Premium Increases and Disenrollment from SCHIP *

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Abstract

This is the first study to explore the impact of premium variations across individuals, states, and time on enrollment in the State Children's Health Insurance Program (SCHIP).While most states use premiums of modest magnitude to reduce state budget costs and preserve private insurance enrollment, we know little about the extent to which efforts designed to provide uninsured children with health coverage are hampered by the requirement some states impose on beneficiaries to pay premiums. With a sample of income-eligible children from the Medical Expenditure Panel Survey (MEPS), I evaluate the effect of premium changes 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 estimates indicate important declines in enrollment in response to premium increases. I also find that there are differences by children's age group in the enrollment response to premium.

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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. The programs original 10-year authorization period expired on September 30, 2007.

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 one year of monthly enrollment data from the nationally representative Medical Expenditure Panel Survey (MEPS) with information on eligibility rules and premium levels for all states and 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 difference-in-differences strategies that exploit temporal variations in premiums. I consistently estimate a negative effect of premium increases on the probability of enrollment in SCHIP. The results are more clear-cut when children of different age groups are separately analyzed.

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 3 presents the economic model. Section 4 details the methodology. Section 5 describes the data and health insurance eligibility assignment procedure. Section 6 discusses the estimation results. Section 7 concludes.

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 common result is that premium increases lead to disenrollment from public health insurance with the estimates of the magnitude between -0.32 and -18.00 percentage points.

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 change. Although these studies do not control for other factors that might impact 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 premium impact in a regression setting using data from Florida (Shenkman et al., 2002, 2006); New Hampshire, Kansas, and Kentucky (Kenney, Allison, Costich, Marton and McFeeters, 2006c); Arizona and Kentucky (Kenney, Costich, Marton and McFeeters, 2006a), 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 increase 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 (2006b) 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 uninsurance 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 reexamine 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 two separate states making use of the specific features of each state's income group[1] assignment process. 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 approach to examine the impact of the temporal variation in premium.

[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.

3 SCHIP Enrollment Decision. Economic Model

In this section I present a one-period model of the SCHIP enrollment decision. Each family faces a certain probability of its child becoming sick that 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 an 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) 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 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 nonnegative amount of other health goods regardless of whether the child is sick or well as their utility depends on the final health stock. 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 child. 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 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 strengthen child's health and an increase in G leads to an increase in the health stock for any level of necessary medical treatment.

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.

$$\pi_s(\overline{H}) = 1 - \pi_w(\overline{H}) \tag{3.1}$$

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. The product αC denotes the out-of-pocket expenditures of a medical visit, which reflects the total price C of a visit, and the out-of-pocket rate α, $\alpha \in [0, 1]$. The variable α reflects the exogenous proportion of the total value of medical care for which an insured individual is responsible. Thus, $\alpha = 0.0$ implies no out-of-pocket payment by the consumer and $\alpha = 1.0$ 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:

$$Z^j = \begin{cases} Y - P^j - p_g G^j_w & \text{if the child is well} \\ Y - P^j - M^j \alpha^j C - p_g G^j & \text{if the child is sick} \end{cases} \tag{3.2}$$

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.

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

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

With the associated value function:

$$V^{j,s}(Y, p_z, p_g, \alpha^j, C, P^j) \equiv U(Z^{j^*}_s, H^s(M^{j^*}_s, G^{j^*}_s, \overline{H}))$$

When the child is well:

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

With the associated value function:

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

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 associated with the maximum expected value function.

For simplicity, in the case of both, SCHIP and private insurance, $\alpha = 0$. Assuming that insurances differ only in two dimensions and given 0 copay, 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 et al., 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 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. Thus, for child i the decision to enroll in public coverage is determined by the difference between the expected value function associates with the SCHIP plan and the value function associated with the most preferred option other than SCHIP.

$$EN_i^* = EV_i^1 - \max(EV_i^2, EV_i^3) \tag{3.3}$$

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 difference in expected utility associated with the choice to enroll in SCHIP or not can be defined as

$$EN_i^* = \tau_i + \delta(P_i - P_i^A) + v_i \tag{3.4}$$

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.

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 is not available to the researcher. With P_i^A unobserved, the utility difference can be written as

$$EN_i^* = \tau_i + \delta P_i + \varepsilon_i \tag{3.5}$$

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. In addition, P_i could be correlated with the unobserved preference component v_i. For example, premiums for children's coverage may be lower in the SCHIP insurance, but parents may be more or less attracted to SCHIP, regardless of the premium payment, because of the medical benefits the SCHIP insurance covers. 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:

$$\begin{aligned} Pr(EN_i^* = 1) &= Pr(\delta P_i + \varepsilon_i > 0) \\ Pr(EN_i^* = 0) &= 1 - Pr(EN_i^* = 1) \end{aligned} \tag{3.6}$$

The enrollment decision could be described by a linear probability model specification for Eqn. 3.6:

$$EN_i = \beta + \alpha P_i + u_i \tag{3.7}$$

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 4 addresses the different approaches of dealing with the endogeneity issue.

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 pays 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 an individual 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 are assigned to the high income group.

The premiums differ by income group with higher premiums for higher-income families.

[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.

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

I focus on the theoretic and econometric considerations under the sharp design as all children with $I \geq \overline{I}$ are assigned to the treatment group conditional on being covered by public insurance. If, however, the goal is an evaluation of the effect of SCHIP premium levels on enrollment in private health insurance, the problem fits into the framework of a fuzzy RD. For example, a sharp design in this case would correspond to the hypothetical situation in which, for children with $I \geq \overline{I}$ and with access to private insurance, the substitution of public for private coverage has been avoided completely.

