The Effects of Continued Enrollment in the Children's Health Insurance Program on Health and Educational Outcomes

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Abstract

We determine how enrollment in the Children's Health Insurance Program (CHIP) over an extended period of time affects medical and dental care use, health status and academic achievement. In contrast to prior research, which focuses on the program's effects during infancy and early childhood, we examine CHIP enrollment among elementary and middle school students. Using the 1999-2007 panels of the Early Childhood Longitudinal Study, Kindergarten Class and an instrumental variables model to address selection bias, we find that an additional year of CHIP enrollment increases the regular use of routine medical care by 16 percent, but has no detectible effects on overall parent-reported health status, obesity or test scores in reading and math.

Keywords: CHIP; Continued Enrollment; Child Health; Academic Performance
JEL classifications: I13, I21, H75

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1. Introduction

The Children's Health Insurance Program (CHIP), provides children in low- and moderate-income households who do not qualify for traditional Medicaid coverage with free or low-cost health insurance. Depending on the child's state of resident, CHIP is administered through Medicaid, or as a separate program. By 2020, approximately half of U.S. children were enrolled in CHIP, making it a critical component of the social safety net.[21] A large literature in the social sciences that investigates both Medicaid and CHIP coverage finds that very young children have greater access to health care, and has documented some improvements in health status.[5] Studies also find that public health insurance coverage through Medicaid and CHIP improves human development by freeing up income for non-medical expenditures.[18] The longer term benefits of early-life exposure to Medicaid and CHIP through both direct and indirect channels include higher educational attainment, better labor market outcomes, and fewer risky behaviors in adulthood.[4,9, 21] However, many of these studies only measure eligibility for CHIP, not actual enrollment, and they focus on exposure to CHIP during infancy or early childhood. Much less is known about CHIP enrollment during middle childhood (ages 6-14) when children begin to build human capital through educational investments.[3]

Our paper is among the first to evaluate the health and education effects of CHIP enrollment during middle childhood. Our empirical analysis uses the restricted-use version of the Early Childhood Longitudinal Study, Kindergarten Class of 1998-1999.[35] This dataset contains detailed information on academic performance and parent-reported medical and dental care use and health status. Importantly, parents were asked whether their child had public insurance in the first through eighth grade waves of the ECLS-K. The longitudinal aspect of the data allows us to calculate CHIP enrollment over an eight-year period for each child.

Our empirical strategy relies on cross-state variation in CHIP enrollment caused by changes in the program's income eligibility criteria, similar to the seminal work of Currie and Gruber.[11] In particular, we estimate a multivariate regression model with an instrumental variable constructed using differences in state eligibility rules. This allows us to remove the bias from endogenous program participation (i.e., spurious changes in child outcomes due to factors other than exposure to CHIP coverage). The results show that CHIP enrollment during middle childhood improves take-up of routine medical care. Specifically, our estimates indicate that one additional year of CHIP enrollment leads to a 9 percentage-point increase in the parent-reported probability that a child received an annual medical checkup, which is a 16 percent increase relative to the sample mean. However, we do not detect any statistically significant effect of CHIP enrollment on parent-evaluated child health status, obesity status, or test scores in reading or math.

Our study makes two contributions. First, most research examining the effects of Medicaid/CHIP expansions in the 1980s and 1990s is limited to pregnant women and children aged up to 5.[4-5,12,14,17,19,26,28,34,36] We extend the literature by considering CHIP enrollment during middle childhood. To the best of our knowledge, there is only one other study that analyzes this age range, finding that CHIP enrollment has no statistically significant impact of academic test scores in the first and third grades. [10] Our paper complements this earlier study by extending the analysis period through middle school and considering health outcomes and the use of medical care.

The second contribution concerns how we measure CHIP enrollment. Previous studies measure either CHIP eligibility or enrollment during a single year, but we measure total years of CHIP enrollment from first through eighth grade. The distinction between single and multiple year enrollment is important because by 2001, all states extended CHIP eligibility to children through age 18, creating a potentially large gap in health insurance coverage between CHIP-eligible and ineligible children.[13] In addition, using multi-year enrollment to measure health insurance coverage allows us to account for the potential benefits of medical care investments over an extended period of time.[34]

2. Empirical Strategy

We assess the impact of cumulative CHIP enrollment on child outcomes using a parametric regression model, specified as:

$$Outcome\_8th_{ijs} = \alpha + \beta Years\_Enroll_{ijs} + \gamma' X_{ijs} + \varepsilon_{ijs}, \qquad (1)$$

where $Outcome\_8th_{ils}$ is one of the outcomes measuring medical or dental care utilization, health status, or academic performance for child i attending school j in state s, measured in eighth grade, $Years\_Enroll_{ijs}$ is the number of years that the child has been enrolled in CHIP during the sample period (i.e. the duration of CHIP enrollment), X_{ijs} is a vector of individual, household, school, and state characteristics and ε_{ijs} is a white noise error term. The parameter of interest is β, which measures the change in the outcome due to an additional year of CHIP enrollment. Equation (1) represents a linear regression model that is appropriate for modeling continuous outcome variables using ordinary least squares. When the outcome is a 0/1 indicator that the child belongs to a category (e.g., the child has excellent health), we use a probit model. Since the probit model is nonlinear, the effect of a one-year increase in CHIP enrollment is measured using a marginal effect that is a function of all model parameters, including β.

