I make use of the Health Insurance Eligibility Unit (HIEU) definition. This variable identifies family members who would normally be eligible for family coverage under the adults' private health insurance family plans. These families, or HIEUs, comprise adults, their spouses, and their unmarried natural/adoptive children aged 18 and under. For these traditional families with parents and children, I calculate annual family income by summing up the annual wage and salary income for each adult in the HIEU. If there are children aged 18-24 in an HIEU who are full-time students, their income is omitted from the family income calculation. However, if the student is a parent and not an older sibling, her income is counted towards the calculation of family income.

Unmarried minors not living with their natural/adoptive parents are included in the family of their stepparent, grandparent, or aunt/uncle. State rules vary for the counting of income and family size for these "nontraditional" families. To simplify, following previous MEPS studies that use simulated eligibility (Hudson, Selden and Banthin (2005), Hudson, Banthin and Selden (2004)), I assume that all "nontraditional" guardians who are both low-income and disabled are included in the unit for both income and size because this helps the family's case for being eligible. Otherwise, the family is treated as a child-only case and the child is eligible for public insurance despite the income of the adults.

I use the Urban Institute Welfare Rules Database (see Table 2.12) to determine which states allow minor parents to head their own household. For states that allow minor parents to head their own household, I follow rules similar to those for nontraditional families: I include the parent/adult relative only if they were both low-income and disabled. Otherwise the minor parent heads her own household. For states that do not allow minor parents to head their own household, I include the parent/adult relative in the family unit for income and size.

The constructed family income measure is converted into a percentage multiple of the 2003 poverty guideline, which is the SCHIP income measure for determining eligibility. Children's monthly eligibility for public insurance is calculated for the population of children in the MEPS using state-level rules. Individual eligibility for public insurance is defined by the following mutually exclusive categories: 1) eligible for Medicaid, 2) eligible for SCHIP, and 3) not eligible for public insurance. If a child is age- and income-eligible for public insurance (Medicaid or SCHIP) and is observed in the data to have public insurance, then Medicaid coverage is assigned if the family incomes falls below the income cutoff value separating Medicaid from SCHIP and SCHIP coverage is assigned if family income is higher than the threshold value. Determining eligibility on a month-by-month basis incorporates the possibility of a change in state eligibility rules. Thus transitions of children between income groups or out of SCHIP coverage could be the result of changes in state eligibility rules and/or premium payments and/or child age.

A child who was enrolled at any point in a given month is considered a current enrollee and disenrollees are defined as children enrolled in SCHIP for at least one month, but not enrolled in SCHIP the subsequent month.

1.5.3 Descriptive Statistics

The sample used in the evaluation of premium effects on SCHIP enrollment consists of children aged 0 to 18 who are income-eligible for the first or second income group.

Description of Individual States

Table 1.1 shows the family income, premium, age, and the enrollment rate for the largest state in my data set, referred to as state X. The eligibility rule in this case is well known: children under six years with derived income measure, I, such that $I \leq 134$ of the Federal Poverty Line (FPL) are eligible for Medicaid, while, for older children, the income border is set at $I = 100$ of the FPL. State X has determined that families with $I \leq 150$ of the FPL are responsible for the payment of a \$7 monthly premium. Families with income between 151 and 250 percent of the FPL pay \$9 for the enrollment of their SCHIP eligible children. I find that those enrolled in the first income group are on average slightly older than those in the second. Family income, by construction, increases monotonically by group. Table 1.1 compares enrollment for SCHIP-eligible children for the two income groups. The table shows that enrollment in the state X program was lower for the high income group than for the low income group. For states where premiums are increased in 2003 the statistics are based on data as of the month before the premium change and for states with no temporal variation in premium statistics are as of January of the same year. There are 270 and 380 eligible children in the first and second income group respectively.

Sample for Cross-Sectional Analysis

Table 1.1 presents the average enrollment, family income, premium payment, and age at a point in time for all study states with two income groups except state X. The table shows that premium payment and enrollment in SCHIP change monotonically with group, with premium increasing and enrollment decreasing from the low-income (Group I) to the high-income group (Group II). Children in the lower income group are on average slightly older than those in the higher income group. There are 317 children in Group I and 664 children in Group II. Statistics are based on data from the month prior to the premium change for states that increased their premium. I have used January data for states that did not change their premiums.

Sample for Longitudinal Analysis

The sample includes children aged 18 and younger with positive full-year weights applied for 2003. There are 953 children who are income-eligible for Group I and Group II. Table 1.2 shows the average family income, premium, child age, health status, and SCHIP enrollment as of January and December of year 2003. Summary statistics are presented separately for the low- and high-income group. For the low-income group the average family income, child age and health remain relatively constant over the the course of the year, but the average premiums increased. The average SCHIP enrollment remained the same over the course of 2003. Summary data for the high-income group show that public insurance enrollment, family income, age and health status of the child stay relatively constant over the course of the year, while premium outlays increase.

1.6 Estimation Results

I present my results in four subsections. First, I discuss simple LOESS results. Second, I examine the impact of premium on enrollment in the largest state in the data set, state X. There are two income groups in state X and their beneficiaries are paying different premiums. These effects are observable and precisely estimated given the data. I also extend my conclusions by exploring the effect of the premium jump by age group. Next, I explore the effect of the cross-sectional variation in premiums on enrollment when data on all states are combined. Finally, I study the impact of premium increases over time on the SCHIP enrollment rate of children.

To illustrate how discontinuities in the family income assignment rule possibly affect enrollment decisions, I first plot the enrollment rate as a function of the family income index using the LOESS technique, more descriptively known as locally weighted polynomial regression. At each point in the data set, a low-degree polynomial is fitted to a subset of the data, with explanatory variable values near the point whose response is being estimated. The polynomial is fitted using weighted least squares which gives more weight to points near the point whose response is being estimated and less weight to points further away. The value of the regression function for the point is then obtained by evaluating the local polynomial using the explanatory variable values for that data point (for detailed discussion on LOESS, see e-Handbook of Statistical Methods, NIST/SEMATECH (2003)).

1.6.1 A Case Study of the Largest State

State X is the largest state in my data set. Since the assignment rule for each state has a simple structure, to better understand the influence of premium it is useful to first separately analyse enrollment in this one state before considering several states together with cutoffs and premiums at different levels.

As a first exploration for a possible effect of premium payments on enrollment decisions, I obtain separate LOESS estimates of enrollment in public insurance on each side of the income cutoff as a function of family income and then display their scatter plots on the same graph to see how estimated enrollment for each income group compares at the cutoff. Figure 1.3 shows a scatter diagram of the estimated point-by-point, locally-weighted linear regressions for each income group as a function of the family income index for all age-eligible children in state X. The plot presents strong evidence of a jump at the 150 percentage points of the FPL cutoff between the two income groups. In addition, I obtain estimates of average enrollment on each side of the cutoff for children with family income within 15, 20, and 25 percentage points of the income cutoff score. As shown in Table 1.3 the average enrollment rate of children of all ages in the high-income group is estimated to be between 17 to 18.1 percentage points lower than the enrollment rate for children in the group below the cutoff.

A more exacting demonstration of the cutoff comes from separately analyzing the enrollment behavior of older children as well as all children. In state X, the cutoff between SCHIP and Medicaid is set at $I = 134$ percentage points of the FPL for children less than six years old, while the threshold for the older children is at a lower $I = 100$ percentage points of the FPL. Analysis of older children enrollment is arguably based on a more uniform set of points. Figure 1.4 for the group of older children, reveals a clear discontinuous jump at the income cutoff. The effect estimates in Table 1.3 show that the enrollment of older children in the treatment group decreases by 14.4 – 14.5 percentage points.

Figure 1.3 reveals that the enrollment rate mostly declines with family income. This result is consistent with the findings of Hadley et al. (2006) that children in families with higher incomes are more likely to have private coverage than Medicaid or SCHIP coverage. Figure 1.4, the plot for older children, also demonstrates that the probability of enrollment after the cutoff decreases monotonically with family income over the income range of the second income group.

For sufficient sample sizes[7] the premium increase estimates for the sample of older children in state X are negative with magnitude in the range of $(-.195; -.462)$ as presented in Table 1.4. That is, the increase in premium from \$7 to \$9 above the point of discontinuity leads to a decrease in the probability of enrollment in the range of 19.5 to 46.2 percentage points depending on bandwidth, with the estimate for the smallest bandwidth being $-.462$. The estimate based on the smallest bandwidths is arguably the one with the least bias but the largest standard error. The relatively large standard errors for these estimates obviously reflect the modest sample sizes on

[7]Assuming at least 10 observations are needed for the estimation of each parameter.

which these local estimates are based (as observed in Van der Klaauw (2002)). I specify the alternative hypothesis that larger premiums are associated with larger declines in enrollment. My null is that premium-induced disenrollment in the high income group is as large as premium-induced disenrollment in the lower income group. The estimates for the $-15/+15$ and $-20/+20$ bandwidths provide significant evidence at the 5 percent level to reject the null. The effect estimates for state X correspond to an estimated enrollment elasticity[8] with respect to group premium evaluated at the mean in the range of -1.444 to -2.943.

Discontinuity and elasticity estimates for all children are presented in Table 1.4. The results consistently demonstrate that higher levels of premium are associated with lower probability of enrollment. In magnitude the premium estimates range from -0.17 for the largest sample to -0.305 for the smallest. The point estimates support an earlier finding that standard errors decrease as the size of the sample increases. For the $-20/+20$ interval, at the 5 percent level, I reject the null that the disenrollment effect for the higher income group is as large as the disenrollment effect for the lower income children. The elasticity estimates point to a high sensitivity of enrollment to small premium changes.

The point and elasticity estimates demonstrate that small changes in premium in State X lead to large disenrollment effects. Whether the \$2 increase in monthly premium per child makes the public insurance alternative unaffordable and the child loses insurance coverage, or less desirable and the child is switched to private insurance is an empirical question. Background information suggests that the issue of affordability

[8]Elasticity is calculated using the mid-point formula

$$\varepsilon = \left(\frac{\Delta EN}{(EN_1 + EN_2)/2}\right) \times \left(\frac{(P_1 + P_2)/2}{\Delta P}\right) \tag{1.29}$$

The treatment dummy point estimate is ΔEN. Enrollment below the cutoff (EN_1) is obtained by predicting the enrollment probability at the cutoff point using the RD coefficient estimates. Enrollment above the cutoff (EN_2) is just the sum of the EN_1 and ΔEN.

is particularly acute in State X because of the high cost-of-living which means that low- and moderate-income families spend a higher share of their family income on essential items, like food and housing, leaving them fewer resources with which to pay for health premiums.

1.6.2 Cross-Sectional Estimates

Table 1.5 displays the estimates and standard errors for the premium jump variable J for three different bandwidths and two samples. Using data on children with family income within the $-15/+15$ income interval the premium jump is estimated to have a negative statistically significant effect on SCHIP enrollment ($\beta_J = -0.018$). That is, an additional increase in the high-income group premium of \$1 will lead to a decrease in their SCHIP enrollment of 1.8 percentage points. The effect estimate for the $-20/+20$ and $-25/+25$ income intervals is smaller and insignificant. A \$1 jump in the premium across the point of discontinuity is estimated to cause, respectively, a 1.2 and 1 percentage points decline in enrollment for those whose family income is at or higher than the income cutoff level. The premium jump estimates for the group of older children are slightly larger. The coefficient estimate $\widehat{\beta_J}$ points to a 2.2 to 1.4 percentage points decrease in public enrollment for individuals just above the cutoff in response to an additional \$1 increase in the premium with the decline for those within $+15/-15$ percents of the state-specific cutoff being statistically significant.

The national estimates affirm the single-state findings that higher premiums are related to a decline in enrollment. In magnitude, the national estimates rank below the point estimate values for the individual states. To better understand these results, recall that we assumed that people around the cutoff are the same in terms of all observable (income) and unobservable characteristics. However, in different states the cutoffs are at different income levels and the magnitude of the premium jump varies as well implying that people near the cutoff are not the same. This heterogeneity in the cross-sectional analysis leads to weaker results.

For every state with two income groups I have included a state-specific dummy θ_s to capture the state heterogeneity. While the premium jump variable controls for the effect of premium on enrollment in the high-income SCHIP group, θ_s captures the effect of all state-specific factors that impact on enrollment in the low-income group, with the low-income group premium being one of them. For comparison, in the RD estimation the intercept estimate measures the probability of enrollment for children with family income below the state cutoff. Testing the joint significance of the state-specific dummies confirms the hypothesis that the low-income group SCHIP enrollment varies significantly by state. Additionally, a test of income polynomial significance shows that, when observations are close to the the state-specific cutoff, family income does not have a statistically significant effect on the probability of enrollment in the SCHIP program. Pooled regression with all included states demonstrates that there is a significant difference between state X and the rest of the states in the sample.

1.6.3 Difference-in-Differences Estimates

Small sample sizes for individual states that increase their premiums over time prevent DD evaluation of the premium effect at the state level. In the multiple-state analysis (see Eqn. 2.14) I examine the effect of premium increases using data on children of all ages as well as children aged 6-18 whose family income puts them within the $-15/+15$ or $-20/+20$ or $-25/+25$ income intervals (for explanation on the bandwidth choice see section 1.6.2).

The premium increase estimates for all samples and bandwidths are negative and significant, as presented in Table 1.6. The estimates obtained with data on all children point to a decrease in the probability of enrollment of 2.1 to 1.4 percentage points in response to a variation of $1 in the difference in changes in premium for the two groups. Considering only children aged 6-18, I obtain approximately the same estimates for the premium increase variable. A $1 variation in the difference between the premium increases for the two groups leads to a decrease of 1.9 to 2.1 percentage point for the considered intervals. These are significant effects associated with important declines in SCHIP enrollment.

The estimates of the treatment dummy vary with bandwidth, with the results for older children being more variable in response to interval choice. The estimate of β is the difference between lower income group enrollment in the two periods after controlling for the change in premium. The results point to no effect of treatment on enrollment rates. The period dummy point estimates reflect the change in SCHIP enrollment in response to all time-varying factors that are not explicitly controlled for. The γ estimates are sensitive to bandwidth selection and their impact is not significant. A joint test of income polynomial significance reveals that income is not a significant determinant of the probability of being of publicly enrolled when children close to the cutoff are considered. Testing jointly the statistical importance of state dummies shows that state-specific factors impact enrollment. Re-estimating the model with all states with two income groups included in the sample reinforces the cross-sectional finding that state X differs from the rest of the states, though the conclusions are not qualitatively different.