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. A standard regression model representation of the evaluation problem with the sharp regression-discontinuity design is

$$y_{di} = \alpha_i + \beta_d d_i + u_{di} \tag{4.1}$$

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. Increasing the interval around the threshold is likely to produce a bias in the effect estimate as the premium fee is determined by I that itself has been documented to impact the SCHIP enrollment decision. Since I is the only systematic determinant of the premium fee, the inclusion of a smooth function g(I) which is continuous at the income cutoff solves the endogeneity issue. In the case of the RD design it is assumed that the "true" functional form of I can be approximated by some known polynomial. The model for the observed SCHIP enrollment is specified

$$y_{di} = \alpha_i + \beta_d d_i + g(I_i) + u_{di} \tag{4.2}$$

Note that Eqn. 4.2 can be rewritten

$$y_i = \alpha_i + \beta_d d_i + g(I_i) + u_i \tag{4.3}$$

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

$$\lim_{I \downarrow \bar{I}} E(u|I) = \lim_{I \uparrow \bar{I}} E(u|I) \tag{4.4}$$

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

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

$$y_{1i} - y_{0i} = \beta_d + u_{1i} - u_{0i} \tag{4.5}$$

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

$$\beta_d + \lim_{I \to \bar{I}} E(u_1 - u_0|I) \tag{4.6}$$

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 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 et al. (2001) I minimize

$$\sum_{i \in \mathcal{J}} (y_i - \alpha_i - \beta_d d_i - g(I_i))^2 \tag{4.7}$$

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.

4.2 Cross-Sectional Model

To see how premium effect can be identified and estimated when data on all states are combined, notice that 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. 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 premium jump on enrollment of children in the high-income SCHIP group. The estimate of the constant θ_1 captures the impact of the low-income group premium on the outcome. The state 1 regression equation is specified as

$$y_{i1} = \theta_1 + \beta_1 J_1 * \mathbf{1}\big(I_{i1} \geq \overline{I}_1\big) + g(I_{i1}) + u_{i1} \tag{4.8}$$

Analogously, the regression equation for state 2 is

$$y_{i2} = \theta_2 + \beta_2 J_2 * \mathbf{1}\big(I_{i2} \geq \overline{I}_2\big) + g(I_{i2}) + u_{i2} \tag{4.9}$$

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

$$\underset{i \in \mathcal{J}_1 \bigcup \mathcal{J}_2}{y_{is}} = \theta_1 * \mathbf{1}(i \in 1) + \theta_2 * \mathbf{1}(i \in 2) + \beta_J \sum_{s=1}^{2} J_s * \mathbf{1}\big(I_{is} \geq \overline{I}_s\big) + g(I_i) + u_{is} \tag{4.10}$$

where J_s is the size of the increase in premium above the point of discontinuity for state s. The estimate of β_J captures the impact of premium variation on enrollment of children whose family income is at or above the state income cutoff. 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:

$$\underset{i \in \bigcup \mathcal{J}_s}{y_{is}} = \sum_{s=1}^{S} \theta_s * \mathbf{1}(i \in s) + \beta_J \sum_{s=1}^{S} J_s * \mathbf{1}\big(I_{is} \geq \overline{I}_s\big) + g(I_{is}) + u_{is} \tag{4.11}$$

The regression specification assumes that the premium increase effect is linear and proportional for all states. 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.

4.3 Difference-in-Differences Design

Closely 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 quickly 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. Oftentimes, however, families that renege on their current payments are provided with a grace period[3] before their child becomes disenrolled and its length 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, 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

[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 treatment group's past before the treatment is available as a control group.

To explore the temporal variation created by premium changes over time, I compare the SCHIP enrollment 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, including only these 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 evalution, the high-income group from within the state is selected as "treatment" ($d = 1$) and is assumed to differ from the control group only in the the amount of the premium fee. Thus, by choosing as control the low-income group within the state, 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 just the premium level which varies over time and by income group. The estimate of its coefficient δ_0 supposedly captures the effect of premium increase on SCHIP enrollment in the high-income group and is measured against the change in SCHIP enrollment in response to low-income group premium changes. This leads to:

$$y_{it} = \alpha + \beta_0 d + \gamma_0 t + \delta_0 V_{it} + \beta_z' \mathbf{z}_{it} + \varepsilon_{it} \tag{4.12}$$

where $\mathbf{z}$ 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[4]. In addition, the composition of the treatment and control group must remain stable over the

[4]For comparison, in RD specification the control for potentially confounding effects is done by inclusion of a known smooth function of the assignment variable.

examined period.

Unlike the individual-state specification (Eqn.4.12), the all-state specification should take into account states' heterogeneity. To control for it, in Eqn.4.13, I introduce a set of state dummies θ_s. The treatment dummy d indexes by one all children in the higher-income group for all states. The variable V is the level of premium which is time-, group, and state-varying. The premium variable V controls for the impact of temporal changes in premium on SCHIP enrollment of children.

$$\underset{i \in \bigcup \mathcal{J}_s}{y_{ist}} = \sum_{s=1}^{S} \theta_s * \mathbf{1}(i \in s) + \beta_s d + \gamma_s t + \delta_s V_{ist} + \beta_z' \mathbf{z}_{ist} + u_{ist} \tag{4.13}$$

Coefficients β_s, γ_s are respectively the mean enrollment of the high income group in the pre-period and the enrollment of the control group in the post-period.

5 Data and Assignment Method

5.1 Data

The data for the analysis come from the Medical Expenditure Panel Survey (MEPS) panels covering calendar year 2003. 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). 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, and 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 file at the state level.

The main focus is on premiums and insurance status of children age 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. When a limit on the maximum payment per family is in effect, family-level analysis of enrollment will provide additional information to the researchers that is not available at the child level. Future work using information on families with only one child will likely provide a better understanding of the 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 enrollment over time. My sample for longitudinal analysis includes children 18 and younger with positive full-year weights for 2003[5]. 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. I extracted a subset of children in the full-year population who were encompassed by the survey at the very first day of 2003. I created further a subset of children who were available for interview for all three rounds of data collection to avoid drawing comparisons across children who entered MEPS at different times during that year. 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 hike, those states have been omitted from the longitudinal 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 SCHIP/Medicaid enrollment. Information on the insurance coverage of each child is ascertained on the MEPS by asking: "Were you covered by Medicaid or SCHIP" for each separate month of the year. However, because of grace periods, insurance coverage studies using the MEPS are susceptible to the timing of the enrollment response following

[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.

a premium change. To circumvent the timing issue, I compare the January and December enrollment outcomes of SCHIP eligible children. This time span effectively captures the enrollment response in all states that chose to increase their premiums over time as no state has a grace period that would last until December. As mentioned in Hudson, Banthin and Selden (2004), MEPS is widely regarded as providing more accurate and consistent public coverage estimates than the CPS, perhaps because MEPS asks numerous detailed questions regarding the presence, source, and duration of coverage.