Ordinary regression methods will not generate an accurate estimate of the parameter β, or the marginal effect of an additional year of CHIP enrollment more generally, due to selection bias. There are three different possible types of selection that we need to address. First, children from low-income families who are less healthy and less prepared to succeed in school may be more likely to enroll in CHIP. Second, families who seek to enroll in CHIP may move to states with less onerous eligibility requirements or more comprehensive CHIP coverage. Third, states with healthier or wealthier populations may offer more generous insurance coverage.

We correct for selection bias using the method of instrumental variables (IV), which makes use of variation in CHIP enrollment that is beyond the individual's control to identify the effect of CHIP enrollment on the outcome variable. This variation is not subject to selection bias, so it generates an accurate (unbiased) estimate of β. The IV method is most easily described as a two-stage estimation process whereby the endogenous variable, $Years\_Enroll$, is first projected onto an instrument that isolates exogenous variation, and the predicted value of the endogenous variable is included in a second stage equation, such as equation (1). To generate reliable estimates, the instrument must be strongly correlated with $Years\_Enroll$, but not correlated with unobservable factors that determine the outcome. Following Currie and Gruber, we use a "simulated instrument" that leverages exogenous changes in state-level CHIP eligibility rules and is less affected by potential migration of individuals to states with generous benefits or eligibility than alternative formulations of the instrument.[11] We implement this approach by simulating CHIP eligibility on a fixed national sample to circumvent the confounding effects of both individual selection into CHIP and changes in state demographic composition that could be correlated with CHIP enrollment and child outcomes.

To construct the simulated instrument, we first draw a nationally representative sample of kindergarteners from our data. Critically, this sample is fixed prior to our study timeframe, such that the demographic characteristics of the kindergarten cohort do not vary across states or over time. We then collapse the fixed sample to household size-race-gender-age cells, and calculate the proportion of children in each cell that would have qualified for CHIP if they had lived in each individual state and in every year of the relevant timeframe, using the CHIP income eligibility limit for that particular state-year pair. For example, the fraction of black girls eligible for CHIP in our sample who are 5 years and 3 months old and live in a family of four is 0.58 when we apply the CHIP income limit for Pennsylvania in 2000, whereas the eligible fraction for the same cell is 0.16 when we apply Tennessee's 2004 CHIP income eligibility criteria. We then calculate the duration of simulated eligibility by summing up the fraction of years that the children could have been eligible for CHIP during our sample period by state and year cell. As a final step, we link simulated eligibility duration to the children in our analysis sample (post-kindergarten) by their demographic characteristics, state of residence, and survey year.

3. Data

We use data from the Early Childhood Longitudinal Study, Kindergarten Class of 1998-1999 (ECLS-K). The ECLS-K tracked the school experiences of a cohort of approximately 22,000 students at their entry to kindergarten in the fall of 1998, progression through elementary school, and transition into middle school. Data were collected from students, parents, teachers, and school administrators on seven occasions: the fall and spring of kindergarten (1998-1999), the fall and spring of first grade (1999-2000), the spring of third grade (2002), the spring of fifth grade (2004), and the spring of eight grade (2007). Due to data availability on CHIP enrollment, we use the spring waves of the ECLS-K from first grade through eighth grade. The surveys were conducted in 43 states and D.C. (excluding AK, ID, MT, NH, ND, SC, VT, and WV). Identifiers for state of residence are contained in the restricted-use version of these data.

We merge to the ECLS-K information on each state's CHIP policy parameters for the years 2000, 2002, 2004, and 2007, which we obtained from various sources (see Table A1). Our sample consists of approximately 2,700 middle school children with family incomes between 100 and 300 percent of the federal poverty line (FPL) who were surveyed in the 2007 wave and who had parent-reported information on CHIP enrollment in four survey waves between the spring of first grade and the spring of eighth grade. We use 100 percent FPL as the lower income limit for our sample because the Omnibus Budget Reconciliation Act, 1990 required states to cover all children below the poverty line through the Medicaid program. We set the upper income limit in our sample to 300 percent FPL because, by 2007, some states were covering children at this income level. We also exclude children covered by military insurance and other public insurance plans.