1.7 Conclusions

In this paper, I obtain three sets of estimates for the premium increase effect on disenrollment from the State Children's Health Insurance Program. My main regression-discontinuity findings provide statistical support for the hypothesis that higher SCHIP premiums are associated with an increase in disenrollment from the public insurance program. The cross-sectional analysis based on the two most homogeneous samples reveals enrollment decreases in response to a \$1 change in the premium jump. The difference-in-differences premium estimates point to a statistically significant decrease in public enrollment for children in the higher-income group in response to a \$1 variation in the difference between premium increases for the two groups.

This paper establishes itself in the literature of SCHIP premium evaluation as a thorough quantitative investigation of SCHIP premium increases. Using the MEPS survey which is widely regarded as providing the most accurate and consistent public coverage information, I analyze three different sources of premium variation to evaluate the magnitude of the impact on enrollment rates. While it is important to know the extent to which efforts designed to provide uninsured children with health coverage are hampered by the premium requirement, there is little knowledge about what happens to the children who disenroll. If a child acquires insurance from a private source, then this should not be seen as a policy failure because these children do not become uninsured - it is the lack of *any* insurance that presents a problem since it is associated with adverse health outcomes. Future research to determine the extent to which premium-induced loss of health insurance coverage is an issue for SCHIP will provide important information about the insurance status of children after they drop out of public coverage.

Table 1.1: Summary Statistics – Cross-Sectional Data

Average family income, premium, age, and public enrollment at a point in time for: (i) all states with two income groups, (ii) all states except state X, and (iii) state X only

		All States			All but State X			State X		
Group	Var	Mean	St. D.	N	Mean	St. D.	N	Mean	St.D.	N
Group I	Publ enrollment	0.52	0.50	587	0.46	0.50	317	0.59	0.49	270
	Income	126.20	14.88	587	128.16	14.51	317	123.91	15.02	270
	Premium	5.02	5.52	587	3.33	6.68	317	7	0	270
	Child age	10.97	4.36	587	10.90	4.45	317	11.06	4.26	270
Group II	Publ enrollment	0.303	0.400	1044	0.27	0.44	664	0.366	0.482	380
	Income	189.90	26.52	1044	189.98	25.73	664	189.75	28.03	380
	Premium	12.66	10.31	1044	15.75	13.24	664	9	0	380
	Child age	9.82	5.10	1044	9.86	5.17	664	9.76	4.99	380

Table 1.2: Summary Statistics – Longitudinal Data

Average family income, premium, age, health status, and public enrollment for all states with two income groups as well as for all states excluding State X as of January and December 2003

		All States						All but State X					
		B.Ch.			A.Ch.			B.Ch.			A.Ch.		
Group	Variable	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N
Group I	Publ enroll	0.42	0.49	926	0.42	0.49	932	0.37	0.48	670	0.37	0.48	676
	Income	142.75	43.27	926	143.03	43.35	932	150.28	47.87	670	150.59	47.87	676
	Premium	4.99	7.17	926	5.88	7.16	932	4.22	8.30	670	5.10	8.43	676
	Child age	10.16	4.63	926	10.15	4.65	932	10.02	4.87	670	10.01	4.98	676
	Health state	3.49	1.64	926	3.48	1.65	932	3.48	1.60	670	3.48	1.61	676
Group II	Publ enroll	0.33	0.47	604	0.32	0.47	598	0.26	0.44	283	0.26	0.44	278
	Income	191.94	27.91	604	192.29	27.83	598	193.69	29.82	283	194.48	29.63	278
	Premium	10.55	7.13	604	11.53	7.53	598	12.29	10.13	283	13.91	10.81	278
	Child age	9.88	4.99	604	9.84	4.98	598	9.72	5.21	283	9.64	5.18	278
	Health status	3.47	1.69	604	3.46	1.7	598	3.49	1.70	283	3.47	1.71	278

Table 1.3: Estimated Average Enrollment – State X

LOESS estimates of the probability of SCHIP enrollment of all children in state X

	All Ages			Age 6 and older		
Bandwidth B/A	Av. Enr. B/A	Effect	N B/A	Av. Enr. B/A	Effect	N B/A
-15/15	0.641/0.460	0.181	89/107	0.633/0.488	0.145	61/84
-20/20	0.632/0.455	0.177	98/127	0.624/0.479	0.145	69/99
-25/25	0.617/0.447	0.170	122/147	0.609/0.465	0.144	93/115

Table 1.4: Public Insurance – Regression-Discontinuity Estimates

RD estimates for the three intervals based on data for the largest state.
(*) – indicates significance at the 5 percent confidence level

Bandwidth Below/Above	Treatment Effect	Elasticity	N Below/Above
		Older Children	
-15/15	-0.462** (.275)	-2.943	61/84
-20/20	-0.378** (.220)	-2.664	69/99
-25/25	-0.195 (.193)	-1.444	93/115
		All Children	
-15/15	-0.305 (.212)	-2.203	89/107
-20/20	-0.292* (.178)	-2.236	98/127
-25/25	-0.170 (.16)	-1.327	122/147

Table 1.5: Cross-Sectional Estimates

Premium change estimates for three different bandwidths based on data for all states with two income groups. (**) - indicates significance at the 5 percent confidence level of the one-tail null there is the impact of premium on enrollment in the higher income group is larger.

Bandwidth Below/Above	Premium Jump All States	N Below/Above	Premium Jump No State X	N Below/Above
		Older Children		
-15/15	-0.018	172/125	-0.022**	111/41
	(.012)		(.012)	
-20/20	-0.010	203/145	-0.016	134/46
	(.011)		(.011)	
-25/25	-0.007	247/180	-0.014	154/65
	(.01)		(.01)	
		All Children		
-15/15	-0.014	212/167	-0.018**	123/60
	(.011)		(.011)	
-20/20	-0.009	256/191	-0.012	158/64
	(.009)		(.01)	
-25/25	-0.007	317/230	-0.01	195/83
	(.008)		(.008)	

Table 1.6: Difference-in-Differences Estimates

Premium change estimates for three different bandwidths based on data for all states with two income groups. (*) denotes significance at the 5 percent confidence level.

	All States				All but State X			
Bandwidth Below/Above	Prem. Jump	Treat. Dummy	Period Dummy	N Below/Above	Prem. Jump	Treat. Dummy	Period Dummy	N Below/Above
Older Children								
-15/15	-0.018*	0.051	-0.047	128/142	-0.019*	0.097	-0.030	68/82
	(.007)	(.01)	(.05)		(.007)	(.098)	(.053)	
-20/20	-0.019*	0.012	-0.018	152/174	-0.021*	0.076	-0.030	84/106
	(.0049)	(.082)	(.046)		(.004)	(.086)	(.050)	
-25/25	-0.017*	-0.033	-0.057	188/202	-.020*	0.082	-0.027	90/120
	(.005)	(.08)	(.043)		(.004)	(.079)	(.047)	
All Children								
-15/15	-0.021*	0.028	-0.063	166/164	-0.021*	0.038	-0.041	82/90
	(.005)	(.089)	(.046)		(.005)	(.089)	(.051)	
-20/20	-0.019*	0.032	-0.030	192/210	-0.019*	0.046	-0.036	98/126
	(.004)	(.076)	(.042)		(.003)	(.082)	(.049)	
-25/25	-0.014*	0.005	-0.064**	230/250	-0.014*	-0.036	-0.043	106/148
	(.004)	(.072)	(.04)		(.003)	(.085)	(.049)	

Table 1.7: Special Rules Imposed on Minor Parents Eligibility

Can be the head of unit	Cannot be the head of unit
Alabama	Delaware
Alaska	Idaho
Arizona	Kansas
Arkansas	Louisiana
California	Maryland
Colorado	North Carolina
Connecticut	West Virginia
Florida	Wisconsin
Georgia	
Hawaii	
Illinois	
Indiana	
Iowa	
Kentucky	
Maine	
Massachusetts	
Michigan	
Minnesota	
Mississippi	
Missouri	
Montana	
Nebraska	
Nevada	
New Hampshire	
New Jersey	
New Mexico	
New York	
North Dakota	
Ohio	
Oklahoma	
Oregon	
Pennsylvania	
Rhode Island	
South Carolina	
South Dakota	
Tennessee	
Texas	
Utah	
Vermont	
Virginia	
Washington	
Washington D.C.	
Wyoming	