The MEPS sample used comes from Rounds 3, 4, and 5 of Panel 7 and Rounds 1, 2, and 3 of Panel 8, which are the rounds for the MEPS panels covering calendar year 2003. It includes information on children age 18 and younger who are eligible for the first or second income group. Public insurance eligibility for each child is assigned as described below.

5.2 Assigning Program Eligibility

Assigned eligibility is pivotal to my analysis.[6] The health insurance coverage variable in the data indicates only 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.

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

[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.

family plans. These families or HIEUs comprise adults, their spouses, and their unmarried natural/adoptive children age 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 et al. (2005), Hudson et al. (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 despite the income of the adults.

I use the Urban Institute Welfare Rules Database (see Table 10) 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. Monthly eligibility for public insurance for children is calculated for the population of children in MEPS given 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 assigned Medicaid/SCHIP eligibility and is observed in the data to have public insurance, the respective insurance status is assigned. 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.

5.3 Descriptive Statistics

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

5.3.1 Description of Individual States

Table 1 shows the averages for family income, premium, age, and enrollment for the largest state in my data set, referred to as 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 for the enrollment of their SCHIP eligible child. I find that those enrolled in the first income group are on average the same age as those in the second. Table 1 compares the enrollment as a share of all SCHIP eligibles in a given income group. The table shows that enrollment in the state X program decreases with income group. The statistics are based on data as of January 2003 with 361 and 418 eligible children respectively for the first and second income group.

Table 1 displays also the summary statistics for the second largest state in the data set, referred to as state Y. According to state Y rule, children up to 12 months old with $I \leq 201$ of FPL are eligible for Medicaid. For the rest of the children the income cutoff between Medicaid and SCHIP is set at $I = 161$ of FPL. The income threshold between the income groups is at $I = 222$ percent of FPL. The table also shows that the difference in the average age between groups is negligible. Similar to state X, enrollment in state Y decreases with group. There are 59 children eligible for the first income group and 26 for the second.

5.3.2 Sample for Cross-Sectional Analysis

Table 1 presents the average family income, premium payment, and enrollment at a point in time for all study states with two income groups. The table shows that premium payment and enrollment change monotonically with group, with premium increasing and enrollment decreasing from Group I to Group II. Child's age is on average the same across income groups. There are 901 children that are income-eligible for the first income group and 722 for the second. 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.

5.3.3 Sample for DD analysis

The longitudinal sample includes children 18 and younger with positive full-year weights for 2003. There are 1274 children who are income-eligible for the first and second income group. Table 2 shows the averages for family income, premium, child's age, health status, and SCHIP enrollment as of January and December of year 2003. Summary statistics are presented separately for the first and second income group. For the low-income group the average family income, child's age and health decrease slightly over the the course of the year. As expected premium amount also increases. With data on all states with two income groups the average SCHIP enrollment average is found to increase, a finding supported by the Kaiser Family Foundation which reports that the average SCHIP enrollment increases by 4.16 percentage points between December 2002 and December 2003.

Summary data show that family income and premium for the high-income group increase slightly over the year while the average age and health of the child decrease. The average enrollment of the high-income children marks a small increase.

6 Estimation Results

I present my results in four subsections. First, I introduce the LOESS technique. Second, I examine the impact of premium on enrollment in the two largest states. There are two income groups in each of these two states 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 for the largest state in the data set, state X. Next, I explore the cross-sectional variation in premium on enrollment when data on all states are combined. Finally, I study the impact of premium increases over time on the SCHIP enrollment outcomes of children.

6.1 LOESS

To illustrate how discontinuities in the family income assignment rule possibly affect enrollment decisions, 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 fit to a subset of the data, with explanatory variable values near the point whose response is being estimated. The polynomial is fit 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(for detailed discussion on LOESS, see e-Handbook of Statistical Methods, NIST/SEMATECH (2003)).

6.2 Case Studies of Two States

States X and Y are the first and second largest state, respectively, in my data set. Since the assignment rule for each state has a simple structure, it is useful, for the purposes of better understanding the premium influences, to first separately analyze enrollment in these two states 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 on each side of the 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 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 cutoff at the 150 percentage points of the FPL 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 10, 15, and 20 percentage points of the income cutoff score. The average enrollment of children of all ages in the high-income group is estimated to be between 14 to 17.6 percentage points lower than the control group enrollment.

A more exacting demonstration of the cutoff comes from separately analyzing the enrollment behavior of children in different age groups. In state X, for children less than six years old, the cutoff between SCHIP and Medicaid is set at $I = 134$ percentage points of the FPL, while the threshold for the older children is at a lower $I = 100$ percentage points of the FPL. Age group analysis of enrollment is arguably based on a more uniform set of points. Figure 4 for the group of older children, reveals a clear discontinuous jump at the income cutoff. A LOESS plot of SCHIP enrollment of younger children as a function of family income is presented in Figure 5. The plot is strongly suggestive of discontinuity at the cutoff but, possibly because of small number of observations (for comparison of enrollment statistics by age group, see Table 3), the jump is not that clear-cut. The plots by age group reveal that discontinuity is larger for the group of younger children.

The effect estimates in Table 3 show that the enrollment of older children in the treatment group decreases between 15 to 20 percentage points, while the enrollment of younger children assigned to treatment declines by 30 to 38 percentage points. This evidence points to a structural difference in the decision-making mechanism of families of older and younger children. Figure 3 also 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. The plots by age group show that the probability of enrollment for younger children after the cutoff stays low while, for the group of older children, it decreases monotonically with family income over the income range of the second income group.

Figure 6 shows a LOESS plot of SCHIP enrollment in state Y. The small number of observations on each side of the income cutoff (12 data points below and 23 above for the largest bandwidth) are insufficient to determine the existence of a jump. The estimated averages for state Y enrollment in Table 4 reveal that enrollment of children in the treatment group decreases by 5 to 24 percentage points. The large variation of the enrollment decline points to instability of the estimates for this state.

