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THE IMPACT OF STATE CHIP PROGRAMS ON EARLY CHILDHOOD HEALTH INSURANCE COVERAGE, UTILIZATION AND OUTCOMES

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Abstract

We analyze the dramatic expansion in public health insurance eligibility to children in near-poor households under the CHIP program using student-level data from the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K). We implement both first-difference and level specifications to determine the impact of expanded eligibility on take-up and crowd-out. We then rely on the policy-induced variation in health insurance coverage transitions and status to examine the short- and longer-term impacts on early childhood health care utilization, health and academic attainment.

1. Introduction

The case for broad availability of health insurance coverage for children is based on a compelling narrative. Providing the *possibility* of health insurance coverage to children, through public and private means, enhances the likelihood of take-up and enrollment in health insurance programs. Such enrollment increases the likelihood that health services will be utilized, and that children will be provided adequate diagnostic, preventative, and curative treatments. Better access to health care may lead to not only better health outcomes, but also to more rapid and effective early human capital acquisition.

Although it is plausible that broader access to health insurance will improve child outcomes, there are many intermediate links in the chain of logic. For example, when a new governmental program is established to provide health insurance to low-income children, how many families enroll in the program? What share of those enrollments is of children who were previously uninsured, as opposed to of children previously covered through private insurance? To what extent do those with coverage obtain additional health care services? And, ultimately, does such utilization result in improved health and educational attainment?

In this paper we confront such questions with an analysis of the recent dramatic expansion in the public health insurance system that occurred via the Children's Health Insurance Program (commonly referred to as CHIP). This program, established in 1997 through a federal grant to the states, was designed to provide health insurance to children of low-income families not already covered by Medicaid, typically in the range of 100-200% of the federal poverty level. The grants were sufficiently attractive that every state adopted a CHIP program within two years. States were given substantial leeway to decide how to structure their programs, and early experimentation in design led to myriad modifications in the first several years of the program.

This state-by-state and over-time variation offers an excellent opportunity to explore the benefits of health insurance availability to a vulnerable, but non-poor, population. We take advantage of this opportunity by studying the choices and outcomes of individual children surveyed and assessed over several grades in the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K) during the late 1990s and early 2000s. We rely on the differential levels and rates of expansion of eligibility across states to isolate exogenous variation in both current eligibility and extended exposure to eligibility for public health insurance across otherwise similar children.

The next section provides background on state CHIP programs, emphasizing not only the changes in eligibility rules but also other distinct aspects of the implementation of the programs, as well as a discussion of the most relevant prior studies. Section 3 describes our data and empirical strategies for analyzing both short- and longer-run impacts of expanded eligibility on child health insurance coverage in the first stage, and health-related and academic outcomes in the second stage. Section 4 presents the empirical results. Section 5 offers a brief conclusion.

2. Background

2.1 States' CHIP programs

The CHIP program was adopted by Congress as part of the 1997 Balanced Budget Act. It offered attractive matching grants to the states to expand health insurance for children beyond the Medicaid limits, which were 133 percent of the federal poverty line (FPL) for children up to age five and 100 percent of the FPL for those aged six to thirteen.[1] It was partly prompted by the success of Medicaid waivers that had already expanded eligibility in several states. By the end of 1999, each state had sent a proposal for federal funding to the Health Care Financing Administration, now renamed the Centers for Medicare and Medicaid Services (CMS), which oversees the CHIP program.

Initial state plans for providing health insurance coverage to poor children differed on a number of dimensions, as highlighted in Table 1. The first major decision for the states was whether to adopt the CHIP program as an expansion to their existing Medicaid coverage, as a separate state program, or as some combination of the two approaches. Almost half of the states adopted CHIP as a Medicaid expansion; sixteen states established a separate program; nine used a combination of Medicaid expansion and separate elements.[2]

States set eligibility standards based on family income relative to the federal poverty guidelines. Table 1 shows maximum eligibility levels for children as set in initial state plans. These vary from a low of 133 percent of the FPL to a high of 300 percent of the FPL.[3] Programs also differed in the benefits offered to enrollees. Over half of the states offered the same benefits as those available through the Medicaid program, while the rest relied on the benefits offered to state employees, offered in the state's largest health maintenance organization (HMO), or meeting other statewide benchmarks.

Many state governments were initially uncertain about how families would respond to the CHIP programs they were developing. In hopes of dissuading people from dropping their private (often employer-sponsored) insurance and immediately enrolling their children in the CHIP program, many states imposed a waiting period from the time a family drops its private insurance to the time that the children can be enrolled in CHIP. The waiting period extended up to a year in Alaska, New Jersey, New Mexico, and Virginia. In most states there were exemptions for families losing their private insurance involuntarily, due to job loss or extreme financial hardship.

Also varying substantially across states were the cost-sharing measures utilized. Nearly half of the states adopted some form of cost sharing, typically requiring both a monthly premium and co-payments for doctor visits and prescription medications. Premium levels often varied within each state based on family size and income levels. The highest level was in Missouri, where families above 225 percent of the FPL were offered health insurance with a $65 per month premium. Far more typical were premiums in the range of ten to twenty dollars per child per month. Co-payments, in the range of five to ten dollars per visit, are common across cost-sharing states.

To encourage enrollment in the CHIP program, states relied on a variety of outreach and access activities. For instance, half of the states utilized a direct mail campaign to contact potential CHIP enrollees. A number of states contracted with advertising firms to promote the program. Many states offered a simultaneous Medicaid and CHIP application, simplified their application forms, set up toll-free helplines, established websites, increased staff size, offered staff assistance in filling out forms, and allowed families to mail in their forms rather than having

[1] The program was set up through a series of capped matching grants, with the federal government paying about 65-85 percent of the program's cost, giving a higher matching rate to states with lower per capita incomes.

[2] Under the combined approach, children meeting particular criteria (such as household income below a certain percent of the FPL) enroll in the Medicaid part of CHIP, while others enroll in the separate program.

[3] The TennCare program in Tennessee, adopted through a Medicaid waiver, allows all children to take part in the state's public health insurance program. Tennessee's cost sharing measures provide the main limitation on program size.

to drop them off in person. Taken together, twelve such activities and devices were identified in the state plans. On average, states adopted seven of these measures, ranging from eleven in California down to just three in Nevada and North Dakota.

Beyond these initial policy choices, states amended their programs many times. The more substantive of these changes were sent to CMS for approval. By the end of 2001, more than one hundred state amendments had been approved by CMS, and forty-nine of these amendments substantively changed the state policies listed in Table 1.[4] Often these changes altered many program characteristics simultaneously, such as when Mississippi expanded its program in 1999 to 200 percent of the FPL, while also adding copayments.

The time-varying policy parameter that serves as the centerpiece of our analysis is the eligibility threshold. Changes in eligibility standards meant that new groups of children were exposed to the possibility of receiving public health insurance. Figures 1a and 2a show the number of states with thresholds in various ranges of the FPL by year over the period 1997 to 2002, for both younger and older children. The staged shift toward higher thresholds between 1997 and 1999 is largely driven by the differential timing of implementation of the CHIP program across states. The continued shifts between 1999 and 2000 are primarily due to amendments to existing programs.

Figures 2a-e provide an alternative view of the eligibility expansions over time. These figures show, by year, the average share of months children in different income ranges are calculated to be eligible for CHIP. The statistics are based on the nationally representative ECLS-K sample described in more detail below, and includes children from 39 states.[5] To calculate eligibility, we assign to each child household income as a share of the FPL as reported by his/her parent in the kindergarten survey. The share of months each child is eligible in each year is then calculated holding income constant, but allowing the child to age and state policies to evolve. These values are then averaged across children within the same income group, using the survey weights provided. The figures show a steady progression over the years to near universal eligibility for children in households with income below 200 percent of the FPL, as well as more limited expansions beyond that level. The downward dip in eligibility for near-poor households in 1999 and 2000 reflects children aging onto the often more-restrictive program that applies to older children.[6] Figure 5 shows that there was a coincident decline in the share of children without any insurance and increase in the share with Medicaid/CHIP enjoyed by low-income children across the distribution.

Theoretically, this variation over time and across the states, both in their preexisting Medicaid policies and in their initial and subsequent CHIP eligibility rules, provides ample opportunity to determine whether the availability of public health insurance affects take-up, crowd-out, health care utilization, and positive health and educational outcomes—for those children with household income in ranges that were affected. Although we have not compiled information on the other time-varying program characteristics, we are also able to explore

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[4] Many other changes dealt with administrative matters or disparate aspects of child health and safety (such as the provision of car safety seats in Texas).

[5] Ten states are not represented in the ECLS-K sample (Arkansas, Idaho, Montana, Nebraska, Nevada, New Hampshire, North Dakota, South Carolina, Vermont, and West Virginia). We also exclude Tennessee, which essentially had universal eligibility over the entire period, so provides no over-time or cross-group policy variation.

[6] Given the program rules, otherwise similar children in higher income ranges should always be less likely to be eligible for CHIP than children in lower income ranges. The apparently anomalous upward ticks for those at 250 percent of the FPL in 2001 and 2002 are due to small-sample variation in the representation of specific states across these narrow income groups in our sample.

whether expanded eligibility has differential effects depending on a state's initial program characteristics. Holding the income-eligibility rules constant, the type of program and its benefits may affect enrollment due to the stigma attached to Medicaid and the attractiveness of services offered. The waiting period also affects eligibility and access to the program. The monthly premium and copayments make the program less affordable, but at the same time may affect program perceptions by moving away from a direct government handout. And, outreach aids affect whether families would even be aware of the opportunities available to them. By analyzing the choices of income-eligible families exposed to different CHIP programs, we will have a better sense of which aspects of these programs affected behavior.