Figure 1.1: Production Function of Health Stock

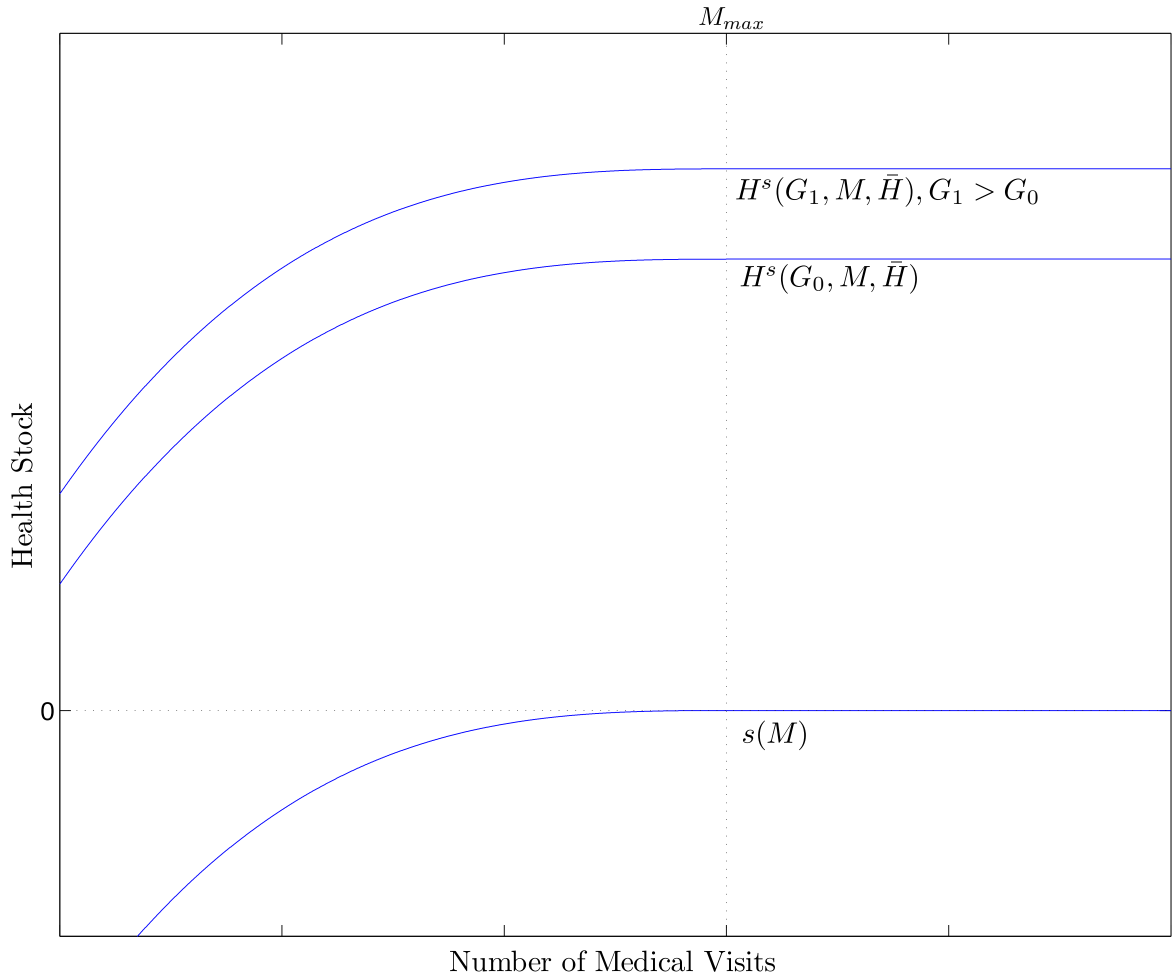


Figure 1.2: Regression Discontinuity Data

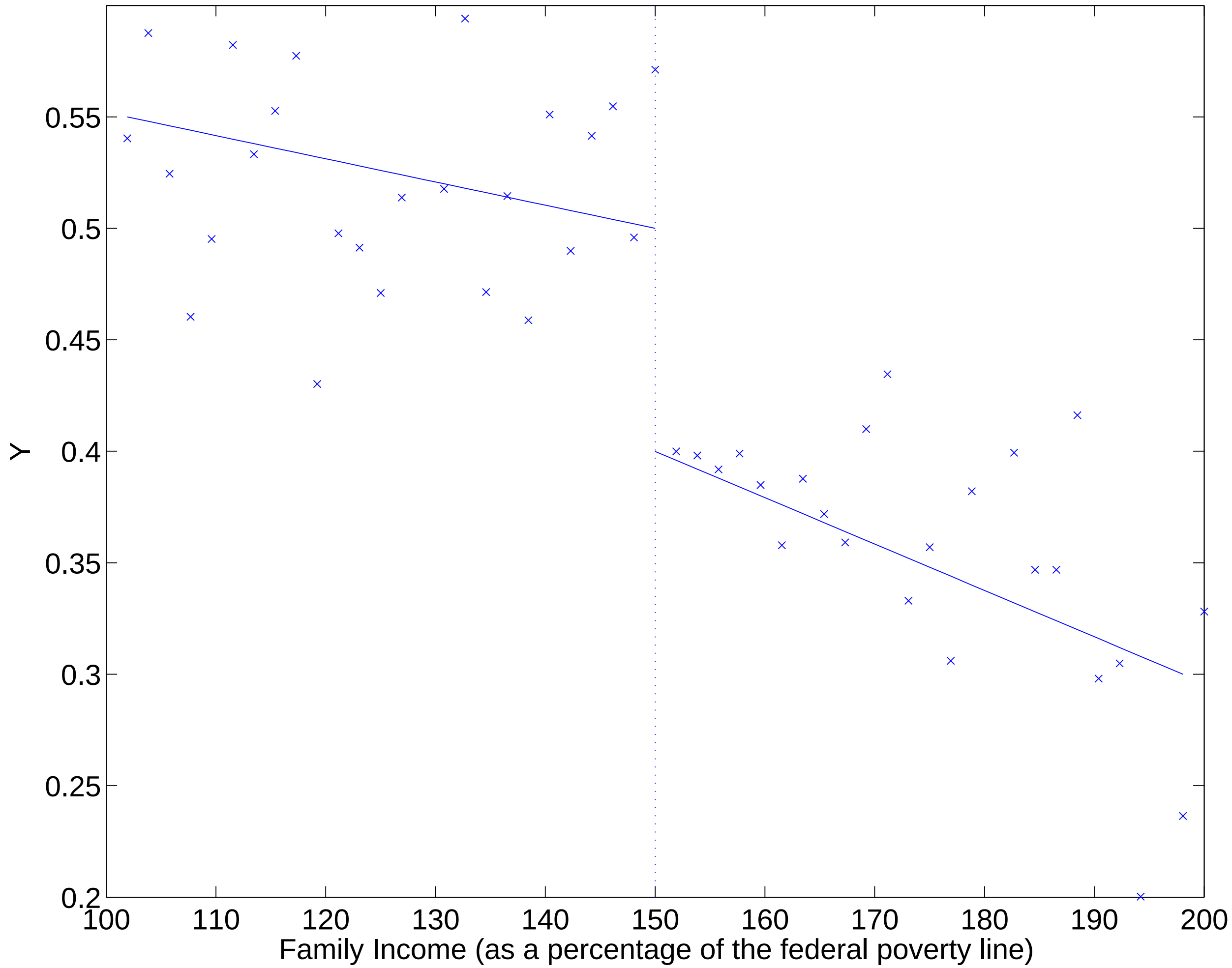


Figure 1.3: Enrollment Rate - State X

Scatter diagram of the LOESS estimates of the probability of SCHIP enrollment as a function of the family income index for children in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.

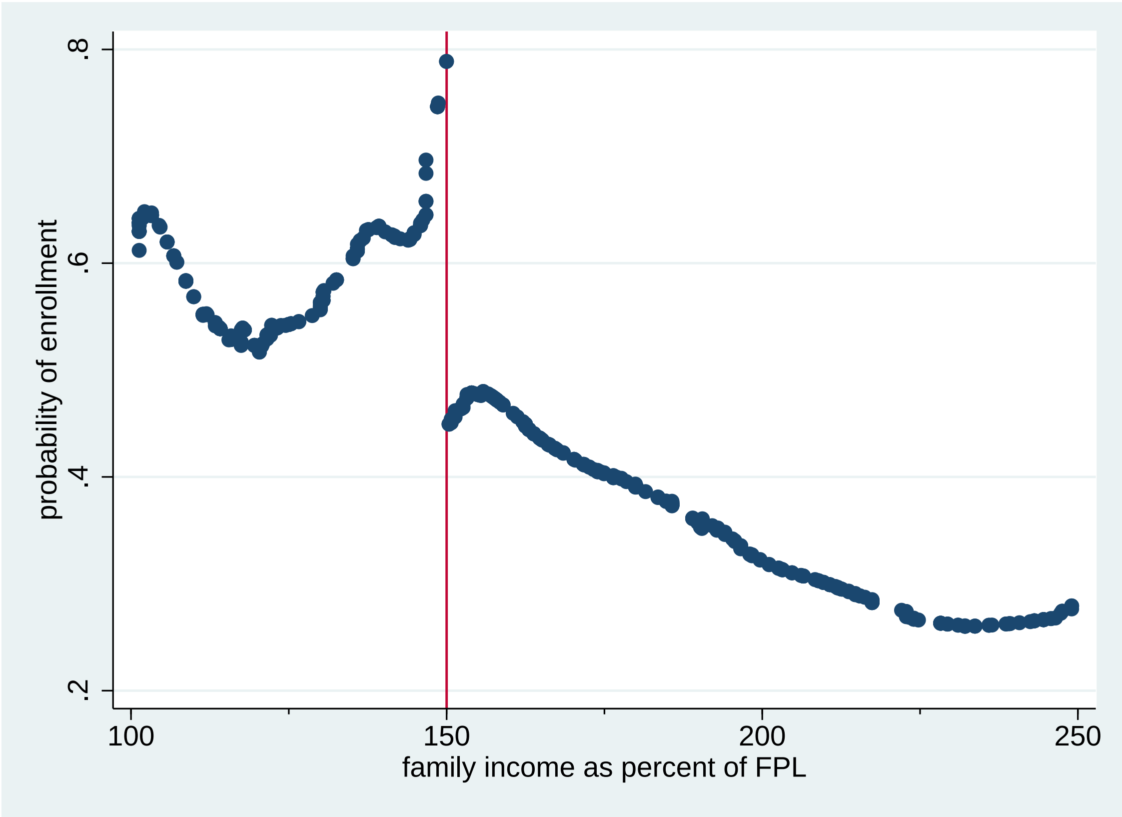
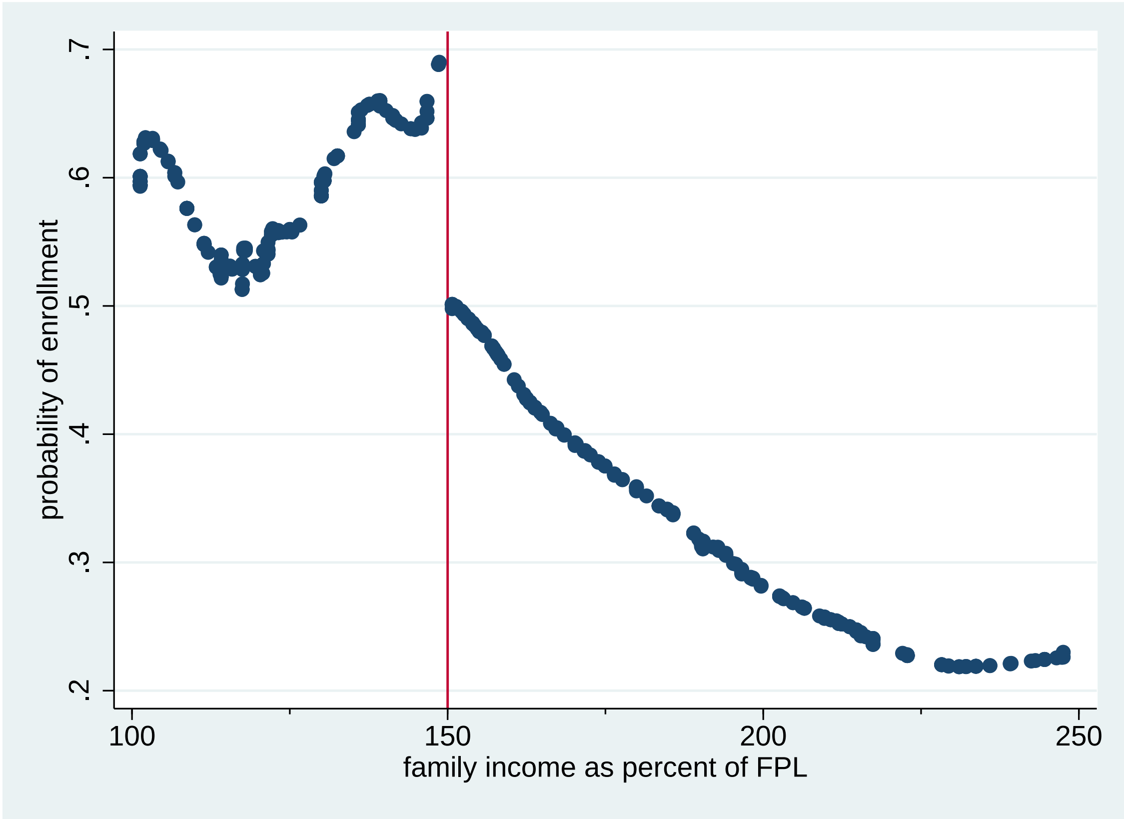


Figure 1.4: Enrollment Rate for Older Children - State X

Scatter diagram of the LOESS estimates of the probability of SCHIP enrollment as a function of the family income index for children who are 6 years of age and older in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.



Chapter 2

What Happens to Children Who Drop Out of SCHIP Coverage?

2.1 Introduction

While higher premiums in the SCHIP have been documented by many researchers to lead to a decline in enrollment in the program, there is paucity of evidence documenting what happens to those children after they leave the program. This papers aims to determine the extent to which premium-induced loss of health insurance coverage is a problem for the SCHIP program.

Children without health insurance are more likely to go without the necessary healthcare in times of illness and are less likely to receive preventive treatment (Newacheck et al., 1998). Some parents may fail to maintain their children's coverage because they plan to re-enroll into an insurance plan if an emergency arrives. However, children with discontinuous coverage are 50 percent more likely to lack a regular source of medical care (Kogan et al., 1995), which is a factor associated with a tenfold increase in the risk of hospitalizations for preventable health problems. Lack of health insurance is associated with lower rates of check-ups, vaccination, and follow-up care (Burstin et al., 1998), and an increase in total medical costs per month (Ku and Ross, 2002). Clearly, if many children are leaving SCHIP and becoming uninsured, it would pose a significant public health and policy problem.

Recently, a number of studies on the impact of premium on SCHIP enrollment appeared in the literature largely in response to the growing number of states that either increased, or introduced premiums in the early 2000's. The body of evidence suggests that higher premiums are associated with a decline in the probability of SCHIP enrollment, although its estimated magnitude varies quite widely (Shenkman et al., 2002; Shenkman, Herndon and Vogel, 2006; Kenney, Allison, Costich, Marton and McFeeters, 2006; Kenney, Costich, Marton and McFeeters, 2006; Marton, 2006; Hadley et al., 2006; Kenney, Hadley and Blavin, 2006; Nikolova, 2007).

The SCHIP program is targeted at families with incomes above Medicaid levels. These households are more likely to have access to private insurance. The availability of cheaper, public insurance has been documented to lead to substitution from private to public health insurance among SCHIP-eligible children who are already privately insured. This phenomenon is generally referred to as "crowd-out" [1]. SCHIP is created with a built-in mechanism intended to keep families away from dropping private coverage in favor of public insurance. Perhaps more important in the era of the SCHIP program is the imposition of non-trivial costs on enrollees, either in the forms of premiums or copayments [2].

Critically, previous research has failed to distinguish between the three different

[1] Cutler and Gruber (1996) first describe that public eligibility expansions crowd out existing private insurance coverage. Their central estimates suggest that the number of uninsured only decreased by one-half as much as the number of publicly insured rose, due to offsetting reductions in private insurance. Subsequently, there has been a substantial body of literature focusing on the crowd-out question that has produced mixed results which magnitude is generally below the magnitude of the findings in Cutler and Gruber (1996).

[2] The literature in the area suggests, in addition to helping the state budget, avoiding the Medicaid stigma, and encouraging prudent spending as other reason for having cost-sharing in SCHIP.

insurance options available to children who are income eligible for the SCHIP public coverage: a) SCHIP; b) private insurance; and c) no insurance. To make appropriate recommendations to inform health policy it is necessary to explore the impact of an increase in public premium paid by the parents of these children on the enrollment rates for each insurance alternative.

Hadley, Reschovsky, Cunningham, Dubay and Kenney (2006) and Kenney, Hadley and Blavin (2006) provide estimates of the effect of increasing the public insurance premium on public enrollment, private enrollment, and uninsurance rates. Using a multinomial logit regression, the authors find that the odds of having private coverage, and being uninsured, increase with increases in the premium. Gruber and Simon (2008) evaluate the impact of total out-of-pocket expenditures and suggest that the financial barriers in the public program may have an unintended negative impact and lower the take-up of the uninsured faster than they have lowered crowd-out from private insurance. Two studies have shown that many children leaving the SCHIP program are losing any form of insurance coverage (Sommers, 2005; Mitchell, Haber and Hoover, 2006). Sommers (2005) finds that 45.4 percent of children were no longer insured despite apparently remaining eligible and having no other insurance.

Overall, the current literature provides several insights into the issue of premium-induced public insurance disenrollment and leaves a few unanswered questions. This paper contributes to the body of previous work in a number of key ways. First, it will provide a rigorous quantitative evaluation utilizing the existence of discontinuities in the states' programs assignment rules and increases in premium over time. More importantly, the study will evaluate the impact of higher public insurance premiums on the transitions of SCHIP-eligible children from public insurance to "no insurance" and private insurance to determine the extent to which increases in premiums are associated with a loss of health coverage.

2.2 State's Children Health Insurance Program

The SCHIP is similar to Medicaid and is a partnership between federal and state governments. Both of these programs are run by the individual states according to requirements set by the Federal Centers for Medicare and Medicaid Services. The SCHIP law offers states three options for covering uninsured children. States can use SCHIP funds to cover children through Medicaid-independent children's health insurance programs (separate child health programs); (2) expand coverage available under Medicaid (SCHIP Medicaid expansion programs); or (3) combine both strategies (SCHIP combination programs). The states with separate child health programs have more latitude than Medicaid programs, which means they have a great deal of flexibility in their cost-sharing and plan benefits structure, as well as in eligibility and enrollment matters. Flexibility is regulated at the federal level and state plans must receive approval prior to implementation. A novel feature of the SCHIP program is the requirement that enrollees share in the cost of coverage and services. States can impose premiums on a sliding scale[3] for the insurance coverage of children in families with income above 150 percent of the Federal poverty line (FPL) to encourage parents to take up employer-provided coverage.