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 $(-.03; -.36)$ as presented in Table 5. 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 3 to 36 percent depending on bandwidth, with the estimate for the smallest sample estimate being $-.36$. 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 which these local estimates are based (as observed in Van der Klaauw (2002)). Given the magnitude of the point estimates for the "-15/+15" bandwidth[8], one would expect to see a larger point estimate for the smaller, more homogeneous sample. A possible explanation for this observation is that eligibility is not observed in my data and must be assigned. As discussed in Section 2, the assignment errors can arise due to misreported family income or because the assignment process fails to replicate completely

[7]The assumption is that at least 10 observations are needed for the estimation of each coefficient.

[8]The "-15/+15" bandwidth encompasses observations that lie within 15 percentage points of the FPL below and above the income cutoff.

the eligibility procedure. The resulting simulation errors will bias the estimate of β_d towards zero. The effect estimates for state X correspond to an estimated enrollment elasticity[9] with respect to group premium evaluated at the mean in the range of ($-.219$ to -2.593).

Discontinuity and elasticity estimates for the group of younger children are presented in Tables 6. The results consistently demonstrate that higher levels of premium are associated with lower probability of enrollment. The results in Table 6 support an earlier finding that standard errors on the point estimates decrease as the size of the sample increases.

The discontinuity results presented in Figure 6 for state Y are not apparent, possibly because of the small number of observations just around the cutoff. Therefore, in the RD estimation I include observations that lie within a wider interval. State Y point estimates and elasticities for three different samples are presented in Table 7. The enrollment rate seems to remain constant or may actually fall (the decrease could be up to 12 percentage points.) This more mixed pattern of estimated discontinuities around the cutoff could be attributed to two factors: small number of observations allowing for outliers to drive the results, or observations are most likely heterogeneous and the included income function does not control well for the different ways in which income impacts enrollment. The wide range of estimates of enrollment elasticities correspond reasonably well with the pattern of other state Y results.

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

$$\varepsilon = \left(\frac{\Delta EN}{(EN_1 + EN_2)/2}\right) \times \left(\frac{(P_1 + P_2)/2}{\Delta P}\right) \tag{6.1}$$

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.

6.3 Cross-Sectional Estimates

Table 8 displays the estimates and standard errors for the premium jump variable J for two different bandwidths and samples[10]. With data on all children with family income within the $-15/+15$ income interval the premium jump is estimated to have a small linear effect on SCHIP disenrollment ($\beta_J = -0.0003$). That is, a change in premium of \$10 per month will lead to an additional decrease in SCHIP enrollment of 0.3 percentage points. The effect estimate for the $-20/+20$ income interval is larger. A \$10 jump in premium across the point of discontinuity is estimated to cause a 2.4 percentage points ($\beta_J = -0.0024$) 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 larger. The coefficient β_J is is -0.0072 for the smaller sample and -0.0042 for the larger. The national estimates affirm the single-state findings that higher premiums are related to a decrease in enrollment. In magnitude, the national estimates rank below or around the low end of point estimate values for the individual states. The cross-sectional results provide additional support for the hypothesis that there are substantial differences in the enrollment response by age groups.

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 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 of children with family income below the state cutoff. Testing the joint significance of the state-specific dummies confirms the hypothesis that the

[10]Because the income groups in some states include individuals that lie only within 20 percent of the FPL, I present cross-sectional estimates for -15/15 and -20/20 bandwidths. Smaller intervals do not provide sufficient number of data points for the estimation of the premium change effect by income groups. However, the specified intervals allow only for the evaluation of the effect of premium jump on the SCHIP enrollment of older children.

low-income group SCHIP enrollment varies significantly by state. Additionally, a test of the joint significance of the linear and nonlinear family income variables shows that family income has an important effect on the probability of enrollment in the SCHIP program.

6.4 Longitudinal 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 longitudinal multiple-state analysis (see Eqn. 4.13) I examine the effect of premium increases using data on children of all ages as well as only on children aged 6-18 whose family income puts them within the the -15/15 or -20/20 income intervals (for explanation on the bandwidth choice see section 6.3).

The premium increase estimates for all samples and bandwidths are negative and significant, as presented in Table 9. The premium effect estimates obtained with data on all children point to a decrease in the probability of enrollment of 15.6 or 14.3 percentage points in response to an average increase of $10 in the premium for the high income group. Considering only children age 6-18, I obtain slightly higher estimates for the premium increase variable. A $10 increase in the average premium leads to a decrease of 18.6 and 18.9 percentage point for the -15/+15 and -20/+20 intervals respectively. These are significant effects associated with important declines in SCHIP enrollment.

For the different samples the estimates on the treatment dummy vary with the bandwidth. Although none of the estimates is significant, their variability suggests that the baseline probability that a low-income child is enrolled changes in response to changes in the sample composition.

The period dummy point estimate changes with bandwidth. This finding emphasizes the importance of selecting the smallest possible bandwidth that yields a large enough sample for analysis. Estimates based on samples associated with wider bandwidths are shown to have smaller standard errors but larger bias.

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. Each set utilizes a different source of variation in the data. Using a unique eligibility characteristic of the program involving lower premiums for those children whose family income is below a state-specific income cutoff, I study the effect of premium variation on enrollment in the public health insurance program. My main regression-discontinuity finding is that higher premiums reduce the probability of enrollment with the magnitude of the decrease changing with the age of the child. This result is reinforced by a cross-sectional analysis that evaluates the response using across-state variation in premiums. An exploration of the longitudinal premium-induced effects on disenrollment supports the regression-discontinuity and cross-sectional results that premium effects differ with the age of the child.

From a broader policy perspective, this study, and evidence presented by earlier works assessing premium effects, suggests that SCHIP premium increases are associated with important enrollment declines. SCHIP programs have responded to financial pressures by introducing premiums or increasing their current levels. Thus it is important to know the extent to which efforts designed to provide uninsured children with health coverage are hampered by the requirement some states impose on beneficiaries to pay premiums.