2.2 Related literature

To date, most research on CHIP has focused on access to health care and its use by newly-created beneficiaries. Considerably less work examines issues of program take-up and possible substitution away from private into public coverage. The lack of research on crowd-out is especially surprising since CHIP expanded public health insurance to children in families with incomes between 100 and 200 percent of the FPL (and in some cases even higher), where over half were already covered by some form of health insurance. We are unaware of existing research linking the CHIP expansion to child health or academic outcomes. There is a large existing literature considering all of these questions—program participation, crowd-out, utilization, and health outcomes—with respect to the earlier Medicaid expansions, and we refer to the most relevant studies from this literature as well.

CHIP, coverage dynamics

Although research on CHIP-induced take-up of public insurance and potential crowd-out of private insurance is limited, several studies do focus on trends in child health insurance coverage around the time of program implementation in an attempt to attribute effects to CHIP (e.g., Selden et al., 2004; Rosenbach et al., 2001; Zuckerman et al., 2001). Selden et al. (2004), the most recent of these studies, use data from the 1996, 1998, 2000 and 2002 waves of the Medical Expenditure Panel Survey (MEPS) and find descriptive evidence that CHIP increased both take-up and crowd-out.[7] In particular, the authors find that between 1996 and 2002 children in families with incomes between 100 and 200 percent of the of the FPL experienced an increase in coverage by public insurance of 12 percentage points, the largest increase among groups examined. They find that this increase was due to declines in both uninsurance and private health insurance coverage. With respect to the latter, they note that the decline in private coverage of nearly eight percentage points may reflect crowd-out.

In the most comprehensive study on coverage dynamics, LoSasso and Buchmueller (2002) find that CHIP had a statistically significant, though practically small, impact on child health insurance coverage. They use data from the 1996 to 2000 March Current Population Surveys and empirical methods similar to previous work on Medicaid expansions, as well as to the methods that we implement. In models that include state and year effects, they instrument for eligibility using the percentage of a nationally representative sample of children that would be eligible for public insurance in each state and year in order to isolate variation that comes solely from differences in eligibility rules. The authors find that 5-10 percent of newly CHIP-eligible children gained public insurance as a result of the program, and that there are no

[7] While MEPS data contain overlapping panels where individuals are followed for a period of thirty months, the authors appear to ignore the longitudinal aspect of their data and instead treat them as repeated cross sections.

significant differences by whether eligibility was expanded through Medicaid or a separate program.[8] These estimates are lower than the 20-25 percent marginal take-up rates under the Medicaid expansions of the early 1990s estimated by Shore-Sheppard (1997) and Cutler and Gruber (1996), but roughly equivalent to those found by Ham and Shore-Sheppard (2001). Their estimates of CHIP-induced crowd-out vary considerably from essentially no evidence of crowd-out in models that take parental reports of child health insurance status as completely accurate to 18-50 percent in models that assume certain types of misreporting by parents.[9] The larger magnitudes are consistent with estimates of crowd out associated with the Medicaid expansions (e.g., Shore-Sheppard, 1997; Cutler and Gruber, 1996). The best evidence to date, therefore, suggests that take-up rates may be lower as eligibility for public health insurance extends up the income distribution, but fears of exacerbated crowd-out do not appear warranted.

CHIP, access and utilization

Since its inception, researchers have been conducting assessments of state-specific CHIP programs (e.g., Kempe et al., 2005; Dick et al., 2004; Szilagyi et al., 2004; Damiano et al., 2003; Slifkin et al., 2002). In general, these studies evaluate program effects by comparing relevant outcomes before and after enrollment for a relatively small number of children. Collectively, they focus on outcomes such as whether the child has a "usual" source of care, the ease or difficulty with which parents are able to obtain different types of care (e.g., routine, acute, specialty) for the child, and parental assessments of care quality. These studies tend to find that enrollment in CHIP facilitates access to care and results in increased quality of care. A recent representative study is an assessment of Colorado's CHIP program by Kempe et al. (2005). These researchers find that parents reported greater access to health care providers for a variety of routine and acute health care needs and also reported declines in "unmet health needs". Rates of routine primary care and visits to specialists increased, while rates of emergency room and inpatient visits remained constant. While their findings are consistent with the notion that CHIP increased access to preventive medical services, it is difficult to attach a causal interpretation since they study only new public insurance enrollees.

By contrast, a nationwide study focusing on childhood immunization presents more ambiguous evidence. Using repeated cross-sectional data from the National Immunization Survey for the period 1995 to 2001, Joyce and Racine (2003) find that the probability that a child was up to date for the varicella vaccine increased by 7-16 percent among poor and near-poor children, relative to their non-poor counterparts whose immunization status should not be impacted by extended CHIP coverage.[10] However, the authors find little evidence of such increases for any of the additional three vaccines examined. Since the varicella vaccine was more recently introduced relative to the others examined, the authors posit that their findings may suggest that insurance coverage may be important for the timely adoption of new treatments.

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[8] The authors follow in implementing this strategy that uses "simulated eligibility" to instrument for actual eligibility status.

[9] LoSasso and Buchmueller (2002) are concerned that some parents may report a child having private health insurance when in actuality he or she is enrolled in public health insurance that, for example, contracts with a private firm. The authors note that such misreporting may attenuate estimates of crowd out and find evidence consistent with this possibility.

[10] Similar to other authors, Joyce and Racine (2003) label children in families with incomes below the federal poverty line as "poor", with incomes between 100 and 250 percent of the federal poverty line as "near-poor" and above 250 percent as "non-poor".

CHIP, child health outcomes

While there are no studies relating CHIP to child health outcomes of which we are aware, there are again closely related studies of the Medicaid expansion. Two of the most relevant studies are by Currie and Gruber (1996a; 1996b). Both of these studies use simulated eligibility to instrument for actual eligibility status, as we do. The first paper analyzes the impact of Medicaid expansions on infant health via variation in the timing and generosity of the public insurance eligibility of pregnant women, while the second analyzes child health from the same perspective. The authors find sizeable effects on both infant and child mortality.[11] They also find increases in utilization which may rationalize their mortality findings.

Contrary to these two studies, a study by Haas et al. (1993) does not find health benefits associated with an eligibility expansion to women further up the income distribution. A Massachusetts state program expanded health insurance coverage to women up to 185 percent of the FPL, while Medicaid only provided coverage up to 100 percent. The authors examine records for nearly all live births in 1984 (pre-expansion) and 1987 (post-expansion) and find no evidence that greater health insurance eligibility reduced cases of low birthweight or premature birth. However, the authors are not able to consider the possibility that newly insured women left private health insurance for public coverage, which might attenuate their estimates.

Notably, the existing studies consider only relatively extreme child health outcomes, and very early ones. A major advantage of our study is the broad access that we have to a wide range of childhood outcomes over the early years of health and human capital acquisition.

3. Data and empirical strategies

3.1 Data

Because the nature of the data plays an important role in how we structure our empirical analyses, we begin with a brief introduction to the Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K). The ECLS-K began as a nationally-representative sample of roughly 22,000 kindergartners from about 1,000 public and private schools in the United States. In the study's base year (school year 1998-99), data were gathered both in the fall (1998) and the spring (1999) in order to study issues related to the child's progression through the first year of formal schooling. To date, there have been three follow-up surveys of original sample members.[12] The first of these occurred in the spring of 2000, when most students were enrolled in the first grade. A second follow-up was conducted in the spring of 2002, at which time the majority of students had progressed to third grade. Finally, a third follow-up was conducted in the spring of 2004, when most children were enrolled in fifth grade. Data from the fifth-grade survey are not currently available to researchers. All existing waves contain a rich set of child-specific information as reported by parents, teachers and school administrators, as well as formal assessments of the child's abilities, disabilities, and physical condition. In addition, information on the child's family, school and neighborhood is also collected, allowing for a complete characterization of the child's resources and environment. Importantly, the state of residence is

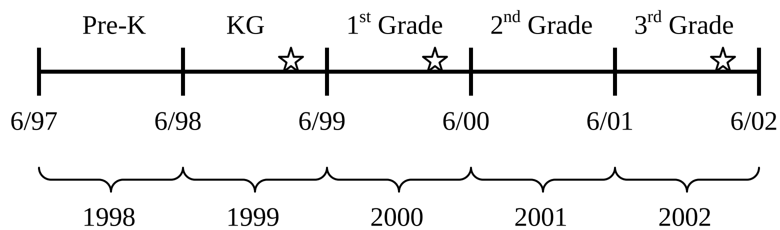
[11] Specifically, they find that the average increase in eligibility (30 percent) led to a decline in the infant mortality rate of nearly nine percent. Child mortality fell by about 1.3 deaths per 10,000 children, off a base of 3.1 deaths. In a similar study that uses variation in the timing in which different provinces enacted universal coverage in Canada, Hanratty (1996) finds a reduction in infant mortality of about four percent.

[12] In addition, there was a first grade survey conducted in the fall of 2000 designed for study of the phenomenon of summer fall-back in achievement, but it includes only a 25 percent sub-sample of the original sample.

identified in the restricted-use version.

Our baseline sample includes students who participated in all three available surveys—in kindergarten, first grade, and in third grade. The size of the longitudinal sample shrinks moving forward in time, primarily due to the explicit policy that determines whether children are tracked as they move schools. Students who do not remain in the initial or the on-track school are randomly selected to be interviewed in subsequent years at a rate of approximately 50 percent.[13] Nearly 12,000 students were tracked through all three grades. Although we rely on this larger sample for some of the descriptive analysis, the regressions are based on the subset of 6,720 students that report income between \$20,000 and \$75,000 in kindergarten—since this is the group of near poor and moderate income students potentially affected by the expansion.