When parents report enrollment in both private insurance and CHIP, we assign them to the latter. Because of the growing trend towards managed care, it is common for states to outsource CHIP to insurers in the hope of ensuring budget neutrality. Consequently, it is reasonable to assume that children whose parents reported they had both CHIP and private health insurance were actually enrolled in CHIP.[18, 27]

Since information on CHIP enrollment was collected at a point in time during each survey wave starting in the spring of first grade (year 2000), the exact start and end date of CHIP enrollment is not observable. We therefore use the mid-point between survey waves to measure when a child enters or exits CHIP. For example, if a child who is uninsured in the third grade enrolls in CHIP by the fifth grade, we use one year as the duration of the CHIP spell (as of fifth grade). We calculate the duration of simulated eligibility using the sample of children in the spring kindergarten wave using the same method.

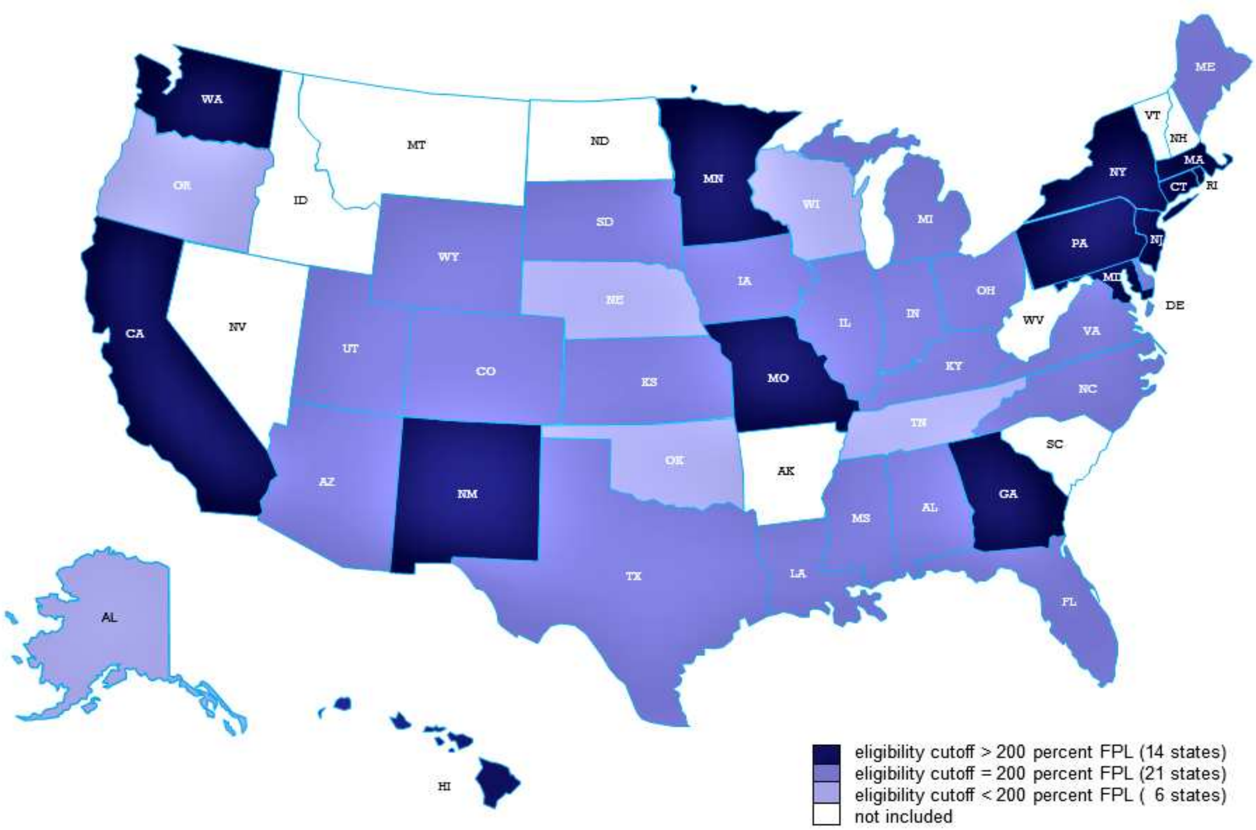
Our health care utilization measures are derived from combined first-, third-, fifth-, and eighth-grade parent interviews, all of which contain questions on how recently children had last seen medical and dental care providers for routine care. We construct two indicator (0/1) variables for whether parents reported that their child had either routine medical or dental care in every survey wave between the first and eighth grades. To measure health outcomes, we construct an indicator for whether parent reported the child was in excellent health, and whether the child was clinically obese in that his/her body mass index (weight in kilograms divided the square of height in meters) was in the 95th percentile or higher of the

U.S. Center for Disease Control growth charts. Both weight and height were measured by trained field staff in the eighth grade. Following the standard value-added model of academic achievement, we measure academic performance using changes in item-response theory theta scores in reading and math between first and eighth grade.[23] These theta scores follow a standard normal distribution in all waves, and have well-documented advantages over other types of scores for measuring longitudinal academic gains.[24]

We include the following individual-, household-, and school-level control variables in our models: child age (continuous in months), gender, race/ethnicity (white, black, Hispanic, and other), birth weight, grade repetition, population density of residence (urban, suburban, and rural), family income, family size, the highest year of schooling the parents completed, school type (public or private), and the proportion of children at the school eligible for a free/subsidized lunch.