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Table 1: Summary statistics of cross-sectional data

Average family income, premium, age, and enrollment at a point in time for state X, state Y, and all states with two income groups

		All States			State X		
Income Group	Variable	Mean	St. D.	N	Mean	St. D.	N
Group I	income	134.9	43.109	901	122.491	14.32	361
	premium	6.425	5.902	901	7	0	361
	child age	9.415	5.49	901	9.435	5.187	361
	enrollment	0.418	0.494	901	0.463	0.499	361
Group II	income	191.322	29.75	722	190.529	28.363	418
	premium	11.242	6.588	722	9	0	418
	child age	9.573	5.449	722	9.663	5.403	418
	enrollment	0.309	0.462	722	0.344	0.476	418

Table 2: Summary statistics of longitudinal data

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

		Before Change		After Change		
Income Group	Variable	Mean	St. D.	Mean	St. D.	N
Group I	Income	139.2	31.74	139.08	31.87	612
	Premium	8.20	8.10	8.94	7.62	612
	Child age	10.16	4.52	10.14	4.48	612
	Health state	3.6	1.53	3.55	1.58	612
	Enrollment	0.4	0.49	0.4	0.49	612
Group II	Income	191.7	28.19	191.29	28.18	662
	Premium	10.69	7.32	11.48	7.9	662
	Child age	9.68	5.13	9.55	5.2	662
	Health status	3.62	1.4	3.7	1.36	662
	Enrollment	0.32	0.47	0.33	0.47	662

Table 3: Estimated Average Enrollment – State X

LOESS estimates for SCHIP enrollment of all children in state X

	All Ages			Age 6 and older			Age 5 and younger		
Band B/A	Av. Enr. B/A	Eff.	N B/A	Av. Enr. B/A	Eff.	N B/A	Av. Enr. B/A	Eff.	N B/A
-10/10	0.625/0.448	0.117	50/63	0.665/0.502	0.163	33/46	0.602/0.220	0.382	17/17
-15/15	0.592/0.452	0.140	95/119	0.630/0.480	0.150	59/90	0.651/0.329	0.322	26/29
-20/20	0.591/0.448	0.143	109/140	0.671/0.471	0.200	78/106	0.650/0.355	0.295	31/34

Table 4: Estimated Average Enrollment – State Y

LOESS estimates for SCHIP enrollment of all children in state Y

Bandwidth Below/Above	Average Enrollment Below/Above	Effect	N Below/Above
-15/15	0.572/0.334	0.238	5/19
-20/20	0.426/0.326	0.100	9/20
-25/25	0.379/0.326	0.053	12/23

Table 5: State X - RD estimates by age group. 6-18 years old

Discontinuity and elasticity estimates and number of observations “below” and “above” cutoff for state X older children for different bandwidths within the income borders of the first and second group that generate samples with a sufficient number of observations.

Bandwidth Below/Above	Income Group Dummy	Elasticity	N Below/Above
-15/15	-0.359	-2.593	69/90
	(.271)		
-20/20	-0.292	-2.232	78/106
	(.215)		
-25/25	-0.132	-1.068	102/123
	(.188)		
-30/30	-0.031	-0.219	141/137
	(.170)		

Table 6: State X - RD estimates by age group. 5 years old or younger

Discontinuity and elasticity estimates and number of observations "below" and "above" cutoff for state X younger children for different bandwidths within the income borders of the first and second group that generate samples with a sufficient number of observations.

Bandwidth Below/Above	Income Group Dummy	Elasticity	N Below/Above
-15/35	-0.366	-3.897	26/45
	(.299)		
-15/40	-0.139	-1.233	26/54
	(.520)		
-20/35	-0.358	-2.946	31/45
	(.301)		
-20/40	-0.239	-1.906	31/54
	(.622)		

Table 7: State Y - RD estimates

State Y discontinuity and elasticity estimates and number of observations "below" and "above" cutoff for different bandwidths within the income borders of the first and second group that generate samples with a sufficient number of observations.

Bandwidth Below/Above	Income Group Dummy	Elasticity	N Below/Above
-50/20	-0.015	-0.081	44/20
	(.398)		
-50/25	0.021	0.111	44/23
	(.364)		
-55/25	-0.122	-0.582	49/23
	(.355)		

Table 8: Cross-Sectional Estimates

Premium change estimates for different bandwidths based on data for all states with two income groups

Bandwidth Below/Above	Premium Jump	N Below/Above
	All Children	
-15/15	-0.0003	196/243
	(.0077)	
-20/20	-0.0024	233/296
	(.0065)	
	Older Children	
-15/15	-0.0072	140/187
	(.0101)	
-20/20	-0.0042	163/222
	(.0092)	

Table 9: Longitudinal Estimates

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

Bandwidth Below/Above	Premium Jump	Treatment Dummy	Period Dummy	N Below/Above
		All Children		
-15/15	-.0156*	-.0018	-.016	182/190
	(.005)	(.0841)	(.0441)	
-20/20	-.0143*	.0019	.0054	212/242
	(.004)	(.0718)	(.0403)	
		Older Children		
-15/15	-.0186*	.0123	-.0378	130/150
	(.007)	(.0978)	(.0492)	
-20/20	-.0189*	-.0026	-.012	156/186
	(.0049)	(.079)	(.0451)	

Table 10: 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: Production Function of Health Stock