Table 2.1 clearly shows how the states with separate SCHIP or combination programs are more likely to charge premiums. Only two of the states offering Medicaid expansion programs charged premiums in 2003. Specifically, in the state of Rhode Island, the cost of covering all SCHIP eligible children in a family was $61 per month. Wisconsin families that were in the SCHIP programme paid premiums equivalent to 5 percent of their income. In 2003, there was a significant within-state variation in premium. Twenty states charged different premiums depending on household income with

[3]In total, premiums, deductibles and other cost-sharing are not to exceed 5 percent of the familys income.

families with higher incomes paying more for the coverage of their children. Since states have freedom in designing the SCHIP program, the cross-state variability in the level of premium for the low-income groups (base premium) and in the difference between the high-income and low-income group premiums (premium jump) is substantial. Eight states also implemented changes in their premiums over the course of 2003. Higher income families pay higher premiums for the public health insurance of their children and they also tend to have better access to private insurance coverage. Therefore, high-income families are less likely to keep their public coverage and also more likely to substitute to private insurance.

In this paper I investigate the impact of higher SCHIP premiums on private coverage and uninsurance status. The analysis is based on a unique data set that combines monthly data on insurance status obtained from the nationally representative Medical Expenditure Panel Survey (MEPS) with information on SCHIP eligibility rules and premium levels for all states and the District of Columbia (D.C.).

2.3 Conceptual Framework

The three health insurance alternatives available to a SCHIP-eligible child are: 1) SCHIP (public) coverage, 2) private health insurance, 3) no insurance. This study builds on the work of Sommers (2005) who discusses the reasons why a person may stop participating in SCHIP and elaborates on the possible exit from SCHIP to one of the other two health insurance categories in response to higher public premiums.

1. *Public Health Insurance* is provided through the SCHIP program described in Section 2.2. The purpose of the federal and state authorities is to oversee the program to provide uninsured children with access to no other form of insurance with low-cost coverage.

2. *Private Health Insurance*: A child may leave the SCHIP after acquiring insurance from another private source, such as, through a parent's employer. However, this should not be seen as a policy failure. These children do not become uninsured, and as discussed earlier, it is the complete lack of any insurance that is associated with adverse health outcomes.

3. *No Insurance*: This category comprises individuals who are still eligible for the program, but do not have any other form of health insurance, and become uninsured. Unlike the previous two categories, this can be viewed as a policy failure, because based on the legislative intent of eligibility standards, these children should be enrolled. However, the children are not enrolled and that makes them susceptible to the adverse health consequences as a result of being uninsured.

SCHIP re-enrollment is free of financial cost, but is not free of other kinds of cost. Enrollees must certify their eligibility at least once a year to remain in the program, and for many reasons, enrollees' parents may not find the process worth their time or effort. Children will therefore only remain in the program if their parents perceive that the marginal benefit of SCHIP coverage outweighs the direct and indirect costs of recertifying. The key issue here is how parents compare SCHIP coverage with the next best option, which may be private insurance or uninsurance with its combination of out-of-pocket payments and charity care. Or, parents may, in many cases appropriately, believe that their children will be able to reenroll in SCHIP in the future should an emergency arrive. However, instability in public insurance coverage does not promote appropriate, timely, and cost-effective care which is associated with an increased use of emergency room visits. The latter are subsidized by the state and can result in substantial costs for the system.

In terms of costs, most households are required to pay direct charges for premiums. There are no direct charges for recertification, but the indirect costs can be numerous, including, but not limited to, transportation, time lost from work, child care, paperwork costs, and postage. Furthermore, the entire recertification procedure can be stressful and demanding of effort and attention, which can be described as psychological costs. Any factors that lead to a high total cost (direct, indirect, or psychological) of take-up or a low marginal benefit of SCHIP may contribute to a loss of coverage.

Premium-induced move out from SCHIP should ideally be absorbed into the other two insurance alternatives. It can be shown that, with no change in the number of eligible children, the total effect of a premium increase must be zero, where the total effect is the sum of the partial effects of premium on enrollment in public insurance, private insurance, and on disenrollment from the program (for technical proof, see Appendix). The key issue for policy making is to determine the share of substituting from SCHIP to private insurance or "no insurance" because of higher premiums. It is the purpose of this paper to establish the magnitudes of the transitions between the health insurance alternatives available to children that are eligible for SCHIP.

2.4 Methodology

The primary aim of this evaluation is to measure the effect of a variation in premium across families, states, and over time on SCHIP insurance coverage. This section describes the theory that underpins the approach to the analysis. The estimation problem arises because SCHIP-eligible children, depending on their family income, can be assigned only to one income group with a fixed premium. No family will be observed paying both low and high premiums at the same time. Therefore, it is not possible to determine what would have been the coverage status of the child had the child not been placed, for example, in the "treatment" group that pays a high premium.

To identify and estimate the treatment effect of interest, comparison must be made between the outcomes of two groups; a treatment ($d = 1$) and a control ($d = 0$). These two groups should be as similar as possible in terms of characteristics other than the treatment itself (Hahn, Todd and Van der Klaauw, 2001). Estimating the effect of premium on SCHIP enrollment uses knowledge of discontinuities in the income group assignment rule and changes in premium levels over time. SCHIP eligible children can be divided into two income groups on the basis of the interval a calculated family income index fell into. These intervals are determined by a state-specific income score $\overline{I}$[4]. Children with household income I at or above $\overline{I}$ are referred to as the treatment group and children with income I below $\overline{I}$ are referred to as the control group.

The actual decision rule for assigning SCHIP eligible children to income groups varies across states and therefore is difficult to characterize by a simple formula. However, within an individual state, the assignment rule is fairly simple and easy to implement. One such rule, adopted by the largest state in the data set referred to as state X, states that children are assigned to the following two groups based on their family income: children with family income below 150 percent of the federal poverty line fall into the low income group and children with income at or above 150 of the federal poverty line are assigned to the high income group. The premiums differ by income group. Higher income families pay more for the insurance of their children. However, within an income group, the premium payment is fixed. In the case of state X, parents pay a premium of $7 per month for the SCHIP insurance coverage of a child assigned to the low income group and $9 for a child in the high income group. Thus, the premium payment, as a function of I, contains a jump at the cutoff between the first and second income intervals.

[4]There can be up to three income cutoffs in a certain state, because of sample size restrictions, the premium effect is estimated based on the the first income cutoff only.

2.4.1 Sharp Regression Discontinuity Design

Assignment to groups based on family income makes the treatment and control group very different, at least in terms of their average income value. This is in sharp contrast with pure randomization. It is assumed that, at the cutoff, the two groups are the same in terms of all observable and unobservable aspects, except the treatment status. This assumption is in agreement with the Regression-Discontinuity (RD) Design framework that is applied to the evaluation of private enrollment and uninsurance. The sharp RD is used because all children with $I \geq \overline{I}$ are assigned to the treatment group. The limitation of using cutoff randomization is that, the number of data points just below and just above the cutoff is often not large enough to produce reliable estimates. This limitation is a key motivation to explore the premium effects on participation beyond the immediate vicinity of the cutoff. Increasing the interval around the cutoff is likely to produce a bias in the effect estimate because the premium fee is determined by I that itself has been documented to influence the private enrollment and drop-out decision. Since I is the only systematic determinant of the premium fee, the inclusion of a smooth function $g(I_i)$ which is continuous at the income cutoff will solve the endogeneity issue, provided that the regression specification includes a treatment dummy d and focuses on observations that are within a narrow interval around the cutoff. In addition, it is assumed that the "true" functional form of I can be approximated by some known polynomial. Therefore, an additional assumption is that $g(I) = 0$ when $I = \overline{I}$. The model for the observed enrollment in private insurance and uninsurance is specified as:

$$y_i = \alpha + \beta_d \mathbf{1}\big(I_i \geq \overline{I}\big) + g(I_i) + \varepsilon_i, \quad i \in \mathcal{J} \tag{2.1}$$

where $\mathbf{1}\big(I_i \geq \overline{I}\big)$ is an indicator function denoting assignment of child i to the high-income group and α is an intercept. $\mathcal{J}$ denotes the subsample such that $\overline{I} - h < I_i <$

$\overline{I} + h$ and h is the bandwidth. The bandwidth around the cutoff determines the share of the sample included in the analysis, with smaller bandwidths producing less biased estimates with higher standard errors. In this notation, the estimate of the intercept $\hat{\alpha}$ captures the impact of the base premium on the outcome of interest for those eligible for the lower-income group for the case when $I = \overline{I}$. In general, the effect for the lower-income group with income $\tilde{I}$ is $\alpha + g(\tilde{I})$. The parameter β_d measures the discontinuity in the expected enrollment for individuals on both sides of the income cutoff between two income groups, or the vertical distance at $I = \overline{I}$. For individuals in the higher-income group with income $\tilde{I}$, the effect is $\alpha + \beta_d + g(\tilde{I})$.

2.4.2 Cross-Sectional Model

The premium levels for the low-income and high-income groups differ not only within the state, a feature explored so far in the study, but also across states. Since state X is relatively larger in size compared to the entire sample, it is necessary to: (1) combine data on states with two income groups excluding state X. (2) check the robustness of results for the sample of all states including state X. Defining the sample in this way is equivalent to splitting all available data into two distinct groups and running separate regressions for each of them.

In the multiple state specification it is assumed that people around the state-specific cutoffs should be the same in terms of their observable (income) and unobservable characteristics. The first step in specifying a multiple-state regression equation for the impact of premium is to define a regression equation for state 1. State 1 is one of the states with two SCHIP income groups. In the individual-state regression specification variable J_1 is a dummy that controls for the impact of the higher-income group premium on public insurance enrollment. The estimate of the constant θ_1 captures the impact of state-specific factors affecting the enrollment of the lower-income group. One of these factors is premium. The state 1 regression equation is specified as:

$$y_{i1} = \theta_1 + \beta_1 J_1 + g(I_{i1}) + u_{i1} \tag{2.2}$$

The regression equation for state 2 is:

$$y_{i2} = \theta_2 + \beta_2 J_2 + g(I_{i2}) + u_{i2} \tag{2.3}$$

Combining across-state data, by imposing linear and constant premium effects as well as constant income effects across states, the two-state regression model representation is:

$$\underset{i \in \mathcal{J}_1 \bigcup \mathcal{J}_2}{y_{is}} = \theta_1 * \mathbf{1}(i \in 1) + \theta_2 * \mathbf{1}(i \in 2) + \beta \sum_{s=1}^{2} J_s + g(I_i) + u_{is} \tag{2.4}$$

where J_s is the magnitude of the premium stepped-increase above the point of discontinuity for state s. The estimate of β captures the impact of a \$1 variation in the premium increase on private insurance enrollment/uninsurance of children whose family income is at, or above, the state income cutoff. Because we assume constant premium effects across states, the effect estimate β is the same for state 1 and state 2. θ_1 and θ_2 are state dummies controlling respectively for the impact of state 1 and state 2 specific factors. These are factors that determine the probability of enrollment into the first group such as the low premium fee. $\mathcal{J}_1 \bigcup \mathcal{J}_2$ denotes the subsamples from both states used in the analysis. For state 1, $\overline{I}_1 - h < I_{i1} < \overline{I}_1 + h$, $\overline{I}_1$ is state 1 specific income cutoff. For state 2, $\overline{I}_2 - h < I_{i2} < \overline{I}_2 + h$ with $\overline{I}_2$ the income cutoff. h is the bandwidth around the cutoff.

Including multiple states in the evaluation of across-state premium variation modifies the two-state regression specification as follows:

$$\underset{i \in \bigcup \mathcal{J}_s}{y_{is}} = \sum_{s=1}^{S} \theta_s * \mathbf{1}(i \in s) + \beta \sum_{s=1}^{S} J_s + g(I_{is}) + u_{is} \tag{2.5}$$

Recall that the underlying assumption for the cross-sectional regression specification is that the premium increase effect is linear and proportional for all states. The β estimate is interpreted as the effect of a \$1 variation in the jump in premium on enrollment of children whose family income places them just above the cutoff. While the high-income groups are constrained to differ only in their premiums, the inclusion of state specific dummies allows the control groups to differ across states regardless of the income cutoff value for the jump in the premium.

2.4.3 Difference-in-Differences Design

A "before-after" (BA) design is related to the RD design. The BA design assumes the discontinuity takes place in the time dimension. The control response comes from a predefined time period before the treatment and the treatment response comes from the time period after the treatment. To identify the impact of premium on enrollment, the child insurance participation is compared before and after the month of the premium change ($\bar{t}$). With t denoting months, $d_t = 1[t \geq \bar{t}]$. For a BA design to be effective the break should be defined clearly and the effect should be measured quickly before other covariates change. This is analogous to the borderline randomization of RD, where in a small temporal neighborhood, the time period just before the treatment should be compared to the time period just after the treatment, because other changes are unlikely to take place over the short term.

SCHIP families that fail to pay their premiums will lose insurance coverage. However, families that renege on their current payments are often provided with a grace period[5] before their child becomes disenrolled. The length of this "grace" period varies by state. This implies that treatment may take place gradually over time which makes it difficult to separate the treatment effect from the "time effect" due to other factors that vary over the same period.

The existence of grace periods with varying length in the SCHIP program motivates the use of "Difference-in-Differences" (DD) method. The advantage of DD over BA approach is that there is a control group, which incurs the time effect but not the treatment effect. Using the control group, the treatment can be identified even if the treatment takes place gradually. In a DD design, the treatment is given only to a certain group of individuals, and those left out constitute the control group. In contrast, in a BA (and RD) design, everybody gets the treatment without exception. Hence, there is no contemporary control group in a BA design. Only the treatment group's past before the treatment is available as a control group. In addition, the parameter estimates from the DD design will vary depending on the length of the time period considered.