In Figure 1 we display state CHIP income requirements as of 2007, which corresponds to the ECLS eighth grade wave. It is clear that there is considerable variation across states in CHIP income eligibility, and that high-income states tend to set higher income eligibility cutoffs. This is in part due to differences in the cost of living across states, but it could also reflect policy preferences.[7-8] We account for both factors by including control variables in our models for real per capita income (from the U.S. Census Bureau), the state prevalence of obesity among boys and girls and percentages of overweight and obese adults (from the U.S. Centers for Diseases Control and Prevention), public school student-teacher ratio, real total tax revenues per student, real instruction spending per teacher, percentage of population holding a bachelor degree or above (from the U.S. Department of Education), and the percentages of students participating in the National School Lunch Program, School Breakfast Program, and Summer Food Services Program (from the U.S. Department of Agriculture).

Figure 1. CHIP income eligibility by state, 2007.



In our regression models, we use the ECSL-K longitudinal sampling weights to generate nationally representative estimates, and cluster the standard errors at the state level.

4. Results

4.1. Summary Statistics

Table A2 lists the weighted means and standard deviations of the variables used in our models for the full estimation sample as well as for two sub-samples that include children whose parents reported they were enrolled in CHIP during at least one survey wave (the "ever-CHIP" sample), and those who were never enrolled in CHIP ("non-CHIP"). Children ever-enrolled in CHIP were more disadvantaged in that they had lower family incomes and their parents had less education. On average, the length of the CHIP enrollment during grades first through eighth was four and a half years.

4.2. Model Estimates

Table 1 contains marginal effect estimates from the IV models in Panel B that measure the effect of an additional year of CHIP enrollment on the specified outcome. For comparison purposes, we report in Panel A estimates from an ordinary regression model that does not account for selection bias. Columns 1-2 contain estimates from models where the outcome measures medical or dental care utilization; columns 3-4, health status; and columns 5-6, academic performance. Appendix Table A3 contains the key regression parameter from the first stage of the IV model as well as the F-test of statistical power to measure whether the simulated instrument is sufficiently correlated with years of CHIP enrollment to produce reliable estimates. The F-statistic of 17.4 is above the conventional threshold of 10 for a sufficiently powerful instrument. [33]

The estimate from the IV model in column 1, Panel B of Table 1 indicates that an additional year of enrollment in CHIP increases by 9 percentage points the probability that parents report their child had routine medical care for every survey wave between first and eighth grade. This is a 16 percent increase relative to the overall sample mean (see column 1 of Table A2). In contrast, the corresponding estimate from the ordinary regression model in Panel A is 2.6 percentage points, which is more than three times smaller than the IV estimate. This discrepancy suggests that children less likely to receive routine medical care are more likely to enroll in CHIP, and underscores the need to use appropriate statistical methods, such as IV, to accurately estimate the causal effect of CHIP enrollment on the outcomes. While both the IV and non-IV marginal effects for routine medical care are statistically significant at the 1 percent level, the marginal effects for dental care use are not significant, nor are the estimates for the health outcomes (overall excellent health and obesity) or changes in reading and math test scores.

Table 1. Regression of outcome variables on years of CHIP enrollment.

	Health care utilization		Health outcomes		Academic performance	
	Routine care	Dental care	Excellent health	Obesity	Reading score	Math score
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Non-IV marginal effect						
Years of CHIP enrollment, 1st-8th grade	0.026***	-0.007	-0.018	-0.002	0.006	-0.006
	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Panel B. IV marginal effect						
Years of CHIP enrollment, 1st-8th grade	0.090***	0.062	0.010	-0.008	0.035	-0.001
	(0.034)	(0.050)	(0.135)	(0.050)	(0.047)	(0.034)
Observations	2,700	2,700	2,700	2,550	2,600	2,650

Notes: Levels of significance are *p<0.1, **p<0.05, ***p<0.01. Standard errors that are clustered on the state level are reported in parentheses. The numbers of observations are rounded to the nearest 50 in order to comply with Department of Education non-disclosure requirements for ECLS-K, 1998. For routine/dental care (no parent-reported having gone a year or more without routine/dental checkups 1st-8th grade), excellent health (parents reported in 8th grade), and obesity (using measured weight and height in 8th grade), probit and IV probit models are estimated. In particular, we estimate the IV probit model using the two-stage residual inclusion (2SRI) approach. Note that results for these binary outcome variables are qualitatively similar but less precisely estimated when using IV linear probability models. For reading and math scores (changes in theta scores 1st-8th grade), OLS and 2SLS models are estimated. The individual-, household-, and school-level characteristics included, but not shown, are: sex, age, race (white, Hispanic, or other races, with black excluded), birth weight, grade repetition, population density (urban or suburban, with rural excluded), the type of school (with private excluded), the percentage of free/subsidized meals eligible students; family income, family size, highest years of schooling parents completed. The state-level controls included, but not shown, are: real per capita income, the percentage of population with a bachelor's degree or higher, the prevalence of obesity among boys and girls, the percentages of overweight and obese adults, the public school student to teacher ratio, real total state tax revenue per student, real instruction spending per teacher, and the percentages of students participating in the National School Lunch Program, School Breakfast Program, and Summer Food Services Program.