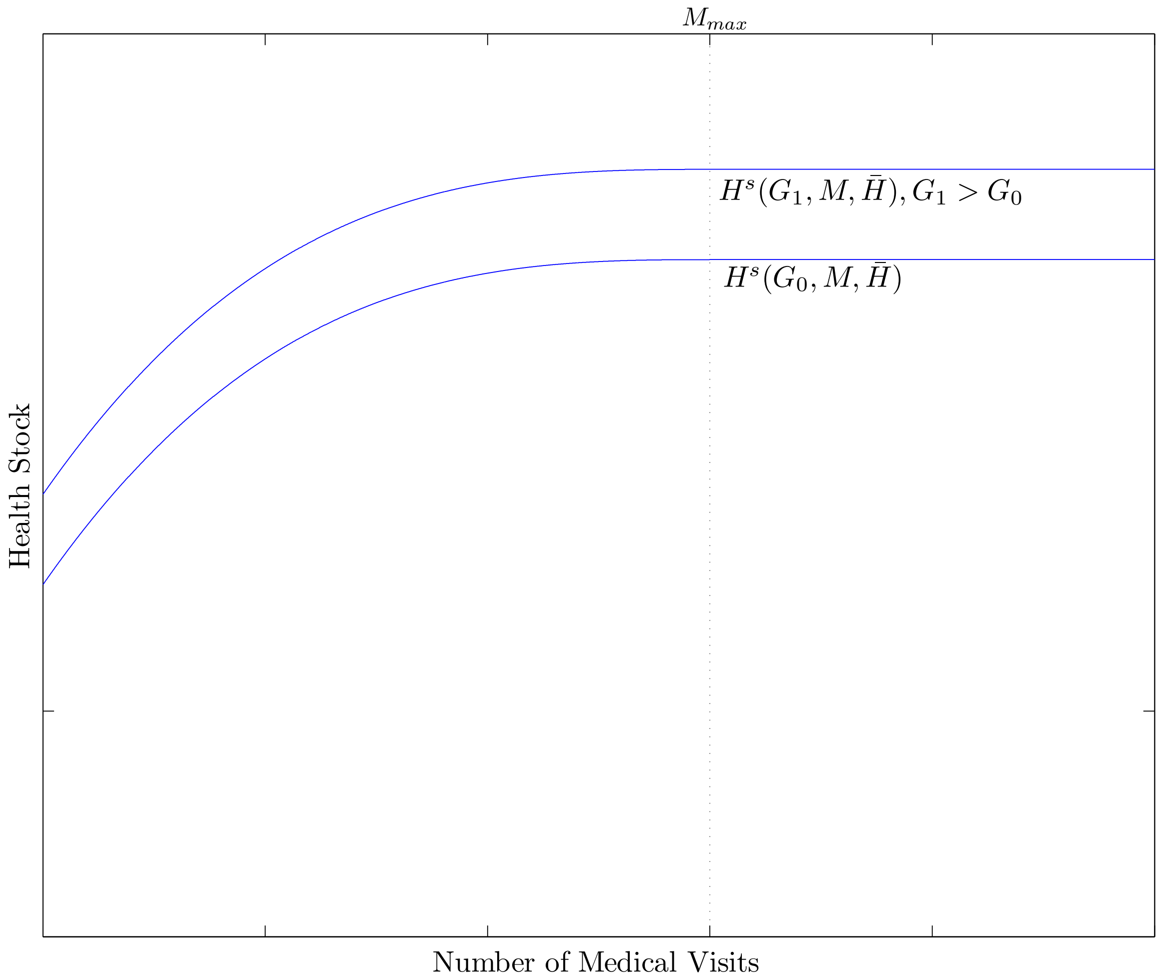

Figure 2: Regression Discontinuity Data

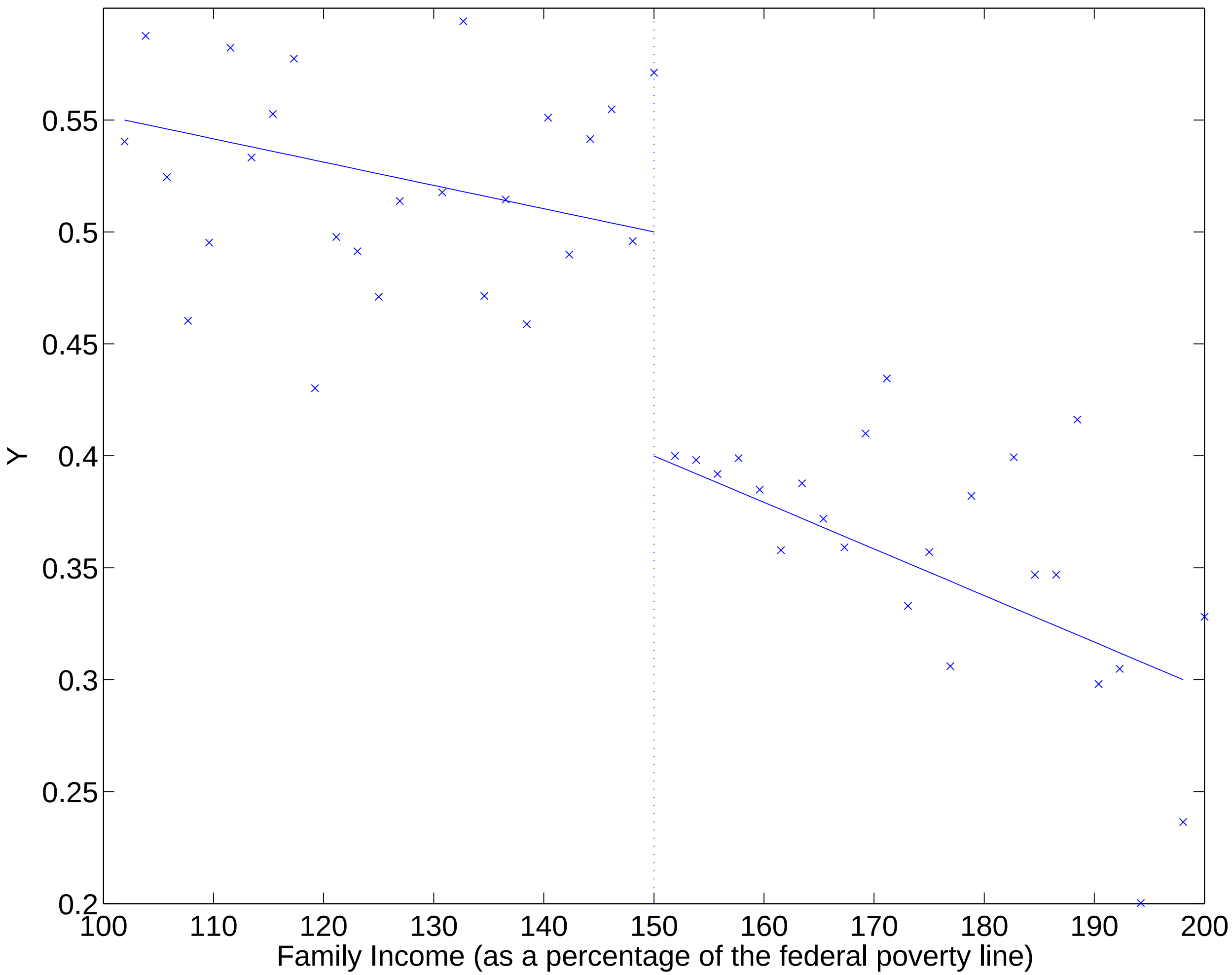

Figure 3: Enrollment Rate - State X

Scatter diagram of the LOESS estimates of 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.