To explore the temporal variation created by premium changes over time, I compare the private enrollment and uninsurance outcomes of children for states with two income groups. Widening the window around the time cutoff shifts the identification from a local regression-discontinuity to a global difference-in-differences one, and includes only the observations that are close to the state income cutoff. Let y_{it} be a (0,1) insurance outcome, respectively, for the private coverage and uninsurance. As in the RD design, the high-income group from within the state is selected as "treatment" ($d = 1$) and is assumed to differ from the control group in the the amount of the premium fee. By

[5]A "grace" period is a specified period of time during which children can continue to access services after the payment due date. This allows families who fall behind in paying their premiums time to catch up on past payments before their children lose coverage.

choosing the low-income group within the state as control, which is presumably similar to the high-income group in some state-specific unobserved aspects, these unobserved aspects are controlled for. I also define a binary time variable t that takes a value of either 0 or 1 depending on whether the child is observed before or after the premium change. The variable V is the premium level which varies over time and by income group. This leads to:

$$y_{it} = \alpha + \beta d + \gamma t + \delta V_{it} + \beta_z' \mathbf{z}_{it} + \varepsilon_{it} \tag{2.6}$$

The DD regression specification implies that, for the average child, the lower-income group enrollment in private insurance/uninsurance in the period before the premium change $t = 0$ is given by:

$$y_{00} = \widehat{\alpha} + \widehat{\delta} * V_{00} + \widehat{\beta_z'} \overline{z} \tag{2.7}$$

The insurance enrollment of low-income group children in the post-change period $t = 1$ is given by:

$$y_{01} = \widehat{\alpha} + \widehat{\gamma} + \widehat{\delta} * V_{01} + \widehat{\beta_z'} \overline{z} \tag{2.8}$$

According to Eqn. 2.6 the higher-income group enrollment at $t = 0$ is:

$$y_{10} = \widehat{\alpha} + \widehat{\beta} + \widehat{\delta} * V_{10} + \widehat{\beta_z'} \overline{z} \tag{2.9}$$

Finally, the private enrollment/uninsurance outcome of the higher-income group in the period after the change is given by:

$$y_{11} = \widehat{\alpha} + \widehat{\beta} + \widehat{\gamma} + \widehat{\delta} * V_{11} + \widehat{\beta}'_z \overline{z} \tag{2.10}$$

From these simple, group specific models it is straightforward to see that the estimate of α captures the probability of enrollment of the lower income group at $t = 0$ after controlling for the effect of premium. $\widehat{\beta}$ is the difference between lower-income group enrollment in the two periods after controlling for the change in premium. The estimate of γ gives the change in private enrollment/uninsurance in response to other time varying factors besides the change in premium. The estimate of the premium variable coefficient δ captures the effect of the difference in changes in premium for the two group on the insurance outcome after correcting for group and time effects. $\mathbf{z}$ is a set of other variables including linear and nonlinear function of family income, child's health indicator, and child's age. The $\mathbf{z}$ variables can vary over time and, therefore, impact the treatment and control groups differently pre- and post-treatment. By controlling for the $\mathbf{z}$ variables, we make the condition of equal time change for both groups plausible. In addition, the composition of the treatment and control group must remain stable over the examined period.

I build the multiple-state regression equation by first defining a regression specification for State 1 only, which is one of the states with two income groups. Let y_{it} be a (0,1) insurance outcome. The treatment dummy d is 1 for all children in the higher income group for all states. The time dummy is 1 for all observations in the period following the month of the premium increase. The variable V is the level of premium which varies by time, group, and state.

$$y_{it1} = \alpha_1 + \beta_1 d_1 + \gamma_1 t_1 + \delta_1 V_{it1} + \beta'_{z1} \mathbf{z}_{it1} + \varepsilon_{it1} \tag{2.11}$$

The regression equation for State 2 is given by:

$$y_{it2} = \alpha_2 + \beta_2 d_2 + \gamma_2 t_2 + \delta_2 V_{it2} + \beta'_{z2}\mathbf{z}_{it2} + \varepsilon_{it2} \tag{2.12}$$

Combining data on state 1 and state 2 the two-state regression representation becomes:

$$\begin{aligned} \underset{i \in \mathcal{J}_1 \bigcup \mathcal{J}_2}{y_{its}} &= (\alpha_1 + \beta_1 d_1 + \gamma_1 t_1 + \delta_1 V_{it1} + \beta'_{z1}\mathbf{z}_{it1} + \varepsilon_{it1}) * \mathbf{1}(i \in s = 1) \\ &+ (\alpha_2 + \beta_2 d_2 + \gamma_2 t_2 + \delta_2 V_{it2} + \beta'_{z2}\mathbf{z}_{it2} + \varepsilon_{it2}) * \mathbf{1}(i \in s = 2) \end{aligned} \tag{2.13}$$

Assuming constant premium, treatment, and time effects across states, the multiple-state difference-in-difference specification becomes

$$\underset{i \in \bigcup \mathcal{J}_s}{y_{ist}} = \sum_{s=1}^{S} \alpha_s * \mathbf{1}(i \in s) + \beta d + \gamma t + \delta V_{ist} + \beta'_z \mathbf{z}_{ist} + u_{ist} \tag{2.14}$$

Unlike the individual-state specification (Eqn.2.6), the multiple-state specification should take into account states' heterogeneity. To control for it, in Eqn.2.14, I introduce a set of state dummies α_s. The specification also explicitly controls for the time-varying $\mathbf{z}$ variables that can impact on the outcome of interest (private insurance and uninsurance). The δ coefficient estimate of the premium variable V captures the effect of a \$1 change in the difference between premium increases for the two group on the insurance outcome. The high-income group's insurance outcome is constrained to be the same across states. The inclusion of state specific dummies allows the control groups' enrollment to be different in the different states.

2.5 Data and Assignment Method

2.5.1 Data

The data for the analysis come from the 2003 panel of the Medical Expenditure Panel Survey (MEPS). The MEPS provides information on a nationally representative sample of the non-institutionalized civilian population. It is sponsored by the Agency for Healthcare Research and Quality (AHRQ) and the National Center for Health Statistics (NCHS). The survey has an overlapping panel design, gathering two years of data for each household. MEPS is designed to produce nationally representative estimates for insurance coverage, medical expenditure, and a wide range of other health-related and socioeconomic characteristics. The data can also be used to support behavioral analysis that informs researchers and policymakers about how the characteristics of individuals and families, including their health insurance, affect medical care use and spending, as discussed in Cohen (1997). The MEPS cannot support the estimation of state-specific models for every state. However, in the context of a multivariate model, the effect of a state specific variable is identifiable when data on all states are used, as in Hudson, Selden and Banthin (2005)

I collected data on SCHIP premium schedules for all states and the District of Columbia. Premium information was obtained from websites maintained by the Centers for Medicare and Medicaid Services, the National Conference of State Legislatures, the American Academy of Pediatrics, and from several published sources by the Maternal and Child Health Policy Research Center (Fox, Levtov and McManus (2003), Fox and Limb (2004)). The constructed data set has information on premium payments, their frequency (monthly or annually), and the maximum premium amount that a family could pay. The premium data are merged to the 2003 full-year consolidated MEPS files at the state level. The analysis focuses on premium variation across individuals, states and over time in 2003.

The main focus is on the premiums and insurance status of children aged 18 and younger. Each state's premium information is used to assign the premium amount that the family unit will face to cover a given child for one month. I assess the extent to which the premium per child in a particular age/income/month/state group affects the enrollment decision. For states that have introduced a maximum total premium for families with multiple children, child-specific premiums were constructed by dividing the maximum premium by the number of children for which the cap becomes effective. If families were not subject to the family-level maximum, the child-specific premium was assigned. Enrollment decisions, however, are likely to be made at the family level. Family-level decision making will take into account the total number of children in a family unit and the possible decrease in total outlays on premiums because of the cap. Future work using information on families with only one child will likely provide a better understanding of family decision making regarding SCHIP enrollment.

Eleven states increased their premiums in 2003. This feature of the data allows us to look at changes in private insurance and uninsurance rates over time. My sample for panel analysis includes children aged 18 and younger with positive full-year weights for 2003. The weight variable, when applied to the children who participated in that year, allows the researcher to obtain estimates of child-level changes in the health coverage variable[6]. I extracted a subset of children from the full-year population who were included in the survey at the very first day of 2003. To avoid drawing comparisons across children who entered the MEPS at different times during that year I also created a subset of children who were available for interview for all three rounds of data collection. In 2003, six states (Alabama, Colorado, North Carolina, Nevada, Texas, and Utah)

[6]A person with a positive full-year weight for 2003 is a key in-scope person who responded for his or her entire period of 2003 eligibility. A person is considered as in-scope during a round if he or she is a member of the U.S. civilian, non-institutionalized population at some time during that round.

charged annual premiums. Since one goal of this paper is to trace the monthly changes in enrollment following the premium increase, these states have been omitted from the panel and cross-sectional analysis.

Previous national studies of premium that use repeated cross-sections of the March supplement to the Current Population Survey (CPS) have imputed yearly measures of public insurance coverage for a number of consecutive years. With respect to precision of insurance status information, the MEPS data set provides a definite advantage to studies that track changes in public/private health insurance rates. Information on the insurance coverage of each child is ascertained on the MEPS by asking: "Were you covered by Medicaid or SCHIP" and "Were you covered by private insurance" each month. However, because of grace periods, insurance coverage studies using the MEPS are susceptible to the timing of the enrollment response following a premium change. To circumvent the timing issue I compare the January and December enrollment outcomes of SCHIP eligible children. As no state has a grace period that would last until December this time span effectively captures the enrollment response in all states that chose to increase their premiums during the year. As mentioned in Hudson, Banthin and Selden (2004), the MEPS is widely regarded as providing more accurate and consistent public coverage estimates than the CPS, perhaps because the MEPS asks numerous detailed questions regarding the presence, source, and duration of coverage.

The MEPS includes information on children aged 18 and younger who are eligible for the first or second income group. Public insurance eligibility for each child is assigned as described below.

2.5.2 Assigning SCHIP Eligibility and Insurance Plan Participation

Assigning eligibility is pivotal to my analysis.[7] The health insurance coverage variable in the data only indicates that the person has Medicaid or SCHIP coverage. Whether the coverage is Medicaid or SCHIP is not directly observed and therefore must be assigned. To assign Medicaid/SCHIP elibility, I use data on family income, family structure, child age, and state-specific eligibility rules. In all cases, I have attempted to assign the rules as they would be applied to new applicants. Given assigned eligibility and observed private insurance and uninsurance status, private coverage for SCHIP-eligible children is recorded.

For the purpose of determining Medicaid or SCHIP eligibility I make use of the Health Insurance Eligibility Unit (HIEU) definition. This variable identifies family members who would normally be eligible for family coverage under the adults' private health insurance family plans. These families, or HIEUs, comprise adults, their spouses, and their unmarried natural/adoptive children aged 18 and under. For these traditional families with parents and children, I calculate annual family income by summing up the annual wage and salary income for each adult in the HIEU. If there are children aged 18-24 in an HIEU who are full-time students, their income is omitted from the family income calculation. However, if the student is a parent and not an older sibling, her income is counted towards the calculation of family income.

Unmarried minors not living with their natural/adoptive parents are included in the family of their stepparent, grandparent, or aunt/uncle. State rules vary for the counting of income and family size for these "nontraditional" families. To simplify,

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[7]The paper benefits from the experience and help of Julie Hudson and Jessica Banthin from the Division of Modeling and Simulation at the Center for Financing, Access and Cost Trends at the Agency for Healthcare Research and Quality.

following previous MEPS studies that use simulated eligibility (Hudson, Selden and Banthin (2005), Hudson, Banthin and Selden (2004)), I assume that all ”nontraditional” guardians who are both low-income and disabled are included in the unit for both income and size because it would help the family's case for being eligible. Otherwise, the family is treated as a child-only case and the child is eligible for public insurance despite the income of the adults.

Unmarried minors not living with their natural/adoptive parents are included in the family of their stepparent, grandparent, or aunt/uncle. State rules vary for the counting of income and family size for these "nontraditional" families. To simplify, following previous MEPS studies that use simulated eligibility (Hudson, Selden and Banthin (2005), Hudson, Banthin and Selden (2004)), I assume that all "nontraditional" guardians who are both low-income and disabled are included in the unit for both income and size because this helps the family's case for being eligible. Otherwise, the family is treated as a child-only case and the child is eligible for public insurance despite the income of the adults.

I use the Urban Institute Welfare Rules Database (see Table 2.12) to determine which states allow minor parents to head their own household. For states that allow minor parents to head their own household, I follow rules similar to those for nontraditional families: I include the parent/adult relative only if they were both low-income and disabled. Otherwise the minor parent heads her own household. For states that do not allow minor parents to head their own household, I include the parent/adult relative in the family unit for income and size.

The constructed family income measure is converted into a percentage multiple of the 2003 poverty guideline, which is the SCHIP income measure for determining eligibility. Children's monthly eligibility for public insurance is calculated for the population of children in the MEPS using state-level rules. Individual eligibility for public insurance is defined by the following mutually exclusive categories: 1) eligible for Medicaid, 2) eligible for SCHIP, and 3) not eligible for public insurance. If a child is age- and income-eligible for public insurance (Medicaid or SCHIP) and is observed in the data to have public insurance, then Medicaid coverage is assigned if the family incomes falls below the income cutoff value separating Medicaid from SCHIP and SCHIP coverage is assigned if family income is higher than the threshold value. Further, if an SCHIP eligible child is reported to have private insurance, the private insurance coverage is assigned. Lastly, if there is no record of public/private coverage, the SCHIP-eligible child is treated as uninsured. Determining eligibility on a month-by-month basis incorporates the possibility of a change in state eligibility rules. Thus transitions of children between income groups or out of SCHIP coverage into private insurance or "no insurance" could be the result of changes in state eligibility rules and/or premium payments and/or child age.

A child who was enrolled at any point in a given month in a public or private insurance is considered a current enrollee and disenrollees are defined as children enrolled in SCHIP or private plan for at least one month, but not enrolled in the subsequent month.

2.5.3 Descriptive Statistics

The sample used in the evaluation of public premium effects on private insurance enrollment or uninsurance consists of children age 0 to 18 who are income-eligible for the first or second SCHIP income group.

Description of Individual States

Table 2.2 shows the public enrollment, private enrollment, and uninsurance rate, family income, premium, and child age for the largest state in my data set, state X. The eligibility rule in this case is well known: children less than six years old with $I \leq 134$ of the Federal Poverty Line (FPL) are eligible for Medicaid, while, for older children, the income border is set at $I = 100$ of the FPL. State X has determined that families with $I \leq 150$ of the FPL are responsible for the payment of $7 monthly premium. Families with income between 151 and 250 percent of FPL pay $9. I find that children enrolled in the lower income group are, on average, older than children in the higher income group. Family income, by construction, increases monotonically by group. Table 2.2 shows that the private insurance enrollment rate, while public insurance and uninsurance rates decrease from the low-income (Group I) to the high-income group (Group II). The statistics are based on data as of the month before the premium change for states that increased their premium. For states where premiums are increased in 2003 the statistics are based on data as of the month before the premium change and for states with no temporal variation in premium statistics are as of January of the same year. There are 270 and 380 eligible children in the first and second income group respectively.