To demonstrate that our model estimates are accurate, we subject them to several robustness tests, which we describe in Appendix Section B.

5. Conclusions

In this paper we examine the effect of CHIP enrollment over an eighth year period on medical and dental care use, health status and academic test scores of children during middle childhood. By using a model of instrumental variables (IV) we are able to identify the *causal* effects of CHIP enrollment on these outcomes rather than the associations from ordinary regression models that are subject to selection bias. While we find that an additional year of CHIP enrollment increases the probability that children regularly receive routine medical care during by 16 percent, we find no evidence that CHIP enrollment increases regular use of dental care, improves health status or increases reading or math test scores.

5.1. Discussion of Main Estimates

Our finding that CHIP increases use of routine medical care is largely consistent with previous studies. For example, a meta-analysis reports that single-year CHIP enrollment is associated a 12 percentage-point increase in routine well-child checkups.[22] In addition, our inability to find an effect on dental care use is consist with the limited participation of dentists in Medicaid and CHIP during this time period due to low reimbursement rates.[2] It is interesting that we do not find any improvement in child health or educational outcomes despite increased access to routine medical care. However, this result is not necessarily contradictory with the improvements in adult health or educational attainment attributed to the 1980s Medicaid expansions.[9,34] One possible explanation for our findings is that improvements in health and academic performance take time to materialize, and our sample period is too short to measure these effects.[12] Another possibility is that the ECLS-K's relatively small sample size prevents us from identifying statistically significant effects on health and education, when the causal effects are small in magnitude. However, ours is not the first study that fails to find statistically significant effects of CHIP on health outcomes.[5] In contrast, there is only one study that we are aware of that considers the impact of CHIP enrollment on educational outcomes, and it also finds no effect on CHIP on reading and math test scores, also using the ECLS-K.[10]

Our study has some limitations. Because the ECLS-K data are available biannually from 2000-2004 and are available at a lower frequency thereafter, we cannot capture high-frequency changes in CHIP enrollment. This may cause measurement error in the duration of CHIP enrollment, which is often referred to as "seam bias", and could attenuate our estimates.[20] However, most states have provisions that permit children to remain on CHIP up to 12 months, suggesting that it is less likely that changes in CHIP status occurred within waves than between waves.[31] In particular, our data indicate that children experiencing transitions in CHIP between waves make up less than 3 percent of the sample (see column 2 of Appendix Table A6). Therefore, we believe that seam bias should have limited impact on our estimates.

5.2. Policy Considerations

Despite these limitations, our results have important implications in the current policy context. A recent study by Alker, Osorio and Park suggests that the Families First Coronavirus Response Act (FFCRA) reduced uninsurance for children during the Covid-19 pandemic.[1] However, some key provisions in the FFCRA that bar states from involuntarily dropping children from Medicaid/CHIP expired on March 31, 2023 (although states have 12 month to transition to normal eligibility and enrollment procedures). Alker and her colleagues forecast that approximately 6.7 million children are expected to lose their coverage, and three quarters of them will be dropped from their coverage for administrative rather than eligibility reasons. Importantly, states with higher baseline uninsured rates experienced greater coverage gains following the pandemic protection. Taken together, our finding that CHIP increases routine checkups suggests that the FFCRA expiration may exacerbate inequalities in access to preventive care for children. And the children losing coverage might in turn face greater Covid- or other virus-related morbidity/mortality risks.[32]

In addition, disadvantaged populations stand to benefit more from improved access to care due to potential CHIP expansions. For instance, according to the American Community Survey (ACS), in 2019 approximately 43 percent of immigrant children were uninsured, compared to six percent of U.S. citizen children. However, extending CHIP coverage to immigrant children can face legal and practical challenges. On the legal front, undocumented children do not quality for coverage in most cases. And immigrant children with permanent legal status must wait five years before they can enroll in CHIP. These barriers stem from some lawmakers' concerns about the costs and fairness of entitlement programs.[30] Furthermore, language and cultural factors, such as limited English proficiency and fears about becoming a "public charge," may prevent immigrants from accessing and using their Medicaid/CHIP coverage.[29] Policies aimed at expanding public health insurance coverage to immigrant children are an important area for future research.

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Appendix, Section A.

Table A1. Summary of CHIP characteristics by state for the years 2000, 2002, 2004, and 2007.