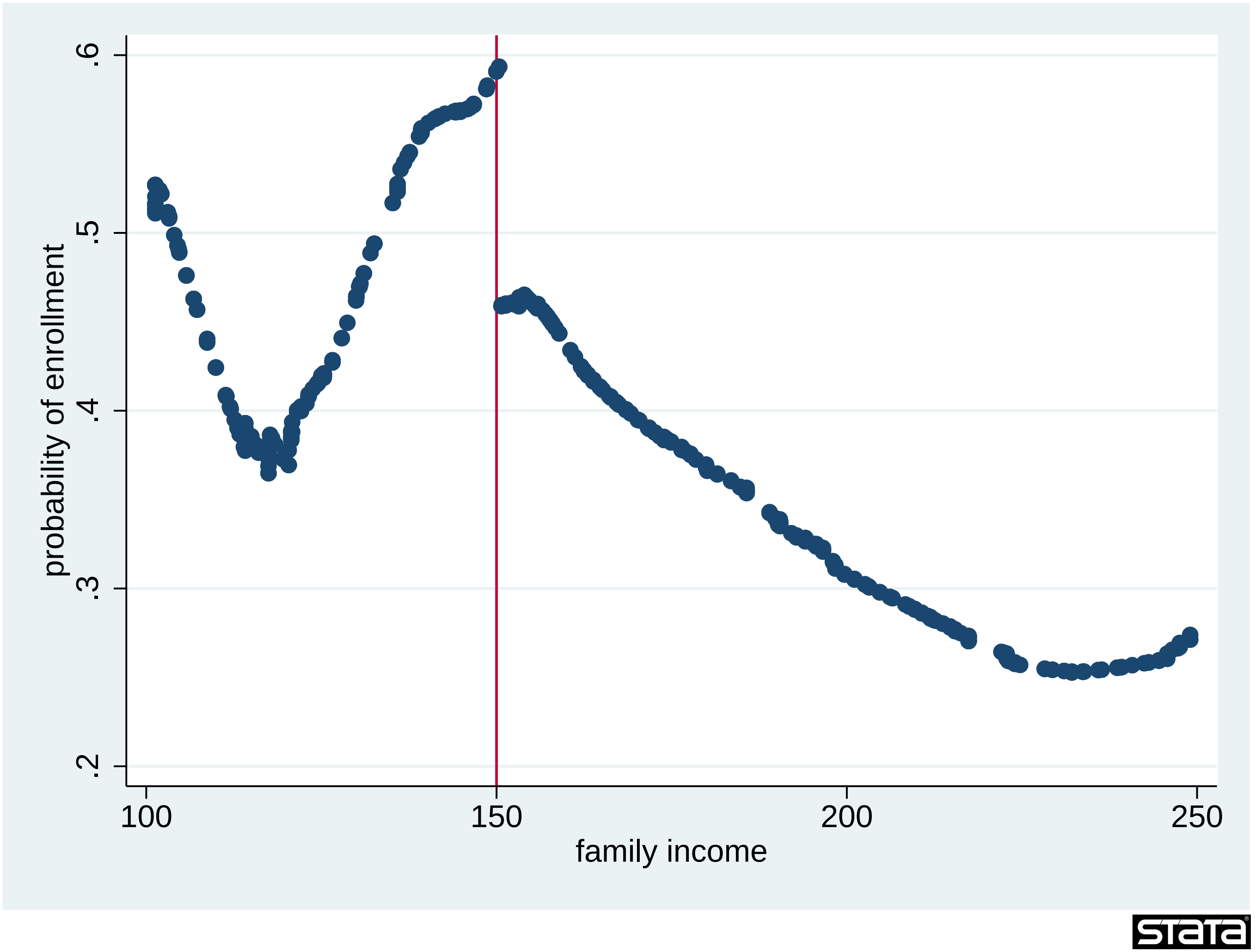

Figure 4: Enrollment Rate for Older Children - State X

Scatter diagram of the LOESS estimates of 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.