Our first glimpse of students' health insurance status is in spring 1999. This is nearly two years after the CHIP program was first introduced, and after the initial dramatic expansion in eligibility that occurred between 1997 and 1999.[14] However, this first report does precede the more gradual increases in eligibility thresholds that have continued to occur. We design our empirical strategies in order to analyze the impact of eligibility on an annual basis, for the years 1997-98 through 2001-02. We organize years into academic calendars, from July to June, and label the year with the year associated with June. For example, we refer to the academic year July 1997 to June 1998 as 1998. The time line below clarifies how our observations coincide with the period of study.



The stars indicate the (approximate) dates of the spring parent interviews that provide the health insurance information. Each spring, parents were interviewed and students were assessed between March and early July.

3.2 First-stage ordinary least-squares empirical strategies

Our empirical strategies for analyzing how eligibility affects pubic and private health insurance coverage status are similar to those used by others in the literature. We begin with a static model of parents' decisions over their child's health insurance.[15] We presume that parents' underlying utility from any given source of coverage at a point in time can be represented by a latent index function. Applying a linear probability model yields the following generic equation:

$$H_{ist}^{k} = \alpha^{k} + \beta^{k} Elig_{ist} + \Gamma^{k}\mathbf{X}_{ist} + \delta_{s}^{k} + \lambda_{t}^{k} + \varepsilon_{ist}^{k}, \qquad (1)$$

where *i* indicates the family, *s* the state of residence, and *t* the year. *H* is an indicator for having coverage of a given type, *k*, which for our purposes is private, public, or any. The propensity to opt for a given a given type of coverage (or any coverage) for their child depends on program

[13] Longitudinal weights are provided that account for attrition due to this sampling scheme, as well as due to any non-response.
[14] Only two states introduced their programs after May 1999—Hawaii and Washington—both on January 1, 2000.
[15] See Ham and Shore-Sheppard (2001) for an insightful comparison of various static and dynamic empirical models of health insurance coverage.

eligibility (*Elig*). Demographic characteristics that might affect preferences over health insurance ($\mathbf{X}$) also enter the equation, as well as state (δ_s) and year (λ_t) indicators to capture unmeasured influences.

In this framework, the coefficient β^{public} measures the extent to which eligible families participate in the public health insurance program. The coefficient $\beta^{private}$ captures the extent to which parents choose to substitute public for private insurance—or the extent of crowd-out. A measure commonly used to gauge the share of public insurance take-up attributable to previously privately insured individuals is $\left|\beta^{private}\right| / \beta^{public}$. One of the reasons that we also estimate models with "any health insurance coverage" as the dependent variable is that our second-stage analysis is concerned with the impact of having health insurance coverage per se on child outcomes. The coefficient β^{any} measures the net increase in health insurance coverage associated with granting eligibility for public health insurance. In addition to estimating these average responses, we can also include interactions between eligibility and key state program characteristics to see how those affect coverage choices.

In order to estimate the causal relationship between eligibility and health insurance coverage choices, it is important to isolate variation in current eligibility that is not otherwise correlated with unobserved or omitted factors that directly affect health insurance coverage decisions. Current eligibility is determined by the eligibility rules in the state where one resides, household income as a percent of the relevant federal poverty guideline (as determined by household size), and child's age. Although it is clearly feasible to control for each of these independently, relevant interactions between these variables may matter as well. For example, different types of households may have different underlying propensities to insure depending on the state, perhaps due to correlated income support policies. In addition, current eligibility may be correlated with past eligibility, so that an omitted variable may be length of exposure to the program. One way to address these problems of omitted variables is to estimate a first-difference model evaluating changes in coverage between any two years:

$$\Delta H_{ist}^{k} = \mu^{k} + \beta^{k}\Delta Elig_{ist} + \Gamma^{k}\Delta\mathbf{X}_{ist} + \Delta\varepsilon_{ist}^{k}, \qquad (2)$$

where Δ indicates the change from the prior to the current year. First-differencing removes time invariant individual-specific and location-specific characteristics, and any time-invariant interactions between the two. In equation (2), β^{k} is identified from differential changes in eligibility across individuals as they correlate with changes in health insurance status. Providing that there is sufficient variation in changes in eligibility, it is also possible to add state fixed-effects (and time-invariant household characteristics) to this model to allow for the possibility of differing trends in coverage.[16]

This is the first method that we implement, considering changes between kindergarten and first grade, kindergarten and third grade, and between first and third grade. For each grade, eligibility is defined as the share of months during the academic year that the student is eligible for the program, based on age by month and the spring report of annual household income as a percent of the federal poverty guideline. Although the health insurance responses refer to a point

[16] In models that do not include state fixed effects, we correct for unspecified correlation in the error terms within states when calculating standard errors.

in time, the information on the specific timing of the report is not known to the researcher, so that it is not obvious that a more precise alternative would be more appropriate.[17]

The amount of detail available on health insurance in the ECLS-K varies by survey year. The kindergarten survey includes only limited information on health insurance coverage—simply whether the child has *any* coverage.[18] In the later two surveys, parents were asked the type of coverage as well.[19] We use this information to separately identify three coverage sources—private health insurance, Medicaid or CHIP, other public insurance—and no coverage.[20] Comparing first to third grade, then, we are able to consider marginal crowd-out and take-up, in addition to changes in net coverage.

A weakness with the first-difference model is the absence of any dynamics in the health coverage decision, such as dependence on prior status. Therefore, we also estimate a model in levels and consider longer-run measures of eligibility. Rather than treat the data as a series of repeated cross-sections, we alter equation (1) to include cumulative eligibility:

$$H_{ist}^{k} = \alpha^{k} + \beta^{k} CumElig_{ist} + \Gamma^{k} \mathbf{X}_{ist} + \delta_{s}^{k} + \varepsilon_{ist}^{k} \qquad (3)$$

The year effects are no longer necessary since we estimate the equation separately by grade level. The key independent variable is defined to be the share of months eligible for the program since the beginning of either the kindergarten academic year (July 1998), or the pre-kindergarten academic year (July 1997).[21] The vector $\mathbf{X}$ also now includes histories of family characteristics over preceding years for the later grades. In addition to considering current coverage, we also estimate models where the dependent variable is specified as the share of years with any health insurance coverage. Since state fixed effects and detailed household characteristics are included, the eligibility parameter in this model is identified by differential insurance coverage rates across higher and lower income individuals across states that expanded coverage at different rates and to different parts of the income distribution. The results will be misleading to the extent that pre-existing differences in coverage across these groups across states is correlated with chosen policies. A great advantage of this approach is that it allows us to incorporate the early, more dramatic policy expansions.

3.3 Simulated instrumental variables

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[17] Ham and Shore-Sheppard (2001) note that most studies of health insurance coverage use data sources (such as the Current Population Survey) that present this same ambiguity about the appropriate time frame over which to calculate eligibility. These authors analyze the more frequent monthly data available in the Survey of Income and Program Participation.

[18] The relevant question asked of the parent respondent (typically the mother) is: "Is the child now covered by a health insurance plan which would pay any part of a hospital, doctor's or surgeon's bill?"

[19] The relevant question is: "What kind of health insurance or health care coverage does the child have? By health insurance coverage I mean any kind of coverage that pays for health care expenses. Please do not include private plans that only provide extra cash while hospitalized." The specific types of coverage referenced are: private, Medicaid or other state plan, CHIP or other state plan, military, another government plan or no coverage.

[20] We chose not to separate CHIP and Medicaid coverage given the existence of combined plans and plans implemented via extensions to Medicaid. For cases where parents reported multiple sources of coverage, we used a priority to assign children to a unique primary category. Children covered by CHIP/Medicaid were assigned to that category alone. Remaining children reported to have both private and other public insurance, were assigned to the private insurance category.

[21] We use household income as a percent of the federal poverty guidelines from the 1999 survey to calculate eligibility in 1998, and from the 2002 survey to calculate eligibility in 2001. Otherwise, we use household income as of spring of the relevant survey year. In all cases, we allow the child's age to vary over the course of the year.

While the two models that we implement suffer from different theoretical limitations, they share a practical difficulty given our use of survey data. There are several sources of measurement error in our calculation of eligibility, and especially changes in eligibility, that would be expected to bias our estimates. The first stems from the way that income information is collected in the ECLS-K. In the spring of kindergarten, household income was elicited as a continuous measure using an effective initial bracketing technique. In the later two grades, income information was gathered only by thirteen income brackets for most respondents, by increments of $5,000 from $0 to $40,000, then $40-$50,000, $50-$75,000, $75-$100,000, $100-200,000, and over $200,000.

A second source of measurement error comes from the uncertain timing of the parent interviews, as mentioned above. Although each child's birthdate is known, so that which age-specific schedule is appropriate can be readily determined for any given date, it is not clear when within a nearly five-month period the health insurance report applies. This leads to especially noisy proxies for children during kindergarten, since many students transition from the younger age group (1-5 years of age) to the older age group (6-14 years of age) during that academic year.

To address these concerns, we follow a similar approach to the one used by Cutler and Gruber (1996) and LoSasso and Buchmueller (2002) and simulate a child's eligibility based only on the reported income bracket, state, and year. We use the full nationally-representative sample of children in the longitudinal sample in the kindergarten year, when income was reported continuously. Holding income as a percent of the FPL constant, we determine whether each child is income-eligible in each state in every month of our sample period given this fixed income, his/her evolving age, and the evolving state eligibility schedule. We then calculate the average share of months (weighting by the survey weights) that children in the broad income categories available in the other two survey years are eligible in each year by state. The state-income group average serves as an instrument for the share of months of eligibility calculated based on the child's own age and reported income. In order to also address the possibility that income might evolve endogenously with policy parameters and to clearly isolate policy-induced changes in eligibility rather those due to changes in economic circumstances, we classify children in our analysis sample into income groups based on income reports in their kindergarten year when assigning our simulated eligibility measures.