State	Type of program	Percent FPL eligibility threshold, 6-16 years old				12-month continuous eligibility
		2000	2002	2004	2007	
Alabama	Combined	200	200	200	200	Yes
Alaska	Medicaid	200	200	175	175	No
Arizona	Separate	200	200	200	200	Intricate
California	Combined	200	250	250	250	Yes
Colorado	Separate	185	185	185	200	No
Connecticut	Combined	300	300	300	300	Intricate
Delaware	Separate	200	200	200	200	Intricate
Florida	Combined	200	200	200	200	Intricate
Georgia	Separate	200	235	235	235	No
Hawaii	Medicaid	100	200	200	300	No
Illinois	Combined	185	185	200	200	Yes
Indiana	Combined	150	200	200	200	Intricate
Iowa	Combined	185	200	200	200	Yes
Kansas	Separate	200	200	200	200	Yes
Kentucky	Combined	200	200	200	200	No
Louisiana	Medicaid	150	200	200	200	Yes
Maine	Combined	185	200	200	200	Yes
Maryland	Combined	200	300	300	300	Intricate
Massachusetts	Combined	200	200	200	300	Intricate
Michigan	Combined	200	200	200	200	Yes
Minnesota	Medicaid	275	275	275	275	Intricate
Mississippi	Combined	200	200	200	200	Yes
Missouri	Medicaid	300	300	300	300	No

Table A1. Summary of CHIP characteristics by state for the years 2000, 2002, 2004, and 2007, continued.

State	Type of program	Percent FPL eligibility threshold, 6-16 years old				12-month continuous eligibility
		2000	2002	2004	2007	
Nebraska	Medicaid	185	185	185	185	Intricate
New Jersey	Combined	350	350	350	350	Intricate
New Mexico	Medicaid	235	235	235	235	Intricate
New York	Combined	222	250	250	250	Yes
North Carolina	Separate	200	200	200	200	Yes
Ohio	Medicaid	150	200	200	200	No
Oklahoma	Medicaid	185	185	185	185	No
Oregon	Separate	170	170	185	185	No
Pennsylvania	Separate	200	235	235	235	Intricate
Rhode Island	Medicaid	250	250	250	250	No
South Dakota	Combined	140	200	200	200	No
Tennessee	Medicaid	N/A	N/A	100	100	No
Texas	Combined	100	200	200	200	No
Utah	Separate	200	200	200	200	No
Virginia	Separate	185	200	200	200	No
Washington	Separate	250	250	250	250	Intricate
Wisconsin	Medicaid	185	185	185	185	No
Wyoming	Separate	133	133	185	200	Yes

Notes: The TennCare program in Tennessee provided an eligibility waiver to children based on their lack of insurance up to 2004, suggesting no upper limit on income. As of 2000, Texas covered children under age 6 up to 133 percent FPL, while all other states in our sample implemented the same income eligibility for children between the ages of 2 and 16. Maryland and South Dakota established separate CHIP programs separate from Medicaid in 2002. States categorized as "intricate" in the last column had gone through changes to the 12-month continuous eligibility provision during the sample period from 2000 to 2007 (Connecticut, Delaware, Indiana, Massachusetts, Nebraska, New Jersey, New Mexico, and Washington) or had differential continuous eligibility provisions across the risk pools of their public health insurance programs (Arizona, Florida, Maryland, Minnesota, and Pennsylvania). We obtained the above information from the National Governors Association Center (NGA) and the Kaiser Notes, continued: Family Foundation (KFF). When there are discrepancies among these sources, we deferred to state Medicaid agencies, including Department of Children & Family Services in Louisiana, Department of Health in New York State, Department of Social Services in South Dakota, and Department of Social Services in Virginia.

Table A2. Descriptive statistics for children in families with income between 100 and 300 percent of the FPL in 2007.

	Full sample	**Ever-CHIP sample**	**Non-CHIP sample**
Outcome variables			
Routine medical care (no parent-reported having gone a year or more without a routine wellness checkup 1st-8th grade)	0.570	0.615	0.545
	(0.495)	(0.487)	(0.498)
Dental care (no parent-reported having gone a year or more without a dental checkup 1st-8th grade)	0.694	0.603	0.744
	(0.461)	(0.489)	(0.437)
Excellent health (parents assessed in 8th grade)	0.493	0.418	0.534
	(0.500)	(0.493)	(0.499)
Obesity (using measured weight and height in 8th grade)	0.206	0.228	0.194
	(0.405)	(0.420)	(0.396)
Reading score (change in reading theta scores, 1st-8th grade)	1.182	1.198	1.173
	(0.371)	(0.414)	(0.346)
Math score (change in math theta scores, 1st-8th grade)	1.363	1.345	1.373
	(0.327)	(0.341)	(0.319)
CHIP enrollment and eligibility			
Duration of CHIP enrollment 1st-8th grade (years)	1.595	4.503	0.000
	(2.516)	(2.185)	(0.000)
Duration of simulated eligibility 1st-8th grade (years)	4.249	4.616	4.047
	(1.717)	(1.709)	(1.688)
Child and household characteristics			
Age (months)	171.535	171.100	171.773
	(4.466)	(4.682)	(4.325)
Female	0.467	0.485	0.457
	(0.499)	(0.500)	(0.498)
White	0.611	0.450	0.698
	(0.488)	(0.498)	(0.459)
Hispanic	0.191	0.262	0.151
	(0.393)	(0.440)	(0.359)

Table A2. Descriptive statistics for children in families with income between 100 and 300 percent of the FPL in 2007, continued.