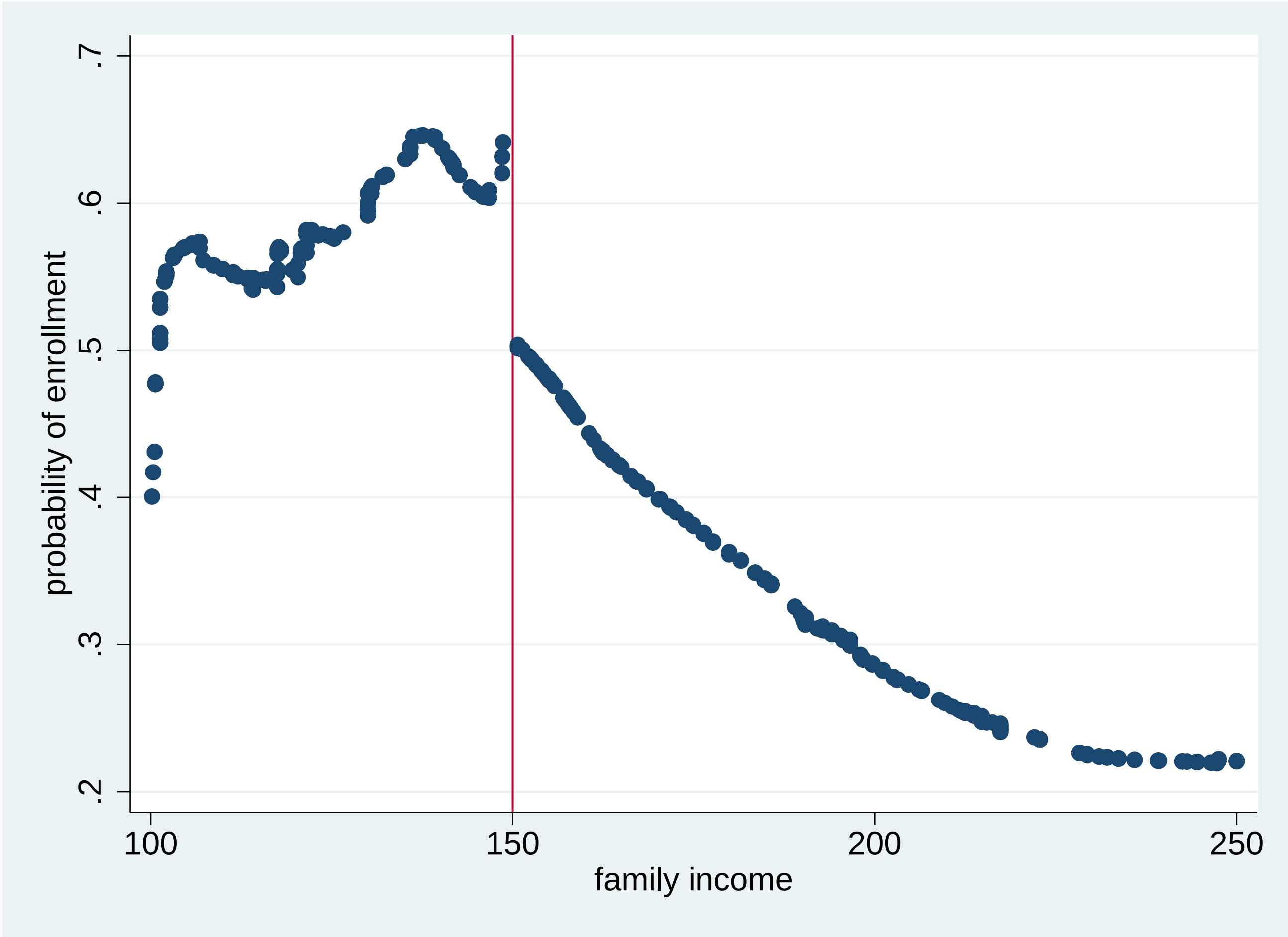

Figure 5: Enrollment Rate for Younger Children - State X

Scatter diagram of the LOESS estimates of enrollment as a function of the family income index for children who are 5 years of age and younger in state X. The results are for smoothing parameter=.8, and local polynomial of first degree.

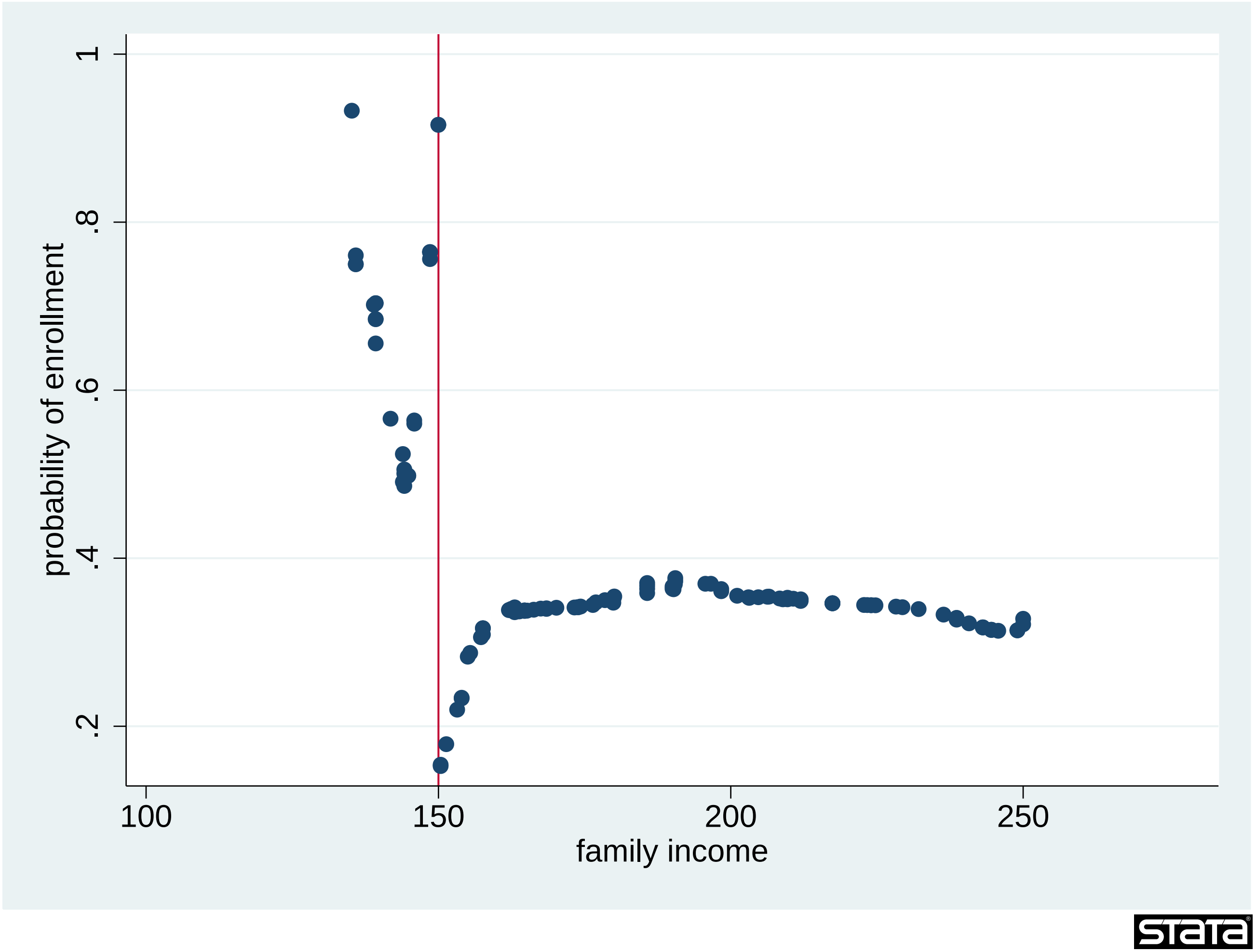

Figure 6: Enrollment Rate - State Y

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