The sample of children that we include in our empirical analyses includes only those with reported household income between $20,000 and $75,000 in the kindergarten survey. A reason to exclude poor students (i.e., those with income below $20,000), is that this group experienced no policy-induced changes in eligibility and is likely to have been affected over the same period by changes in welfare policy.[22] We restrict the sample from above as well to exclude children from high-income families who are not likely to serve as a useful control group for treated children.

Figure 3 shows the variation in the average share of months eligible by year and the six relevant income groups for our analysis sample. There is a shared upward trend in eligibility across all size groups. The substantial heterogeneity in this time pattern across states that is masked in Figure 3 is shown in Figures 4a-f. While Figure 3 uses eligibility calculated based on own current characteristics, Figure 4 uses our simulated eligibility measure based only on state of residence and initial income.

[22] LoSasso and Buchmueller (2002) find that the trends for children below 100 percent of the FPL display confounding effects of the welfare reform.

3.4 Second-stage empirical strategies

We utilize the first-stage relationships estimated between eligibility and health insurance coverage to explore second-stage impacts on child outcomes. The first-difference approach provides us with a means to identify plausibly exogenous changes in health insurance status between years. In order to estimate how newly acquired health insurance affects innovations to outcomes, we relate changes in outcomes to changes in health insurance status, in an estimation model analogous to equation (2). We instrument for changes in health insurance status, which would otherwise clearly be endogenous, using the simulated change in eligibility.

The levels approach delivers instead variation in either current or cumulative health insurance status, which allows us to consider whether health insurance status affects utilization and outcome levels and/or trajectories—consistent with arguably a more plausible underlying model of how health affects development for outcomes and behaviors other than utilization. In models that relate child outcomes to current or cumulative health insurance status (analogous to equation (3)), we again use simulated eligibility over the relevant time period as an instrument.

Although the timing of the data collection requires some compromises, the ECLS-K data provide advantages in terms of the scope of behaviors and characteristics that are measured over time. On utilization, the data contain questions regarding access to routine medical care as well as routine dental care. All waves also include detailed information about child evaluations, diagnoses, and services for a variety of disabilities. Conditional on parent early identification of concerns (e.g., questions about child's difficulty with hearing, vision, speech, and learning are asked in the fall of kindergarten and in subsequent waves), we can ascertain whether those eligible for public insurance were more likely to seek evaluations and to obtain diagnoses in subsequent years. In addition to disability status, the other health outcome measure available to us is based on BMI. Child's height and weight were measured and recorded by the assessor, allowing us to construct measures of obesity, overweight, and underweight conditions.[23]

Given the intended educational focus of the ECLS-K, we have a wide variety of academic achievement and attainment outcomes available to us. The ECLS-K contains two survey components that assess a child's academic development—*direct* and *indirect* cognitive assessments. Both assessments attempt to measure the child's current ability in reading and mathematics. The direct assessment involves tests that are administered to the student, and teachers provide the indirect assessment of the child based on knowledge from having the child in his/her classroom. The ECLS-K also contains information on child school absences as well as grade repetition. Table 2 presents summary statistics for the outcome variables for the analysis sample by grade.

4. Empirical results

4.1 Health insurance coverage

We begin the presentation of our empirical results with the first-stage analyses of the impact of expanded eligibility on health insurance coverage, take-up, and crowd-out. Broad time patterns in health insurance coverage for our analysis sample are shown in Table 2. The rate of any coverage increased from 90.5 percent in 1999 to 94.7 percent in 2002. Over the same period, the rate at which students went without any coverage fell from 9.5 to 5.3 percent, and the

[23] We use standard growth charts by age and gender to determine the applicable BMI cut-offs for each of these categories.

rate of Medicaid/CHIP participation increased from 12.8 to 17.1 percent. Table 4 presents the individual transitions underlying these aggregate shifts. Between 1999 and 2000, about 15 percent of students who had reported having no insurance gained Medicaid/CHIP coverage. The same figure is 33 percent between 2000 and 2002. Of students with private insurance in 2000, 15 percent report Medicaid/CHIP coverage in 2002. To what extent are the transitions shown in these matrices driven by changes in eligibility?

The regression results in Table 5 present our first-difference estimates of the various transitions, based on the specification described in equation (2). The change in the simulated share of months eligible across the relevant survey years is used to instrument for the change calculated based on own characteristics. Recall that any variation in the simulated measure over time is attributable only to the structure of state policies. The regressions include the full set of levels and changes in the background characteristics described in Table 3. This includes indicators for each of the six income categories determined by household income in the kindergarten survey, which is the income measure used to assign the simulated eligibility measures. Each cell reports the coefficient on the change in eligibility from a separate regression.

The estimated net coverage effects of expanded eligibility shown in the first column are highly statistically significant for the transitions between kindergarten and third grade, and between first and third grade. The lack of significance for the single-year kindergarten to first grade transitions compared to the other longer-term transitions may be a signal that there are underlying dynamics in health insurance coverage decisions across time for families that are not accounted for in the first-difference model. We focus the discussion on the estimates for transitions between first and third grades, since for these grades we can analyze transitions by type of insurance. The coefficient on the share of months eligible is 0.102 for any health insurance coverage, 0.114 for Medicaid/CHIP coverage, and -0.039 for private coverage (although this last estimate is not statistically significant). The point estimates are very much in-line with those found by LoSasso and Buchmueller (2002) and suggest that that take-up is relatively strong. The absolute ratio of the private to the Medicaid/CHIP coefficient implies that the fraction of take-up attributable to crowd-out is on the order of 30 percent, although this is clearly tentative given the lack of precision. Assuming that the difference between the net increase in any coverage and in public coverage is due to crowd-out generates a back-of-the-envelope estimate closer to 10 percent. The estimated coefficients for any health insurance coverage and Medicaid/CHIP coverage are robust to including state fixed effects, as we do in the second column, and the estimated coefficient for private insurance coverage remains statistically insignificant.

In results not shown, we included interactions between the change in the share of months eligible and initial state program characteristics. Implementing the CHIP program via an extension of Medicaid is significantly negatively related to take-up and positively related to private insurance, while the existence of cost-sharing has the reverse relationships. Although these estimated interactions are statistically significant, including them produces estimates outside the bounds of zero and one too frequently for them to be taken too seriously.

Table 6 presents the health insurance coverage analysis based on the levels specification described in equation (3). The dependent variables are cumulative, measuring the share of years with any form of health insurance coverage across elapsed surveys. The key independent variable is the cumulative share of months eligible since July 1999 (in column 1) or July 1998 (in column 2) up until June of the survey year. Simulated cumulative eligibility, based only on initial income and state of residence, is used as an instrument for a child's own cumulative eligibility. In addition to a detailed set of background and location characteristics, these specifications include state fixed effects and indicators for each of the six initial income categories.

The pattern of estimated coefficients across grades is broadly consistent with a growing take-up response with additional exposure to eligibility. The shorter-run take-up response for kindergarten is very similar in magnitude to the estimates from the first-difference specifications. Here we again see evidence that eligibles appear to be less likely to participate in states that implemented their program via Medicaid expansions. This could perhaps reflect that there is stigma associated with participation in the pre-existing transfer program. None of the interactions between eligibility and the other key initial program characteristics is significant.

4.2 Health care utilization and child health and academic outcomes

We intended to analyze the impact both of health insurance transitions and of health insurance status on utilization and outcomes. Unfortunately, the second-stage estimates from the first-differences specification were simply too noisy to be informative for any of the outcome measures. We are in the process of analyzing the outcome data using the levels specification, and have only preliminary results to report.

Table 7 shows the results from estimating a reduced form model for the medium term—after kindergarten and first grades. Rather than using the simulated cumulative share of months of eligibility (since July 1998) as an instrument for a composite health insurance measure, we include the simulated measure directly. Each row corresponds to a different outcome measure, where these dependent variables are composite measures based on combined kindergarten and first-grade experiences. Although many of the estimates are imprecise, the general pattern is one of increased access to medical care and evaluative services, with no clear evidence of health or academic benefits. In a future draft, we plan to incorporate additional sources of variation (such as time-varying income reports) into our simulated measures in an attempt to increase precision.

5. Conclusion

[To be added.]