Sample for the Cross-Sectional Analysis

Table 2.2 presents the average enrollment rates, family income, premium payment, and child age at a point in time for all study states with two income groups. The table shows that premium payment and income increase monotonically with group. Children in the low-income group are on average older than children in the high-income group. Children from low-income families have higher participation rates in public health insurance. They have lower rates of private insurance and higher uninsurance rates. There are

317 children who are income-eligible for the first income group and 664 for the second. All statistics are based on data as of the month before any program change took place or as of January for the states that did not implement any new features in their public insurance programs.

Sample for the Longitudinal Analysis

The longitudinal sample includes children aged 18 and younger with positive full-year weights applied for 2003. There are 1631 children who are income-eligible for the first and second income group. Table 2.3 shows the average family income, premium, child age, health status, and public, and private coverage , and "no insurance" as of January and December of 2003. Summary statistics are presented separately for the low- and high-income group. For the low-income group the average family income, child age and health remain approximately the same over the course of the year. Due to the implemented premium changes in some states the average premium increases by \$ 0.88 or 21 percent. The average private, public, and uninsurance rates stayed roughly the same. Summary data for the high-income group show that income, child age, and health remained about the same over the course of the year, while premium goes up by about \$1.62, that is by approximately 13 percent. Public, private, and uninsurance rates do not change.

2.6 Estimation Results

I begin my analysis of public premium crowd-out by graphically representing private enrollment and uninsurance in the largest state in my data set, referred here as state X. I obtain separate LOESS[8] estimates of enrollment on each side of the cutoff as a

[8]LOESS is a technique that fits, at each point in the data set, a low-degree polynomial to a subset of the data, with explanatory variable values near the point whose response is being estimated. The

function of family income and then display the scatter plots on the same graph to see how estimated enrollment for each income group compares at the cutoff. Figure 2.1 shows estimated private enrollment as a function of the family income index for all children with family incomes from 100 to 250 percentage points of the FPL. The plot demonstrates a clear discontinuity in the probability of private insurance enrollment at the 150 percent cutoff where premium jumps from $7 to $9 dollars. Figure 2.1 suggests that families of SCHIP-eligible children that are charged more for their public insurance coverage are more likely to be enrolled in private insurance. Table 2.4 shows that, for children above the cutoff, the probability of private enrollment increases by 32 or 33 percent depending on bandwidth. Reversing the logic of these findings, they indicate that lower public premiums are associated with lower private insurance take-up.

Figure 2.2 provides a LOESS representation of the estimated point-by-point, locally-weighted linear regression of uninsurance as a function of the family income index for all age-eligible children in state X. The plot presents strong evidence of a downward jump in uninsurance at the cutoff at the 150 percentage points of the FPL between the two income groups. I obtain estimates of average uninsurance on each side of the cutoff for different intervals around the income threshold. Average uninsurance is estimated to be 15 percentage points lower for children whose household income places them to right at the cutoff or just above it (see, Table 2.5).

A more exacting demonstration of the cutoff comes from separately analyzing the enrollment behavior of older children in different age groups. Age group analysis of enrollment is thus arguably based on a more uniform set of points. Figure 2.3 for the group of older children reveals a clear discontinuous jump at the income cutoff.

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polynomial is fitted using weighted least squares, giving more weight to points near the point whose response is being estimated and less weight to points further away. The value of the regression function for the point is then obtained by evaluating the local polynomial using the explanatory variable values for that data point

Table 2.4 presents LOESS estimates of the private coverage response to premium. The magnitude of the jump in enrollment for older children is between 32 and 33 percentage points, the same as the decline when the enrollment response of all children is analyzed. Consistent with the findings of Hadley et al. (2006), Figures 2.1 and 2.3 reveal that private insurance coverage increases with family income. Because of the small number of observations on younger children, conclusions about the presence of discontinuity and its magnitude are largely speculative. For this reason, I focus on studying enrollment of all children and older children only.

Table 2.5 shows that the probability of not having any insurance decreases by 17 – 18 percent. The decline in the estimated uninsurance rate for older children is slightly larger than the estimated decrease for all children.

2.6.1 Regression-Discontinuity Estimates

The observed private insurance and uninsurance outcomes can be evaluated more formally by constructing and evaluating regression discontinuity of the two outcomes of interest for children whose income- and age-dependent eligibility places them just below and just above the cutoff between the first and second SCHIP income groups. The regression discontinuity estimates of private enrollment for state X are presented in Table 2.6. Looking first at the enrollment model, when the evaluation is restricted to children aged six and older and to samples with at least 50 observations to estimate the five coefficients of the RD model, the regression-adjusted estimates of premium on private enrollment are very close to the LOESS results. The premium estimates, as premium jumps from \$7 to \$9, point to an increase in the probability of being covered by private insurance with magnitude in the range of $(.272; .366)$. I test the null hypothesis that premium-induced private enrollment for the high income group is as large as premium-induced private enrollment in the lower-income group. The estimates for the $-25/+25$ interval provide significant evidence at the 5 percent level to reject the null. They show that private insurance take-up increases as the premium payments for SCHIP go up. The estimates for the sample of all children are smaller, more variable and less closely aligned with the LOESS results in comparison to the findings for older children. For the sample of all children, the premium effect is positive everywhere and significant for the "$-25/+25$" interval. The effect estimates for state X correspond to an estimate of enrollment elasticity[9] with respect to group premium evaluated at the mean in the range of (4.626 to 6.680) for children age six and older. For the sample of all children, the estimate range is from 1.001 to 4.47 indicating that the cross elasticity of demand is large and positive. Thus increases in public premiums can successfully prevent the substitution of private health insurance for public. At the same time, these findings suggest, that declines in the SCHIP premiums will lead to disproportionately larger declines in private coverage.

The direction of the regression-discontinuity estimates for uninsurance vary with bandwidth. For the $-15/+15$ and $-20/+20$ of the two different samples considered, they point to an increase in the probability of having no health insurance coverage. The results for the $-25/+25$ bandwidth switch sign. All estimates are statistically insignificant.

The regression discontinuity estimates of $1 change in SCHIP premiums on public insurance (reported in Nikolova (2007)), private insurance and uninsurance sum up to 0 which, as demonstrated in the Appendix, should be the case if a child could hold either SCHIP insurance or private insurance or be uninsured. Altogether, the three

[9]Elasticity is calculated using the mid-point formula

$$\varepsilon = \left(\frac{\Delta EN}{(EN_1 + EN_2)/2}\right) \times \left(\frac{(P_1 + P_2)/2}{\Delta P}\right) \qquad (2.15)$$

The treatment dummy point estimate is ΔEN. Enrollment below the cutoff (EN_1) is obtained by predicting the enrollment probability at the cutoff point using the RD coefficient estimates. Enrollment above the cutoff (EN_2) is just the sum of the EN_1 and ΔEN.

sets of state X discontinuity estimates suggest that higher premiums for the public health insurance are associated with a statistically significant drop in the rate of public insurance for children whose family income places them at the income cutoff between the two income groups or just above it (Nikolova, 2007). The results also indicate that there is a statistically significant increase in the probability of private insurance take-up for the higher income children. No significant change in the rate of uninsurance is found. Thus risk-averse parents (as most parents are with respect to the health of their children) in State X will seek the protection of health insurance against the event of illness of a child.

2.6.2 Cross-Sectional Estimates

My second set of estimates is based on pooled data on multiple states from the 2003 MEPS. The results for the $-15/+15$, $-20/+20$, and $-25/+25$ bandwidth are summarized in Table 2.8. These pooled data results suggest that an additional variation of $1 in the jump in premium from the low-income to the high-income group leads to a statistically significant increase in the probability of private insurance for those whose income places them within 15, 20, and 25 percentage points of FPL above the cutoff with the magnitude of the increase, respectively, 4.6, 2.9, and 3.0 percentage points. The jump estimates for all children (3.4, 2.2, 2.0) are smaller in magnitude. Compared to the regression-discontinuity results based on data for State X only, the cross-sectional results are much smaller in magnitude. To understand better these findings, recall that we assumed that people around the cutoff are the same in terms of all observable (income) and unobservable characteristics. However, in the different states the cutoffs are at different income levels and the magnitude of the premium jump varies as well implying that people near the cutoff are not the same. This heterogeneity in the cross-sectional analysis leads to weaker results.

The cross-sectional estimates affirm the single-state findings that higher premiums should be successful at preventing private insurance crowding-out. The pooled data results provide additional support for the hypothesis that private insurance enrollment response is larger for the group of older children. In addition, for every state with two income groups I have included a state-specific dummy θ_s to capture the state heterogeneity. Testing the joint significance of the state-specific dummies shows that the low-income group SCHIP enrollment varies significantly by state. Additionally, a test of income polynomial significance shows that, when observations are close to the cutoff, family income does not have a statistically significant effect on the probability of enrollment in private health insurance. Similar results are found in the cross-sectional evaluation of public premium on SCHIP enrollment (see Nikolova (2007)). Re-estimating the model with data on all states shows that state X is different from the rest of states in the sample. One possible explanation for this observation could lie in the special degree of legal protection that State X workers on private insurance plans enjoy making the option a desirable alternative for low- and moderate-income workers when they are faced with higher premiums for SCHIP. In particular, State X has made it an unfair labor practice for employers to change the employee-employer share-of-cost ratio based upon the employee's wage base or job classification in order that the employee enroll in SCHIP. It also prohibits employers from making any modification of coverage for employees and their dependents in order that they enroll in the public insurance program. The law also prohibits the employer from encouraging employees to drop group coverage in favor of the SCHIP program. State X has also introduced a relatively short period of 3 months before eligible children can enroll in SCHIP reducing the cost of switching between insurance alternatives.

The cross-sectional estimates for the impact of public premium on being uninsured in Table 2.9 point consistently to a decline in the probability of having no coverage in response to higher premiums for the SCHIP insurance. The estimate for the $-15/+15$ and $-25/+25$ bandwidth for the sample of older children points to statistically significant decline in the rate of uninsurance as public premiums increase. The coefficient estimate for the $-15/+15$ bandwidth for the sample of all children demonstrates significance of the hypothesis that SCHIP premium hikes lead to higher private insurance take up for those above the cutoff than those below it. Testing jointly the significance of income polynomial reveals that income does not have an impact on probability of being uninsured. A joint test of the significance of all state dummies reveals that there is no significant variation across state in the probability of being uninsured. The robustness test demonstrates that including state X in the estimation changes the coefficient estimates.

Taken together, these two sets of estimates along with the cross-sectional findings for public insurance reported in Nikolova (2007) point to a statistically significant increase in the probability of being privately insured for the higher-income, higher-premium paying children, and to a statistically significant decline in uninsurance for older children within $-15/+15$ and $-25/+25$ of the state-specific FPL as well as for all children within $-25/+25$ bandwidth.

2.6.3 Longitudinal Estimates

I also evaluate the impact of SCHIP premium variation over time on private insurance enrollment and uninsurance. The results are summarized in Tables 2.10 and 2.11. I consistently find that higher premiums are associated with positive and significant effect on private insurance coverage for those just above the income cutoff. For the sample of older children, a $1 increase in premium is found to lead to 2.5 to 1.4 percentage point increase in the probability of being privately insured for children with family income, respectively, within $-15/+15$ to $-25/+25$ percent of the FPL. The premium effect estimates obtained with data on all children point to an increase in the probability of private enrollment in the range of 2.3 to 1.2 percentage points in response to an average increase of $1 in the premium for the high income group. The estimates of the treatment dummy vary with the bandwidth. After controlling for the premium, treatment status still has a statistically significant impact on enrollment when data for the two samples and three bandwidths are used. The period dummy point estimates are small, negative, and sensitive to bandwidth selection. A joint test of the income polynomial significance reveals that family income is not an important determinant of the probability of being privately insured for children in the $-15/+15$, $-20/+20$, and $-25/+25$ income range. Testing jointly all state dummies shows that state-specific characteristics have a statistically significant impact on enrollment in private plans. Testing the robustness of these findings shows that the full sample produces different point estimates.

Table 2.11 presents the findings for the impact of SCHIP premium temporal variation on having no insurance. A different pattern of results emerges. The premium is estimated to have at most a trivial impact on uninsurance, while higher-income group status appears to have a negative and statistically important effect. These findings hold true for all samples and bandwidths considered. The period dummy does not impact on the insurance status of the child. A joint test of the income polynomial significance reveals that income is not an important determinant of whether the child has any insurance coverage or not. Testing jointly the significance of state dummies provides the same conclusions. A test for robustness shows that including the largest state X in the difference-in-differences estimation leads to a new set of point of estimates.

Since I am looking at the changes in the insurance status of children over time, there could be changes in the number of eligible children due to changes in child age and/or family income. Therefore, the coefficient estimates for the premium effect on public insurance, private insurance, and uninsurance should not necessarily sum up to 0.

2.7 Conclusion

In this paper, I obtain three sets of estimates for the premium increase effect on private insurance enrollment and uninsurance status. My main regression-discontinuity findings provide statistical support for the hypothesis that higher SCHIP premiums are associated with an increase in the probability of being privately insured. Higher SCHIP premiums do not seem to impact the uninsurance status of the child. The regression-discontinuity procedure is shown to produce estimates that are robust to distributional and functional form assumptions and omitted-variables problems. The cross-sectional analysis supports the individual-state findings of statistically important enrollment increases in private insurance. The pooled cross-sections present mixed evidence of a statistically important decline in the probability of having no coverage in response to higher premiums for the SCHIP insurance. The 2003 longitudinal estimates of the impact of SCHIP premium on private insurance reinforces the individual state and cross-sectional findings. The longitudinal uninsurance results point to at most a trivial impact of premiums on uninsurance.