	Full sample	Ever-CHIP sample	Non-CHIP sample
Black	0.141	0.228	0.092
	(0.348)	(0.420)	(0.290)
Other races	0.058	0.059	0.058
	(0.234)	(0.236)	(0.233)
Birthweight (oz.)	91.146	87.909	92.922
	(53.849)	(54.149)	(53.617)
Grade repetition	0.100	0.159	0.068
	(0.300)	(0.366)	(0.251)
Urban	0.389	0.387	0.389
	(0.488)	(0.487)	(0.488)
Suburban	0.350	0.320	0.367
	(0.477)	(0.467)	(0.482)
Rural	0.261	0.293	0.244
	(0.439)	(0.455)	(0.430)
Family income ($1,000s)	54.813	36.163	65.045
	(34.796)	(22.354)	(36.134)
Family size	4.475	4.425	4.502
	(1.242)	(1.381)	(1.158)
Highest year of schooling the parents completed	14.231	13.386	14.695
	(2.277)	(2.152)	(2.210)
School and state characteristics			
Public school	0.913	0.965	0.884
	(0.282)	(0.183)	(0.320)
Students in free/subsidized meals in school (%)	42.806	49.579	39.090
	(22.621)	(23.611)	(21.165)

Table A2. Descriptive statistics for children in families with income between 100 and 300 percent of the FPL in 2007, continued.

	Full sample	**Ever-CHIP sample**	**Non-CHIP sample**
Real per capita income ($1,000s)	37.912	37.622	38.071
	(4.867)	(4.948)	(4.816)
Obese boys (%)	34.315	34.687	34.111
	(3.913)	(3.913)	(3.900)
Obese girls (%)	28.998	29.862	28.524
	(4.529)	(4.206)	(4.629)
Overweight adults (%)	36.579	36.580	36.579
	(1.248)	(1.339)	(1.196)
Obese adults (%)	26.768	27.028	26.625
	(2.675)	(2.665)	(2.671)
Public school student-teacher (%)	15.575	15.463	15.636
	(2.471)	(2.536)	(2.433)
Real total tax revenues per student ($1,000s)	11.012	10.901	11.072
	(2.175)	(2.232)	(2.142)
Real instruction spending per teacher ($1,000s)	59.703	58.968	60.107
	(10.247)	(10.714)	(9.961)
Population with a bachelor's degree or higher (%)	26.372	26.100	26.521
	(3.978)	(3.966)	(3.978)
Students in the National School Lunch Program (%)	63.519	64.266	63.110
	(11.008)	(11.639)	(10.756)
Students in the School Breakfast Program (%)	20.929	22.377	20.136
	(7.306)	(7.520)	(7.064)
Students in the Summer Food Services Program (%)	3.680	3.800	3.615
	(2.685)	(2.819)	(2.608)
Observations	2,700	850	1,850

Notes: Standard deviations in parentheses. Sample sizes are rounded to the nearest 50 in order to comply with Department of Education non-disclosure requirements for ECLS-K, 1998. The "ever-CHIP" sample includes children who have ever gained CHIP coverage at any time during our sample period in 2000 through 2007, while the "non-CHIP" sample includes children who have not.

Table A3. Regression of years of CHIP enrollment on simulated eligibility instrument.

	Years of CHIP enrollment 1st-8th grade
Years of simulated CHIP eligibility, 1st-8th grade	0.176***
	(0.042)
F-statistic	17.39
Observations	2,700

Notes: Levels of significance are *p<0.1, **p<0.05, ***p<0.01. Standard errors that are clustered on the state level are reported in parentheses. The numbers of observations are rounded to the nearest 50 in order to comply with Department of Education non-disclosure requirements for ECLS-K, 1998. The F-statistic corresponds to the hypothesis test that the coefficient on the duration of simulated CHIP eligibility is equal to zero. The control variables are the same as in Table 1.

Appendix, Section B, Robustness Tests.

We conduct a set of falsification tests to assess the validity of our identification strategy. To streamline the presentation of the results, we focus on routine medical care because the IV estimates are statistically significant only for this measure. To explore whether the increase in routine medical care due to CHIP enrollment is driven by preexisting trends in medical care utilization, we regress the probability of having a routine care in kindergarten on the duration of CHIP enrollment between first and eighth grade. Because we do not find a statistically significant association between these two variables it suggests our models are not picking up a spurious correlation (column 1 of Table A4).