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Table 1. Characteristics of initial state CHIP plans

State	Type of CHIP Program	Maximum Eligibility	Benefits Same as For…	Waiting Period	Monthly Premium?	Copay?	Outreach Aids (#)
Alabama	Medicaid	133% FPL	Medicaid	None	No	No	8
Alaska	Medicaid	200% FPL	Medicaid	12 months	No	No	9
Arizona	Separate	200% FPL	State Employees	6 months	No	No	7
Arkansas	Medicaid	133% FPL	Medicaid	None	No	No	8
California	Combined	200% FPL	State Employees	3 months	Yes	Yes	11
Colorado	Separate	185% FPL	State Employees	3 months	Yes	Yes	9
Connecticut	Combined	300% FPL	State Employees	6 months	Yes	Yes	8
Delaware	Separate	200% FPL	State Employees	6 months	Yes	Yes	6
Florida	Combined	185% FPL	State Employees	None	Yes	Yes	7
Georgia	Separate	200% FPL	Other Benchmark	3 months	Yes	No	6
Hawaii	Medicaid	185% FPL	Medicaid	None	No	No	7
Idaho	Medicaid	160% FPL	Medicaid	None	No	No	4
Illinois	Medicaid	133% FPL	Medicaid	None	No	No	9
Indiana	Medicaid	150% FPL	Medicaid	None	No	No	7
Iowa	Medicaid	185% FPL	Medicaid	None	No	No	4
Kansas	Separate	200% FPL	State Employees	6 months	Yes	No	5
Kentucky	Combined	200% FPL	State Employees	6 months	Yes	Yes	9
Louisiana	Medicaid	133% FPL	Medicaid	3 months	No	No	8
Maine	Combined	185% FPL	Medicaid	3 months	Yes	No	7
Maryland	Medicaid	200% FPL	Medicaid	6 months	No	No	8
Massachusetts	Combined	200% FPL	Other Benchmark	None	Yes	No	6
Michigan	Combined	200% FPL	State Employees	6 months	Yes	No	6
Minnesota	Medicaid	280% FPL	Medicaid	None	No	No	7
Mississippi	Medicaid	133% FPL	Medicaid	None	No	No	4
Missouri	Medicaid	300% FPL	Medicaid	6 months	Yes	Yes	6
Montana	Separate	150% FPL	Other Benchmark	3 months	Yes	Yes	4
Nebraska	Medicaid	133% FPL	Medicaid	None	No	No	8
Nevada	Separate	200% FPL	Medicaid	6 months	Yes	No	3
New Hampshire	Combined	300% FPL	Other Benchmark	6 months	Yes	Yes	10
New Jersey	Combined	200% FPL	Other Benchmark	12 months	Yes	Yes	9
New Mexico	Medicaid	235% FPL	Medicaid	12 months	Yes	No	9
New York	Separate	185% FPL	Other Benchmark	None	Yes	Yes	5
North Carolina	Separate	200% FPL	State Employees	2 months	Yes	Yes	9
North Dakota	Medicaid	133% FPL	Medicaid	None	No	No	3
Ohio	Medicaid	150% FPL	Medicaid	None	No	No	6
Oklahoma	Medicaid	185% FPL	Medicaid	None	No	No	7
Oregon	Separate	170% FPL	Other Benchmark	6 months	No	No	7
Pennsylvania	Separate	185% FPL	Other Benchmark	None	Yes	No	7
Rhode Island	Medicaid	250% FPL	Medicaid	None	Yes	Yes	7
South Carolina	Medicaid	185% FPL	Medicaid	None	No	No	7
South Dakota	Medicaid	133% FPL	Medicaid	None	No	No	5
Tennessee	Medicaid	No limit	Other Benchmark	None	Yes	Yes	6
Texas	Medicaid	185% FPL	Medicaid	None	No	No	6
Utah	Separate	200% FPL	State Employees	3 months	No	Yes	7
Vermont	Separate	300% FPL	Medicaid	1 month	Yes	Yes	5
Virginia	Separate	185% FPL	Other Benchmark	12 months	No	No	6
Washington	Separate	250% FPL	Medicaid	4 months	Yes	Yes	4
West Virginia	Medicaid	150% FPL	Medicaid	None	No	No	9
Wisconsin	Medicaid	185% FPL	Medicaid	None	No	No	9
Wyoming	Separate	133% FPL	Medicaid	None	No	No	5

Sources: Centers for Medicare and Medicaid Services website, and Riley and Pernice (1998).

Table 2. Summary statistics for health insurance and outcome variables

Variable	Spring of Kindergarten	Spring of 1st grade	Spring of 3rd grade
Health insurance status and eligibility			
Has health insurance coverage[1]	0.905	0.916	0.947
Private health insurance[1]	–	0.776	0.758
Medicaid/CHIP[1]	–	0.128	0.171
Other public insurance[1]	–	0.013	0.018
Uninsured[1]	0.095	0.084	0.053
Continuously insured[1]	NA	0.866	0.842
Share of elapsed survey years insured[1]	NA	0.911	0.923
		(0.243)	(0.200)
Share of months eligible for CHIP current year	0.256	0.351	0.422
	(0.420)	(0.463)	(0.494)
Cumulative share of months eligible (as of 7/98)	NA	0.303	0.358
		(0.395)	(0.395)
Student outcomes			
Less than one year since last routine doctor visit[1]	0.944	0.861	0.833
Less than one year since last visit to dentist[1]	0.833	0.877	0.908
Obese (BMI above 95th percentile)	0.116	0.135	0.191
Overweight (BMI above 85th percentile)	0.272	0.272	0.356
Underweight (BMI below 5th percentile)	0.033	0.033	0.023
In very good/excellent health[2]	0.842	0.856	0.852
Has a disability[2]	0.142	0.169	0.287
Receives special education services[1]	0.113	0.065	0.047
Has a learning problem[2]	0.271	0.209	0.242
Evaluated for a learning problem[2]	0.143	0.103	0.124
Diagnosed with a learning disability[2]	0.095	0.081	0.097
Enrolled in lower grade-level than peers	NA	0.038	0.082
Share of days absent	0.055	0.050	0.036
	(0.081)	(0.095)	(0.050)
Math scale score	27.89	43.72	85.19
	(8.54)	(8.93)	(17.28)
Reading scale score	32.56	56.37	108.59
	(10.07)	(13.22)	(18.96)
Math proficiency teacher rating	3.58	3.48	3.12
	(0.84)	(0.89)	(0.74)
Reading proficiency teacher rating	3.42	3.48	3.34
	(0.79)	(0.90)	(0.86)

Notes: The cells show the mean for the variable indicated in each row (standard deviations are also shown for continuous variables in parentheses) for the survey year indicated by the column heading. The statistics are based on the sample of 6,720 students whose parents provided valid health insurance information in all three spring surveys and reported household income between $20,000 and $75,000 in kindergarten (excluding students with either missing state identifiers or who were located in Tennessee). The statistics are weighted using the longitudinal weight provided in the ECLS-K that is appropriate to students with completed parent interviews in all three survey years.

[1] Information is from parent spring reports in each survey year.

[2] Information is from parent spring reports in first and third grades, and from parent fall reports in kindergarten.

Table 3. Summary statistics for control variables

Variable	Mean	Variable	Mean
Student Characteristics		*Family characteristics*	
Male	0.518	Two-parent family[1]	0.814
Age[1]	6.14	Age of parent respondent (R)[1]	32.90
Student race/ethnicity		R is in very good/excellent health	0.674
White	0.627	R has a work limitation	0.077
Black	0.123	Parents' highest education level	
Hispanic	0.179	Less than a high school degree[1]	0.059
Asian	0.036	High school degree[1]	0.277
Other race/ethnicity	0.036	Up to 4 years of college[1]	0.264
Home language is not English	0.105	College degree or higher[1]	0.264
Head Start participant before KG	0.111	Household size[1]	4.48
Received WIC benefits as infant	0.442	Number of siblings[1]	1.40
Economic circumstances		*Location characteristics*	
Cash welfare receipt past 12 mths[1]	0.023	Large city	0.149
Food Stamp receipt past 12 mths[1]	0.057	Mid-size city	0.211
Household income		Large suburb	0.287
\$20,000-\$25,000[1]	0.144	Mid-size suburb	0.089
\$25,000-\$30,000[1]	0.141	Large or small town	0.139
\$30,000-\$35,000[1]	0.098	Rural area	0.124
\$35,000-\$40,000[1]	0.119	Share minority students in school	0.359
\$40,000-\$50,000[1]	0.194		
\$50,000-\$75,000[1]	0.304		

Notes: Each cell shows the mean across kindergarten students for the variable indicated by the row heading (standard deviations are also shown for continuous variable in parentheses). The statistics are based on the sample of 6,720 students described in the notes to Table 2, and weighted using the same longitudinal weight.

[1] These variables can vary across the surveys for a given student, and the empirical analysis accounts for changes between surveys when appropriate.

Table 4. Health insurance transition rates

Spring Kindergarten	Insurance status Spring 1st Grade: Private	Medicaid/ CHIP	Other Public	Uninsured	Total
Has coverage	0.741	0.113	0.012	0.039	0.905
Uninsured	0.034	0.015	0.001	0.044	0.095
Total	0.775	0.128	0.013	0.084	

Insurance status Spring 1st Grade	Insurance status Spring 3rd Grade: Private	Medicaid/ CHIP	Other Public	Uninsured	Total
Private	0.687	0.056	0.011	0.021	0.775
Medicaid/ CHIP	0.034	0.083	0.002	0.009	0.128
Other Public	0.005	0.004	0.005	0.000	0.013
Uninsured	0.032	0.028	0.001	0.023	0.084
Total	0.757	0.171	0.019	0.053	

Notes: Each cell in the transition matrices shows the share of students with that combination of insurance statuses across two consecutive springs. The statistics are based on the sample of 6,720 students described in the notes to Table 2, and weighted using the same longitudinal weight.

Table 5. First difference estimation of transitions in insurance coverage

Dependent variable	Specification: Baseline	Specification: Including state fixed effects
Transition from kindergarten to first grade		
Any health insurance coverage	0.055 (0.048)	0.042 (0.105)
Transition from kindergarten to third grade		
Any health insurance coverage	0.093** (0.044)	0.085 (0.067)
Transition from first grade to third grade		
Any health insurance coverage	0.102** (0.035)	0.131** (0.043)
Medicaid/CHIP coverage	0.114** (0.046)	0.118* (0.066)
Private insurance	-0.039 (0.047)	-0.006 (0.069)

Notes: The results are based on linear regressions of the change in the health insurance coverage variable indicated on the change in the share of months eligible for CHIP, where the simulated share of months eligible is used as an instrument. The regression models also include levels and changes in the household and location characteristics shown in Table 3, including indicators for each of the six income categories. The sample consists of the 6,720 students described in the notes to Table 2, and observations are weighted using the longitudinal panel weight. Standard errors for the models without state fixed effects are adjusted for unspecified correlation across children from the same state.