This paper presents a significant amount of evidence that SCHIP-eligible children who opt out of public coverage because of higher premiums are very likely to acquire insurance from a private source. I find no evidence that these children become uninsured instead. Since children transition from public to private insurance coverage, state policies to charge beneficiaries premiums on a sliding scale do not pose a significant public health and policy problem. On the contrary, lowering the premiums is estimated to lead to private insurance crowd-out.

Table 2.1: Summary of SCHIP eligibility limits and premiums, by income group as of Jan 2003, Dec 2003, and Dec 2004:

		GROUP I						GROUP II					
		Jan 2003		Dec 2003		Dec 2004		Jan 2003		Dec 2003		Dec 2004	
St	Type	Elig	Prem	Elig	Prem	Elig	Prem	Elig	Prem	Elig	Prem	Elig	Prem
al	schip	150	0	175	4.17	175	4.17	200	4.17	200	8.33	200	8.33
tn	mdc	100	0	100	0	100	0	.	.	.	.	.	.
ar	mdc	200	0	200	0	200	0	.	.	.	.	.	.
az	schip	150	0	150	0	150	10	175	10	175	10	175	20
ca	comb	150	7	150	7	150	7	250	9	250	9	250	9
co	schip	133	0	133	0	133	0	150	0	150	0	150	0
ct	schip	235	0	235	0	235	0	300	30	300	30	300	30
de	comb	133	10	133	10	133	10	166	15	166	15	166	15
dc	mdc	200	0	200	0	200	0	.	.	.	.	.	.
fl	comb	150	15	150	15	150	15	200	15	200	20	200	20
ga	schip	150	7.5	150	10	150	10	235	7.5	235	10	235	10
ia	comb	150	0	150	0	150	0	200	10	200	10	200	0
id	mdc	150	0	150	0	185	0	.	.	.	.	.	.
il	comb	150	0	150	0	150	0	200	15	200	15	200	15
in	comb	175	11	175	11	175	11	200	16.5	200	16.5	200	16.5
ks	schip	175	30	175	20	175	20	200	45	200	30	200	30
ky	comb	200	0	200	20	200	20	.	.	.	.	.	.
la	comb	200	0	200	0	200	0	.	.	.	.	.	.
ma	comb	200	10	200	12	200	12	.	.	.	.	.	.
md	comb	200	0	200	37	175	0	250	40	250	40	250	41
me	comb	160	5	160	5	160	8	170	10	170	10	170	16
mi	comb	200	5	200	5	200	5	.	.	.	.	.	.
mn	comb	280	0	280	0	280	0	.	.	.	.	.	.
mo	mdc	185	0	185	0	185	0	225	0	225	0	225	0
ms	mdc	150	0	150	0	150	0	175	0	175	0	175	0
mt	schip	150	0	150	0	150	0	.	.	.	.	.	.
nc	schip	150	0	150	0	150	4.17	200	4.17	150	4.17	150	4.17
nd	comb	140	0	140	0	140	0	.	.	.	.	.	.
ne	mdc	185	0	185	0	185	0	.	.	.	.	.	.
nh	comb	250	25	250	25	250	25	300	45	300	45	300	45
nj	comb	200	15	200	16.5	200	16.5	250	30	250	33	250	33
nm	mdc	235	0	235	0	235	0	.	.	.	.	.	.
ny	comb	222	9	222	9	222	9	250	15	250	15	250	15
nv	schip	150	3.33	150	5	150	5	175	8.33	175	11.67	175	11.67
oh	mdc	200	0	200	0	200	0	.	.	.	.	.	.
ok	mdc	185	0	185	0	185	0	.	.	.	.	.	.
or	mdc	185	0	185	0	185	0	.	.	.	.	.	.
pa	schip	200	0	200	0	200	0	.	.	.	.	.	.
ri	mdc	185	61	185	61	185	61	200	77	200	77	200	77
sc	mdc	150	0	150	0	150	0	.	.	.	.	.	.
sd	mdc	200	0	200	0	200	0	.	.	.	.	.	.
tx	schip	150	1.25	150	1.25	150	1.25	185	1.25	185	1.67	185	1.67
ut	schip	150	3.25	150	3.25	150	3.25	200	6.25	200	6.25	200	6.25
va	comb	150	0	150	0	150	0	200	0	200	0	200	0
vt	schip	300	50	300	70	300	70	.	.	.	.	.	.
wa	schip	250	10	250	10	250	15	.	.	.	.	.	.
wv	schip	150	0	150	0	150	0	200	0	200	0	200	.
wi	mdc	200	**	200	**	200	**	.	.	.	.	.	.
wy	comb	185	0	185	0	185	0	.	.	.	.	.	.
ak	mdc	200	0	175	0	175	0	.	.	.	.	.	.
hi	mdc	200	0	200	0	200	0	.	.	.	.	.	.

Table 2.2: Summary Statistics – Cross-Sectional Data

Public, and private enrollment, and "no insurance" rates, average family income, premium, and age at a point in time for: (i) all states with two income groups, (ii) all states except state X, and (iii) state X only

		All States			All but State X			State X		
Income Group	Variable	Mean	St. D.	N	Mean	St. D.	N	Mean	St. D.	N
Group I	Publ enroll	0.518	0.5	587	0.46	0.5	317	0.589	0.493	270
	Priv enroll	0.269	0.444	587	0.38	0.49	317	0.133	0.341	270
	No insurance	0.213	0.41	587	0.16	0.36	317	0.278	0.449	270
	Income	126.203	14.881	587	128.16	14.51	317	123.912	15.016	270
	Premium	5.016	5.524	587	3.33	6.68	317	7	0	270
	Child age	10.973	4.36	587	10.90	4.45	317	11.063	4.257	270
Group II	Publ coverage	0.303	0.4	1044	0.27	0.44	664	0.366	0.482	380
	Priv coverage	0.576	0.494	1044	0.61	0.49	664	0.513	0.5	380
	No insurance	0.122	0.327	1044	0.12	0.33	664	0.121	0.327	380
	Income	189.895	26.52	1044	189.98	25.73	664	189.75	28.034	380
	Premium	12.658	10.305	1044	15.75	13.24	664	9	0	380
	Child age	9.822	5.102	1044	9.86	5.17	664	9.755	4.989	380

Table 2.3: Summary Statistics – Longitudinal Data

Public, and private enrollment, and “no insurance” rates, average family income, premium, child age, and health as of January and December of 2003 for: (i) all states with two income groups, (ii) all states except state X

		All States						All but State X					
		B.Ch.			A.Ch.			B.Ch.			A.Ch.		
Group	Variable	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N	Mean	St.D.	N
Group I	Publ enroll	0.423	0.494	926	0.42	0.494	932	0.37	0.48	670	0.37	0.48	676
	Priv enroll	0.367	0.482	926	0.368	0.483	932	0.45	0.50	670	0.45	0.50	676
	No insurance	0.217	0.412	926	0.216	0.411	932	0.18	0.38	670	0.18	0.38	676
	Income	142.75	43.27	926	143.03	43.35	932	150.28	47.87	670	150.59	47.87	676
	Premium	4.99	7.17	926	5.88	7.16	932	4.22	8.30	670	5.10	8.43	676
	Child age	10.16	4.63	926	10.15	4.65	932	10.02	4.87	670	10.01	4.90	676
	Health state	3.49	1.64	926	3.48	1.65	932	3.49	1.60	670	3.48	1.62	676
Group II	Publ coverage	0.33	0.47	604	0.32	0.47	598	0.26	0.44	284	0.26	0.44	278
	Priv coverage	0.575	0.495	604	0.577	0.494	598	0.69	0.46	284	0.69	0.46	278
	No insurance	0.101	0.302	604	0.100	0.301	598	0.06	0.23	284	0.05	0.22	278
	Income	191.94	27.91	604	192.29	27.83	598	193.69	29.82	284	194.48	29.63	278
	Premium	10.55	7.13	604	11.53	7.53	598	12.29	10.13	284	13.91	10.81	278
	Child age	9.88	4.99	604	9.84	4.98	598	9.72	5.21	284	9.64	5.18	278
	Health status	3.47	1.69	604	3.46	1.7	598	3.49	1.70	284	3.47	1.71	278

Table 2.4: Private Enrollment Estimated Average – State X

LOESS estimates of private enrollment in State X for separately all children and older children

	All Ages			Age 6 and older		
Band B/A	Av. Enr. B/A	Effect	N B/A	Av. Enr. B/A	Effect	N B/A
-15/15	0.073/0.404	0.331	89/107	0.061/0.387	0.326	61/84
-20/20	0.080/0.407	0.327	98/127	0.071/0.393	0.322	69/99
-25/25	0.092/0.415	0.323	122/147	0.087/0.404	0.317	93/115

Table 2.5: No Insurance Estimated Average – State X

LOESS estimates of uninsurance in State X separately for all children and older children

	All Ages			Age 6 and older		
Band B/A	Av. Enr. B/A	Effect	N B/A	Av. Enr. B/A	Effect	N B/A
-15/15	0.286/0.136	0.150	89/107	0.306/0.125	0.181	61/84
-20/20	0.289/0.138	0.151	98/127	0.306/0.128	0.178	69/99
-25/25	0.291/0.139	0.152	122/147	0.305/0.128	0.177	93/115

Table 2.6: Private Insurance – Regression-Discontinuity Estimates

RD estimates for the three smallest samples based on data for the largest state. * - indicates significance at the 5 percent confidence level of the two-tail null there is no difference in the impact of premium on enrollment in two groups.

Bandwidth Below/Above	Treatment Effect	Elasticity	N Below/Above
Older Children			
-15/15	0.323	6.68	61/84
	(.229)		
-20/20	0.272	4.626	69/99
	(.184)		
-25/25	0.366*	6.525	93/115
	(.158)		
All Children			
-15/15	0.067	1.001	89/107
	(.176)		
-20/20	0.201	3.032	98/127
	(.149)		
-25/25	0.282*	4.47	122/147
	(.133)		

Table 2.7: No Insurance – Regression-Discontinuity Estimates

RD estimates for the three smallest samples based on data for the largest state

Bandwidth Below/Above	Treatment Effect	Elasticity	N Below/Above
Older Children			
-15/15	0.139	3.112	61/84
	(.214)		
-20/20	0.107	2.169	69/99
	(.173)		
-25/25	-0.171	-2.903	93/115
	(.157)		
All Children			
-15/15	0.238	5.37	89/107
	(.169)		
-20/20	0.091	1.703	98/127
	(.143)		
-25/25	-0.111	-1.895	122/147
	(.130)		

Table 2.8: Private Insurance - Cross-Sectional Estimates

Cross-sectional estimates for the three smallest samples using pooled data on all states with two income groups and all states excluding state X. * - indicates significance at the 5 percent confidence level of the two-tail null that the impact of premium on enrollment on either side of the income cutoff is the same

Bandwidth Below/Above	Premium Jump All States	N Below/Above	Premium Jump No State X	N Below/Above
		Older Children		
-15/15	0.028*	172/125	0.046*	111/41
	(.011)		(.012)	
-20/20	0.021*	203/145	0.029*	134/46
	(.01)		(.011)	
-25/25	0.022*	247/180	0.030*	154/65
	(.009)		(.010)	
		All Children		
-15/15	0.022*	212/167	0.034*	123/60
	(.01)		(.011)	
-20/20	0.018*	256/191	0.022*	158/64
	(.009)		(.010)	
-25/25	.017*	317/230	0.020*	195/83
	(.008)		(.009)	

Table 2.9: No Insurance - Cross-Sectional Estimates

Premium change estimates for three different bandwidths based on data for all states with two income groups and all states excluding State X. * - indicates significance at the 5 percent confidence level of the two-tail null that the impact of premium on enrollment on either side of the income cutoff is the same ** - indicates significance at the 5 percent confidence level of the one tail null

Bandwidth Below/Above	Premium Jump All States	N Below/Above	Premium Jump No State X	N Below/Above
		Older Children		
-15/15	-0.011	172/125	-0.023*	111/41
	(.01)		(.009)	
-20/20	-0.012	203/145	-0.013	134/46
	(.01)		(.009)	
-25/25	-0.015*	247/180	-0.015*	154/65
	(.008)		(.008)	
		All Children		
-15/15	-0.008	212/167	-0.016**	123/60
	(.009)		(.009)	
-20/20	-0.009	256/191	-0.010	158/64
	(.008)		(.007)	
-25/25	-0.010	317/230	-0.010	195/83
	(.006)		(.006)	

Table 2.10: Private Insurance - Difference-in-Differences Estimates

Difference-in-differences estimates for three bandwidths using data on all states and all states excluding State X. * - indicates significance at the 5 percent confidence level of the two-tail null that the impact of premium on enrollment on either side of the income cutoff is the same

	All States				All but State X			
Bandwidth Below/Above	Prem. Jump	Treat. Dummy	Period Dummy	N Below/Above	Prem. Jump	Treat. Dummy	Period Dummy	N Below/Above
Older Children								
-15/15	0.021*	0.270*	-0.014	128/142	0.025*	0.389*	-0.030	68/82
	(.007)	(.099)	(.049)		(.009)	(.123)	(.066)	
-20/20	0.014*	0.151	-0.008	152/174	0.014*	0.210 *	0.005	84/106
	(.005)	(.08)	(.045)		(.005)	(.102)	(.060)	
-25/25	0.014*	0.205*	-0.018	285/312	0.015*	0.258*	-0.006	90/120
	(.004)	(.071)	(.039)		(.005)	(.010)	(.057)	
All Children								
-15/15	0.022*	0.240*	-.009	166/164	0.023*	0.330*	-0.019	82/90
	(.005)	(.08)	(.042)		(.006)	(.107)	(.062)	
-20/20	0.016*	0.107	-0.012	152/174	0.015*	0.153	-0.005	98/126
	(.004)	(.07)	(.039)		(.004)	(.096)	(.057)	
-25/25	0.011*	0.189*	-0.017	351/387	0.012*	0.239*	-0.010	106/148
	(.003)	(.062)	(.035)		(.004)	(.089)	(.054)	

Table 2.11: No Insurance - Difference-in-Differences Estimates

Difference-in-differences estimates for three bandwidths using data on all states and on all states excluding State X. * - indicates significance at the 5 percent confidence level of the two-tail null that the impact of premium on enrollment on either side of the income cutoff is the same

	All States				All but State X			
Bandwidth Below/Above	Prem. Jump	Treat. Dummy	Period Dummy	N Below/Above	Prem. Jump	Treat. Dummy	Period Dummy	N Below/Above
Older Children								
-15/15	-0.01	-0.416*	0.073	128/142	-0.012**	-0.643*	0.082	68/82
	(.007)	(.092)	(.046)		(.007)	(.103)	(.056)	
-20/20	0.001	-0.238*	0.042	152/174	0.002	-0.415*	0.050	84/106
	(.004)	(.071)	(.04)		(.004)	(.082)	(.048)	
-25/25	-0.000	-0.270*	0.086*	285/312	0.002	-0.446*	0.055	90/120
	(.004)	(.069)	(.038)		(.004)	(.080)	(.046)	
All Children								
-15/15	-0.004	-0.331*	0.080	166/164	-0.005	-0.481*	0.074	82/90
	(.005)	(.082)	(.042)		(.004)	(.090)	(.051)	
-20/20	0.000	-0.202*	0.055	192/210	0.001	-0.307*	0.062	98/126
	(.004)	(.066)	(.037)		(.003)	(.073)	(.043)	
-25/25	-0.001	-0.232*	0.086*	351/387	0.000	-0.307*	0.063	106/148
	(.003)	(.061)	(.034)		(.003)	(.067)	(.040)	

Figure 2.1: Estimated Private Coverage - All Children

Scatter diagram of the LOESS estimates of private insurance enrollment as a function of the family income index for children in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.