While we cannot formally test the exclusion criteria of our instrument, we can examine whether the instrument has a direct effect on the outcome. Specifically, we include as a regressor the instrument in a probit model. This indirect test has been used by another paper examining the effect of attending Catholic schools on educational outcomes.[15] The estimates in column 2 of Table A4 indicate that the duration of simulated CHIP eligibility is not directly associated with the outcome variable.

In order to assess potential policy endogeneity, we also regress the duration of simulated eligibility on the set of state economic and demographic characteristics. None of the estimated coefficients are statistically significant, providing little evidence for the presence of policy endogeneity (see Table A5).

Finally, we subject our analysis to alternative analytical samples. It is not uncommon for children to experience short gaps in enrollment (generally 2-4 months) because CHIP's means-tested rules involve income and asset verification for enrollment and renewal.[16] If children with enrollment gaps were less likely to have access to routine medical care, then our estimates will be upwardly biased.[6] To address this concern, we investigate the sensitivity of our results by re-estimating two sets of models after removing: (i) children with multiple CHIP spells (trimming about 2.6% of the sample), and; (ii) states that provide 12 months of continuous eligibility (regardless of changes in household income during the year) in their CHIP programs during the sample period (AL, CA, IL, IA, KS, LA, ME, MI, MS, NY, NC, and WY). The estimates (Table A6) are largely unchanged using these subsamples, suggesting that short gaps in CHIP enrollment are unlikely to affect our main results.

Table A4. Falsification tests for the validity of the instrument.

	Kindergarten routine care	Routine care 1st-8th grade
	(1)	(2)
Panel A. Non-IV marginal effect		
Years of CHIP enrollment, 1st-8th grade	-0.002	0.026***
	(0.003)	(0.006)
Panel B. IV marginal effect		
Years of CHIP enrollment, 1st-8th grade	-0.001	0.025***
	(0.027)	(0.006)
Years of simulated CHIP eligibility, 1st-8th grade		0.015
		(0.011)
Observations	2,600	2,700

Notes: Levels of significance are *p<0.1, **p<0.05, ***p<0.01. Standard errors that are clustered on the state level are reported in parentheses. The numbers of observations are rounded to the nearest 50 in order to comply with Department of Education non-disclosure requirements for ECLS-K, 1998. For column 1, an IV probit model is estimated. In column 2, we include the duration of simulated eligibility as a regressor in a probit model. All other control variables remain as described in the notes to Table 1.

Table A5. Regression of duration of simulated eligibility on state characteristics.

	OLS marg. effect
Real per capita income ($1,000s)	0.000
	(0.000)
Obese boys (%)	-1.464
	(5.518)
Obese girls (%)	0.858
	(5.737)
Overweight adults (%)	-0.314
	(0.210)
Obese adults (%)	0.019
	(0.135)
Public school student-teacher (%)	-0.042
	(0.177)
Real total tax revenues per student ($1,000s)	-0.000
	(0.000)
Real instruction spending per teacher ($1,000s)	0.000
	(0.000)
Population with a bachelor's degree or higher (%)	0.086
	(0.104)
Students in the National School Lunch Program (%)	-2.561
	(2.478)
Students in the School Breakfast Program (%)	5.013
	(4.692)
Students in the Summer Food Services Program (%)	4.802

	(8.757)
Observations	2,700

Notes: Levels of significance are *p<0.1, **p<0.05, ***p<0.01. Standard errors that are clustered on the state level are reported in parentheses. The numbers of observations are rounded to the nearest 50 in order to comply with Department of Education non-disclosure requirements for ECLS-K, 1998.

Table A6. Estimated effect on access to routine medical care under alternative samples.

	Baseline	Excluding children experiencing multiple CHIP spells	Excluding states providing 12-month continuous eligibility
	(1)	(2)	(3)
Panel A. Non-IV marginal effect			
Years of CHIP enrollment, 1st-8th grade	0.026***	0.028***	0.024***
	(0.006)	(0.007)	(0.006)
Panel B. IV marginal effect			
Years of CHIP enrollment, 1st-8th grade	0.090***	0.108***	0.086**
	(0.034)	(0.029)	(0.040)
First stage F-statistic	17.39	14.72	10.95
Observations	2,700	2,600	1,600

Notes: Levels of significance are *p<0.1, **p<0.05, ***p<0.01. Standard errors that are clustered on the state level are reported in parentheses. The numbers of observations are rounded to the nearest 50 in order to comply with Department of Education non-disclosure requirements for ECLS-K, 1998. In column 2, we exclude children experiencing multiple CHIP spells during the sample period in 2000 through 2007. In column 3, we exclude the states of Alabama, California, Illinois, Iowa, Kansas, Louisiana, Maine, Michigan, Mississippi, New York, North Carolina, and Wyoming, all of which have the 12-month continuous provision during this period. All other control variables remain as described in the notes to Table 1.