Table 6. Levels specification of insurance coverage

Dependent variable	Definition of cumulative eligibility: Share of months since July 1999	Share of months since July 1998
Any health insurance coverage in kindergarten		
Coefficient on share of months eligible	0.112** (0.042)	0.154** (0.057)
Coefficient on share of months eligible	0.165* (0.088)	0.258** (0.117)
Coefficient on share × Medicaid program	-0.067** (0.034)	-0.106** (0.046)
Coefficient on share × cost-sharing	-0.023 (0.043)	-0.015 (0.052)
Coefficient on share × waiting period (mths)	0.003 (0.005)	0.006 (0.000)
Coefficient on share × outreach activities	-0.003 (0.009)	-0.009 (0.011)
Share of KG- and 1st-grade years covered		
Coefficient on share of months eligible	0.195** (0.047)	0.192** (0.047)
Share of KG-, 1st-, and 3rd-grade yeas covered		
Coefficient on share of months eligible	0.174** (0.056)	0.162* (0.057)

Notes: The results are based on linear regressions of the health insurance coverage variable indicated at the top of each panel on the cumulative share of months eligible for CHIP. Each cell reports either the coefficient on the cumulative share of months eligible (calculated from the start date indicated in the column heading), or the coefficient on the interaction between that share and an initial state program characteristic. In all cases, the simulated share of months eligible over the same period (and interactions with this variable when relevant) is used as an instrument for eligibility calculated based on own characteristics. The control set also includes levels in the household and location characteristics shown in Table 3 for any of the relevant grades represented in the coverage variable, as well as a full set of state fixed effects and indicators for the six income categories. The sample consists of the 6,720 students described in the notes to Table 2, and observations are weighted using the longitudinal panel weight.

Table 7. Levels reduced-form specification of the impact on outcomes

Dependent variable based on KG and 1st grades	Coefficient on simulated cumulative share of months eligible since July 1998
Never reported more than year between routine doctor visits	0.088** (0.042)
Never reported more than year between routine doctor visits	0.067* (0.036)
Ever evaluated for a hearing difficulty	0.098** (0.048)
Ever evaluated for a sight problem	0.046 (0.063)
Ever evaluated for a learning disability	0.101* (0.054)
Ever obese	-0.016 (0.043)
Ever overweight	-0.033 (0.057)
Math IRT score in 1st grade	1.48 (1.15)
Reading IRT score in 1st grade	1.14 (1.57)

Notes: The results are based on linear regressions of the dependent variable indicated in each row (cumulated over kindergarten and first grade) on the simulated cumulative share of months eligible starting July 1998 through the end of first grade. The control variables and sample are otherwise the same as described in Table 6.

Figure 1a. Eligibility Thresholds for Children Aged 1-5 Years

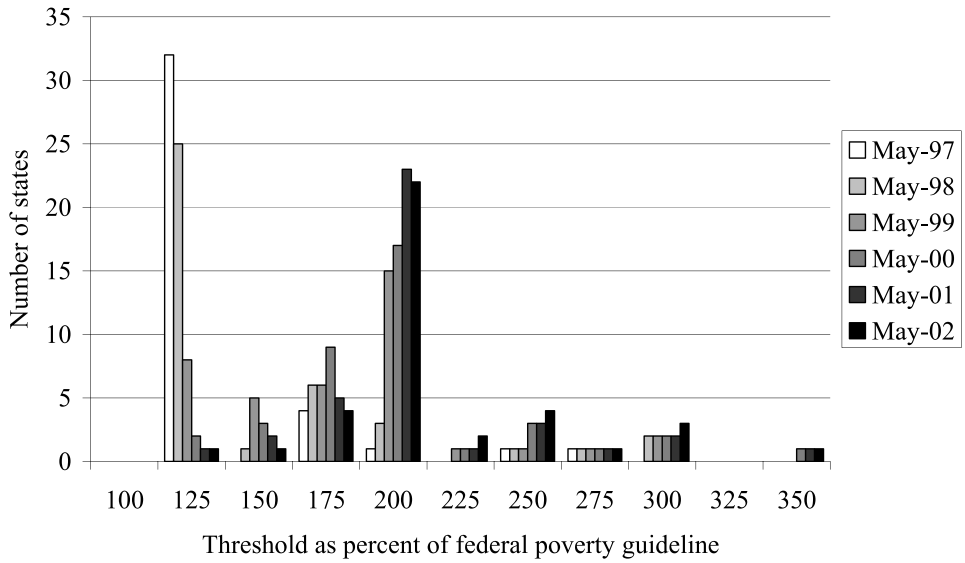
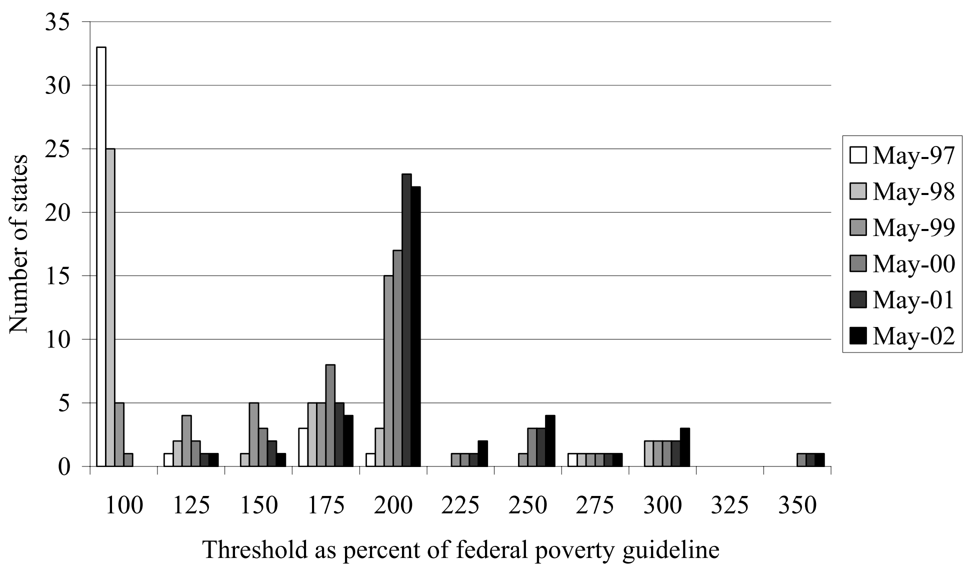


Figure 2a. Eligibility Thresholds for Children Aged 6-14 Years



Notes: The values on the horizontal axis represent the lower limits of 25 percentage point ranges of income as a percent of the federal poverty guideline. For example, the category “100” indicates eligibility thresholds ranging from 100 to 124 percent of the federal poverty guideline. The height of each bar shows the count of states (among the 39 states represented in our analysis) with eligibility policies falling into each range by year (as of May). Figure 2a describes the policies in place for younger children (aged 1-5 years), and Figure 2b describes those for older children (aged 6-14 years). Older and younger children are defined in the same way for all states except for Rhode Island, where the break point occurs at 8 years of age rather than 6 years.