Figure 2.2: Estimated Uninsurance Rate - All Children

Scatter diagram of the LOESS estimates of the rate of uninsurance as a function of the family income index for children in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.

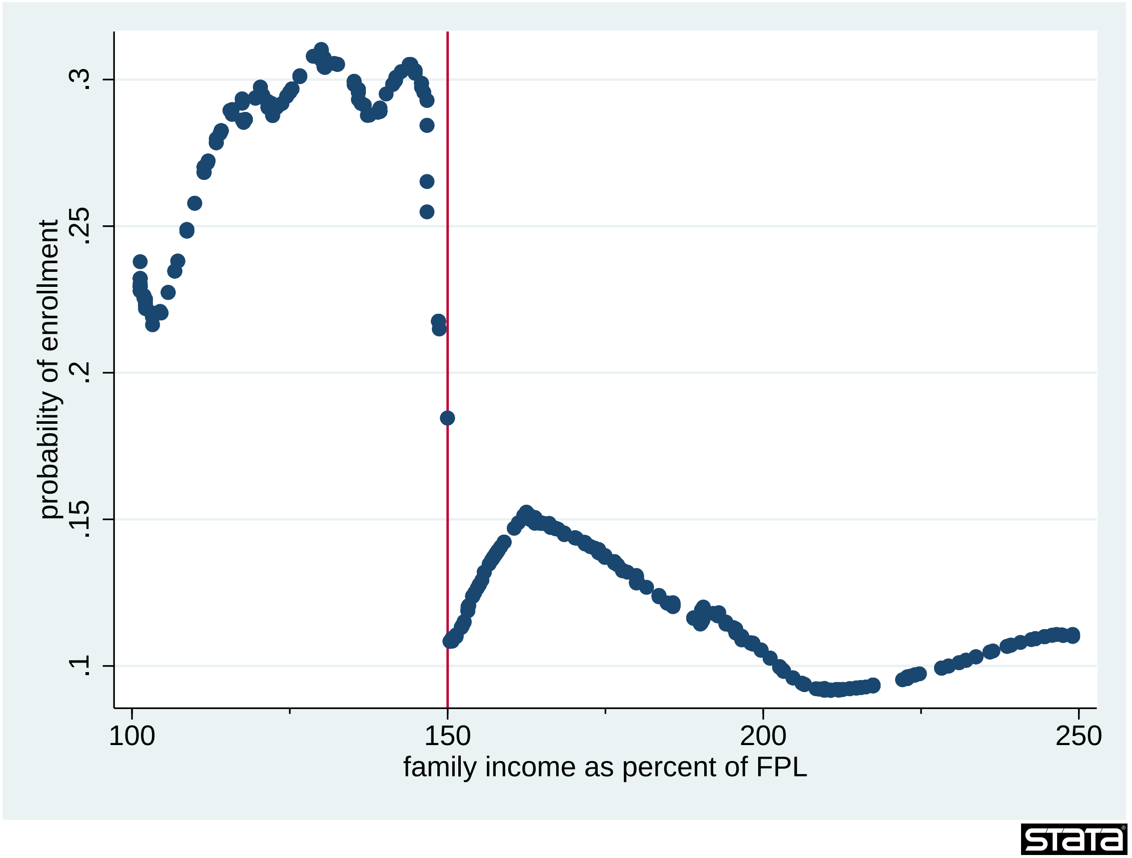

Figure 2.3: Estimated Private Coverage - Older Children

Scatter diagram of the LOESS estimates of private insurance enrollment as a function of the family income index for children who are 6 years of age and older in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.

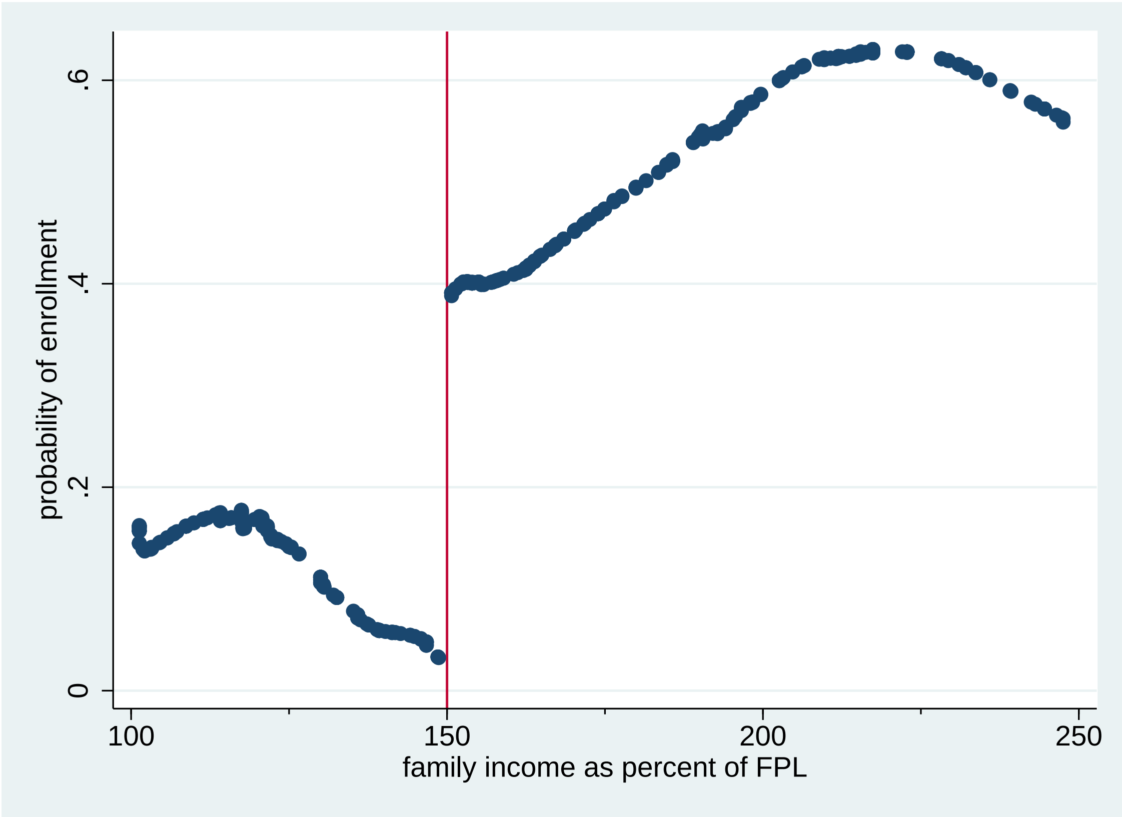

Figure 2.4: Estimated Uninsurance Rate - Older Children

Scatter diagram of the LOESS estimates of the rate of uninsurance as a function of the family income index for children who are 6 years of age and older in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.

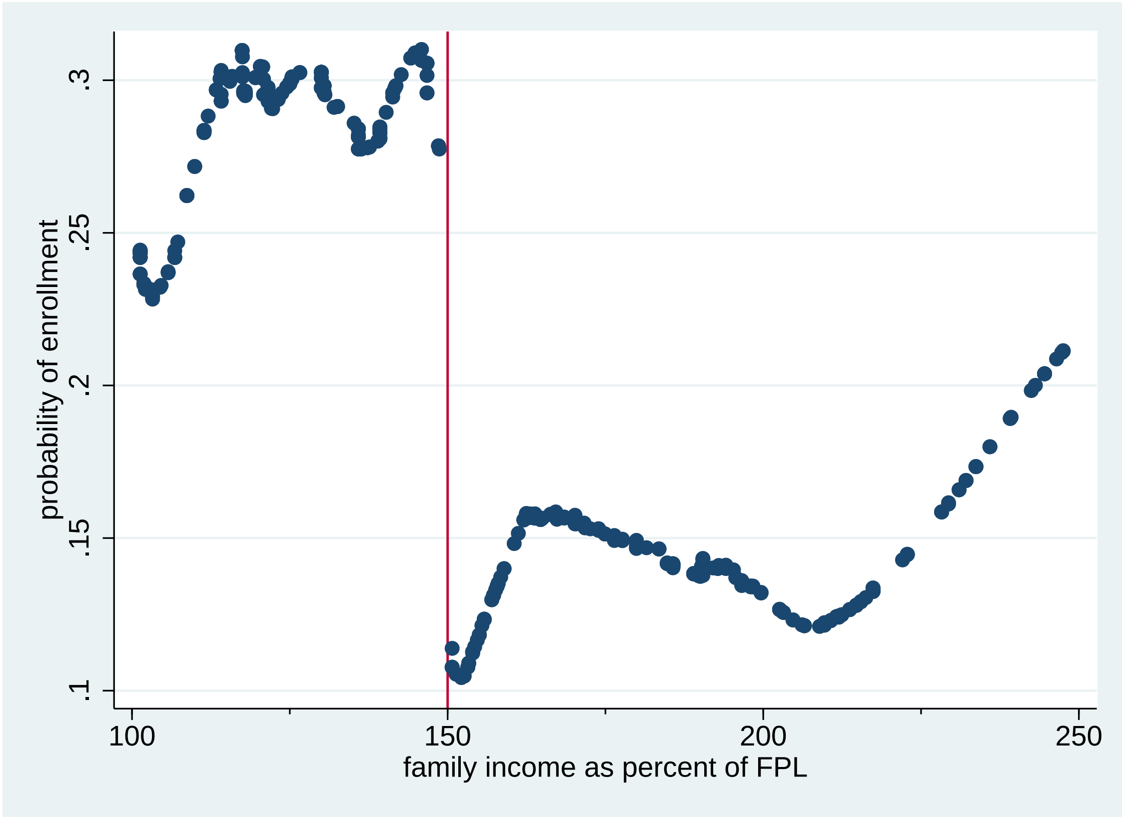

Table 2.12: Special Rules Imposed on Minor Parents Eligibility

Can be the head of unit	Cannot be the head of unit
Alabama	Delaware
Alaska	Idaho
Arizona	Kansas
Arkansas	Louisiana
California	Maryland
Colorado	North Carolina
Connecticut	West Virginia
Florida	Wisconsin
Georgia	
Hawaii	
Illinois	
Indiana	
Iowa	
Kentucky	
Maine	
Massachusetts	
Michigan	
Minnesota	
Mississippi	
Missouri	
Montana	
Nebraska	
Nevada	
New Hampshire	
New Jersey	
New Mexico	
New York	
North Dakota	
Ohio	
Oklahoma	
Oregon	
Pennsylvania	
Rhode Island	
South Carolina	
South Dakota	
Tennessee	
Texas	
Utah	
Vermont	
Virginia	
Washington	
Washington D.C.	
Wyoming	

Appendix

Lemma 2.7.1 *Let X is a matrix $n \times (m+1)$, $X'X$ is full-rank and one of the column-vectors of matrix X is a vector of ones, then $(X'X)^{-1}X'\mathbf{1} = [1, 0, \ldots, 0]'$.*

Proof:

Let the matrix X consists of a vector of $\mathbf{1}$, $\widetilde{X}_{n\times m}$ matrix of other explanatory variables, $\overline{\widetilde{X}}$ is a column vector of sample means. Then the $(m+1) \times (m+1)$ matrix $X'X$ can be partitioned in the following way:

$$\begin{pmatrix} c & b' \\ b & A \end{pmatrix}$$

where $A = \widetilde{X}'\widetilde{X}$, $b = n\overline{\widetilde{X}}$, $c = n$. The inverse of $X'X$ is

$$(X'X)^{-1} = \begin{pmatrix} \frac{1}{k} & -\frac{1}{k}b'A^{-1} \\ -\frac{1}{k}A^{-1}b & (A - \frac{1}{c}bb')^{-1} \end{pmatrix} = \begin{pmatrix} \frac{1}{k} & -\frac{1}{k}b'A^{-1} \\ -\frac{1}{k}A^{-1}b & A^{-1} + \frac{1}{k}A^{-1}bb'A^{-1} \end{pmatrix}$$

where $k = c - b'A^{-1}b$, and

$$X'\mathbf{1} = \begin{pmatrix} n\overline{\widetilde{X}} \\ n \end{pmatrix} = \begin{pmatrix} b \\ c \end{pmatrix}$$

Then,

$$(X'X)^{-1}X'\mathbf{1} = \begin{pmatrix} -\frac{b'A^{-1}b}{c-b'A^{-1}b} + \frac{c}{c-b'A^{-1}b} \\ A^{-1}b + \frac{A^{-1}bb'A^{-1}b}{c-b'A^{-1}b} - \frac{A^{-1}bc}{c-b'A^{-1}b} \end{pmatrix} = \begin{pmatrix} 1 \\ \mathbf{0} \end{pmatrix} = \widehat{\gamma}$$

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