Figure 2a. Average share of months eligible 1998

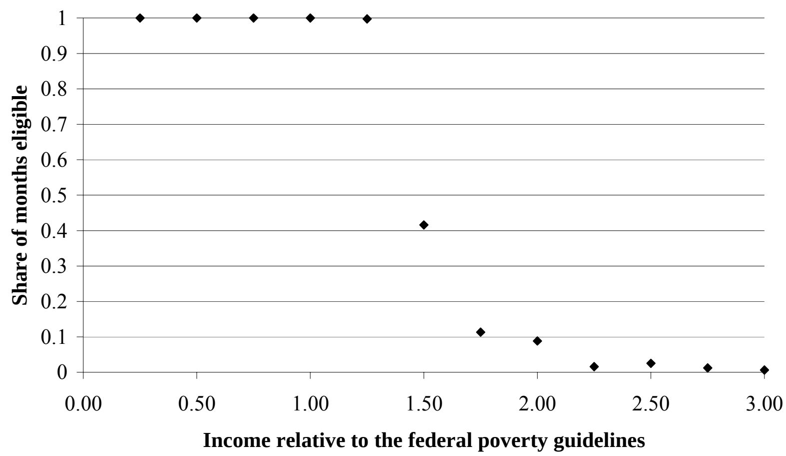


Figure 2b. Average share of months eligible 1999

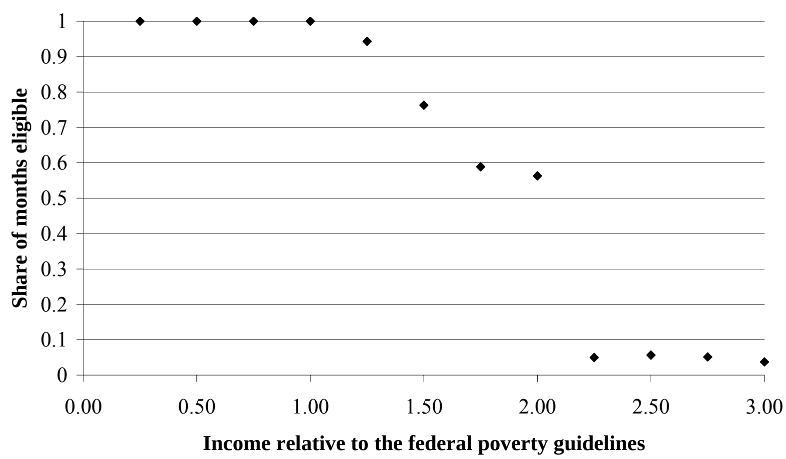


Figure 2c. Average share of months eligible 2000

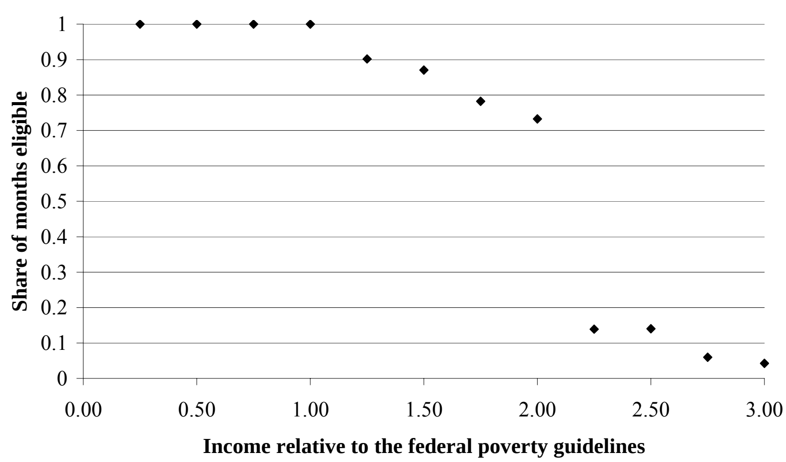


Figure 2d. Average share of months eligible 2001

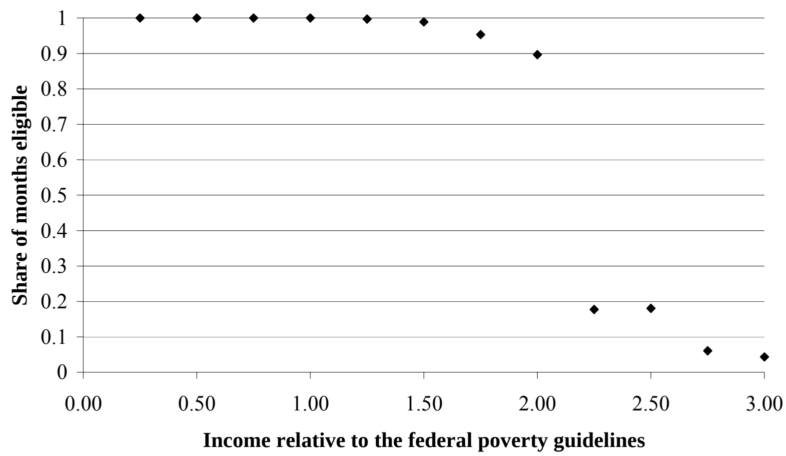
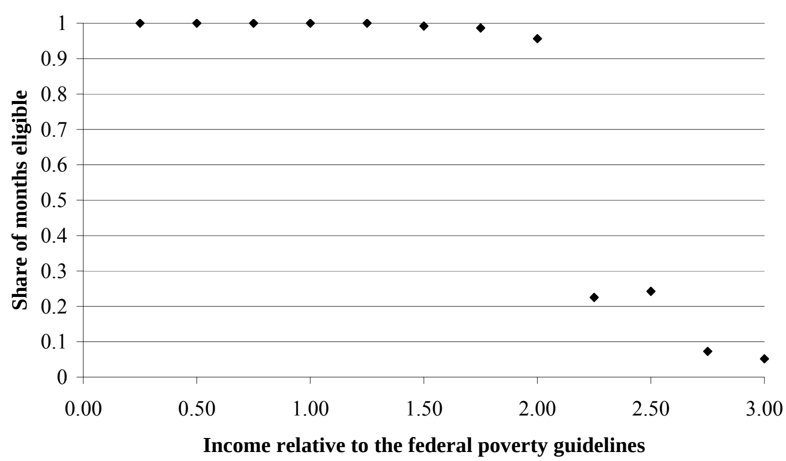
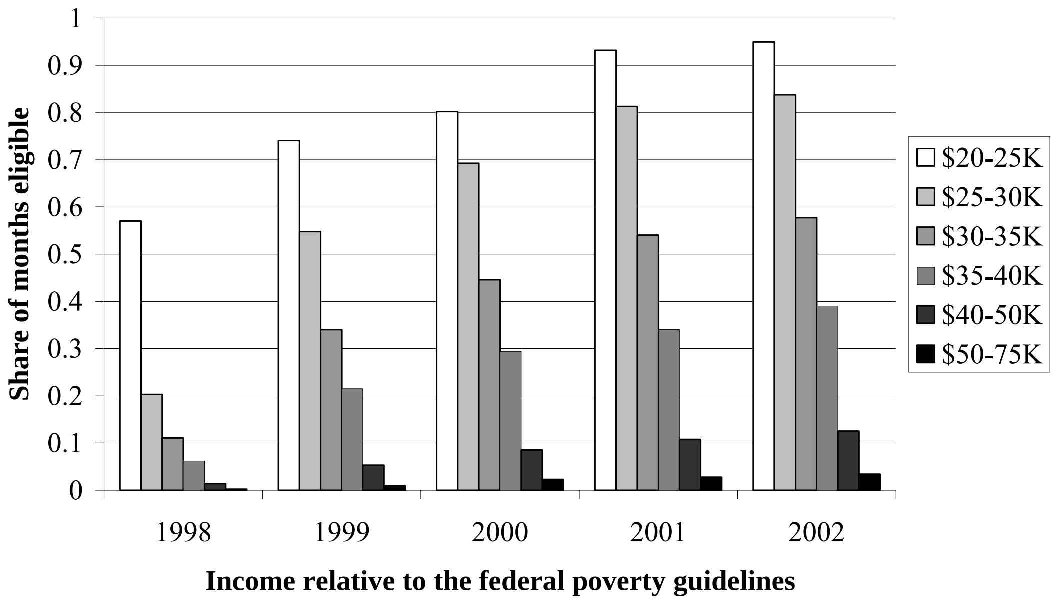


Figure 2e. Average share of months eligible 2002



Notes: The figures show the mean share of months out of the academic year (July to June) that children in our sample with household income falling in various ranges are computed to be income-eligible for state CHIP programs. The years are defined according to the ending year—that is, academic year 1997-98 is referred to as 1998. The statistics are based on the sample of students whose parents provided valid health insurance information in all three spring surveys and reported household income below $75,000 in kindergarten (excluding students with either missing state identifiers or who were located in Tennessee). For these calculations, household income as a share of the relevant federal poverty guideline (based on household size) is held constant at its value in kindergarten, while the child's age and the state's eligibility rules are allowed to change across years. The means reported are derived by weighting the underlying student data by the longitudinal weight provided in the ECLS-K that is appropriate to students with completed parent interviews in all three survey years

Figure 3. Average share of months eligible by year



Notes: This figure shows the mean share of months out of the academic year (July to June) that children in our sample with household income falling in various ranges are computed to be income-eligible for state CHIP programs. See the notes to Figures 2a-e for other details. The only difference between this figure and those is that students are grouped into the income categories that align with our simulated instruments.

Figure 4a. Household income $20-25,000

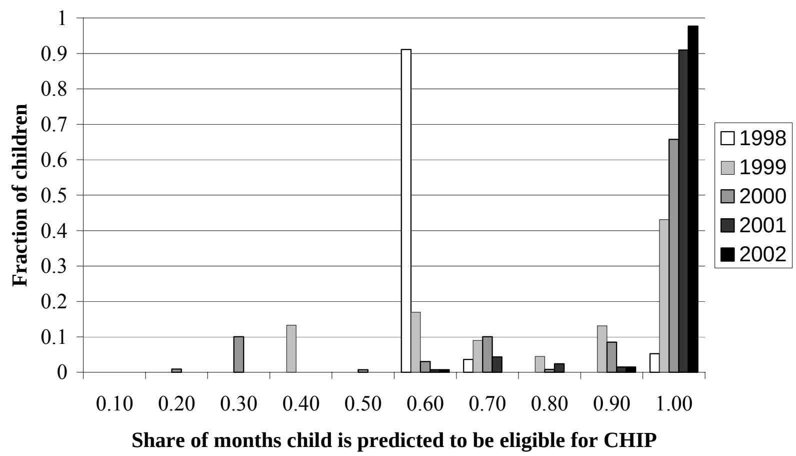


Figure 4b. Household income $25-30,000

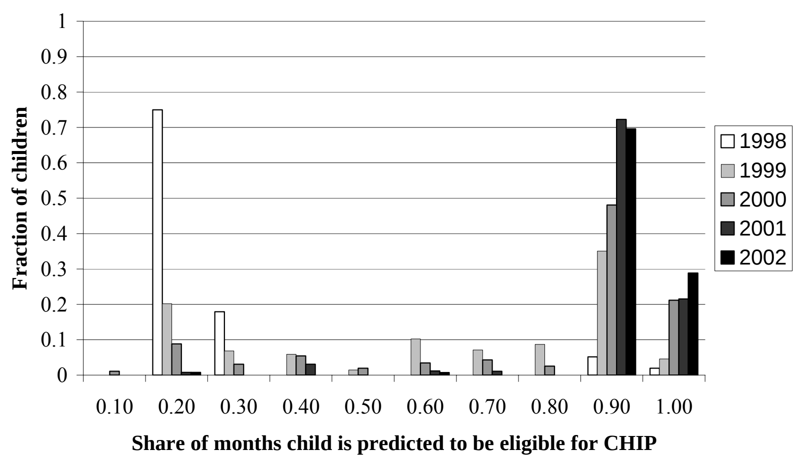


Figure 4c. Household income $30-35,000

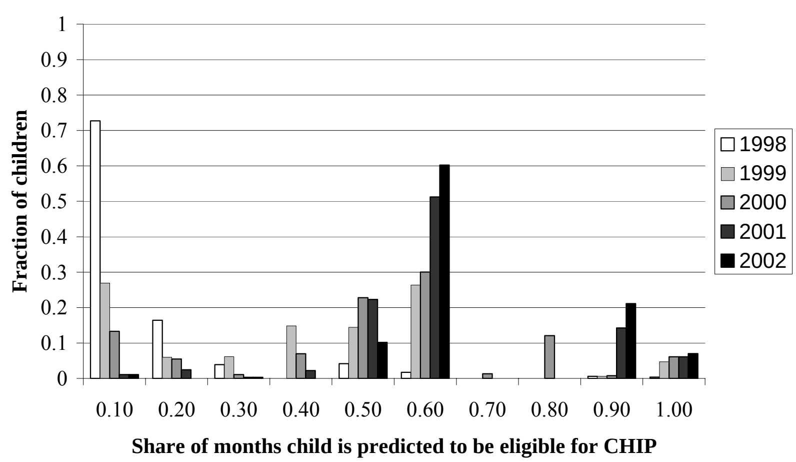


Figure 4d. Household income $35-40,000

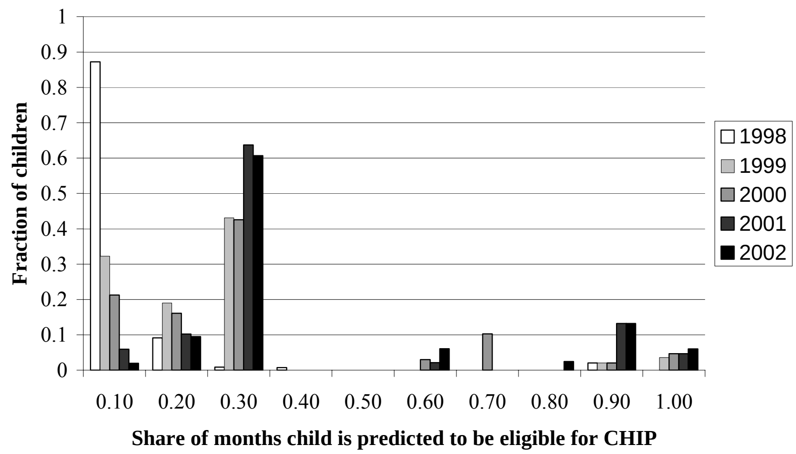


Figure 4e. Household income $40-50,000

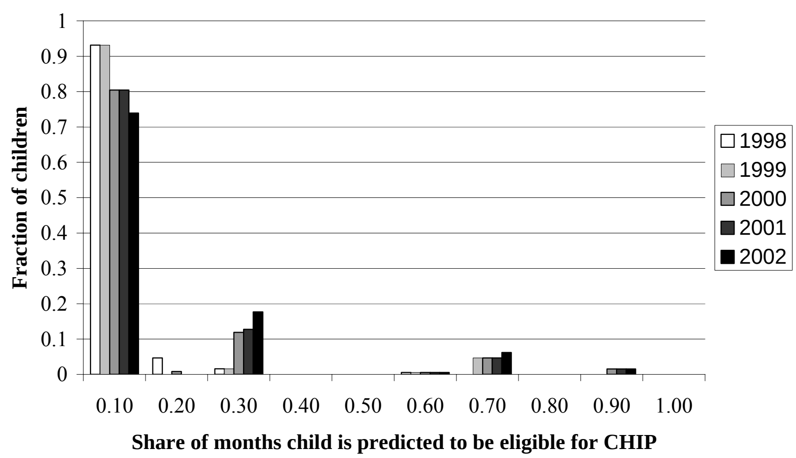
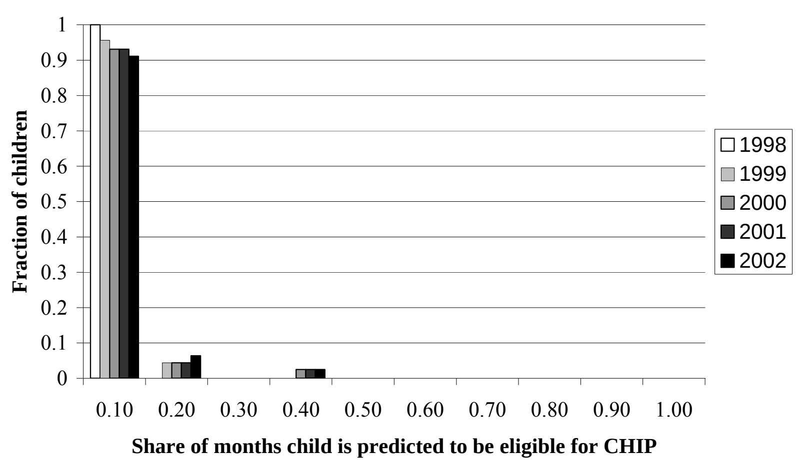


Figure 4f. Household income $50-75,000



Notes: The figures show the distribution of our simulated measures of the share of months eligible by year, separately for each of our size income groups. Child-level measures are weighted by the longitudinal weight.

Figure 5a. Fraction of students uninsured

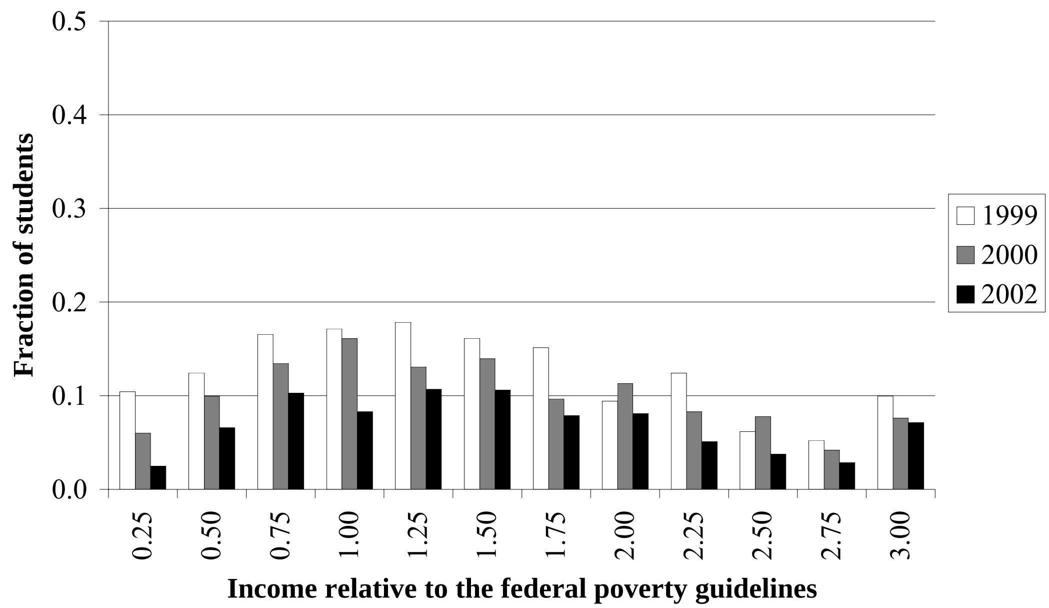
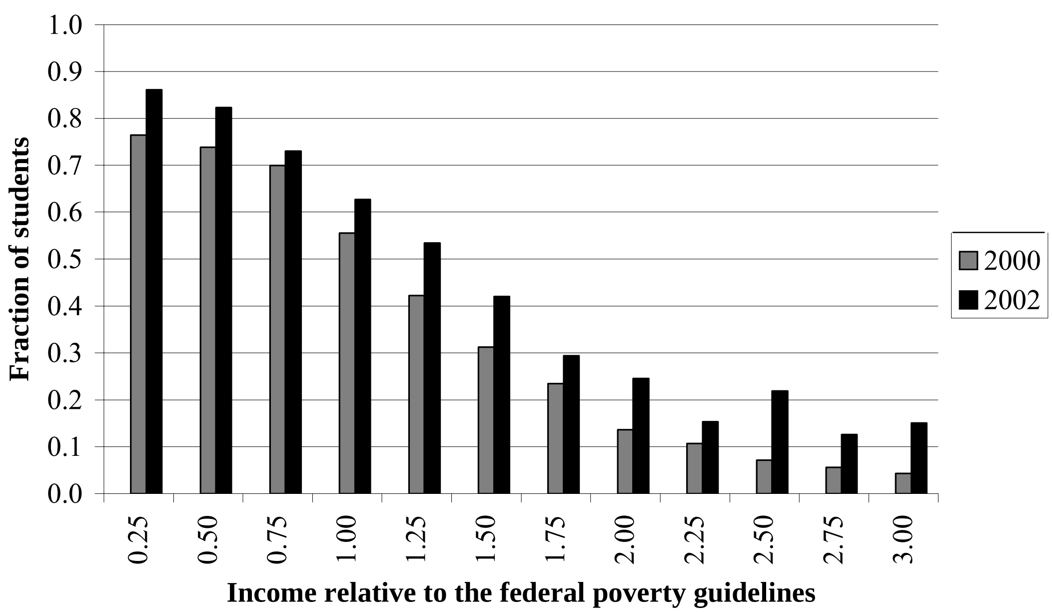


Figure 5b. Fraction of students with Medicaid/CHIP



Notes: These figures show the fraction of students in our weighted longitudinal sample that is uninsured (Figure 5a) and that is covered by Medicaid or CHIP (Figure 5b) by household income as a percent of the FPL. The information on coverage type is not available in 1999.