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State Variability in Children's Medicaid/CHIP Crowd-Out Estimates

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Background: Health insurance crowd-out occurs when individuals enrolled in a public health insurance plan would have enrolled in a private plan but for the public option. The crowding-out of private insurance is often used to criticize state Medicaid and Children's Health Insurance Program (CHIP) expansion, as already insured children move their coverage to the states at the public's expense. A difficulty in discussing crowd-out comes from inconsistent estimates. Previous work focusing on the expansion of public programs has led to estimates ranging from 0% to 50% of the children newly insured on public plans being crowded-out.

Methods: We apply a regression discontinuity approach to estimate how many children near the state Medicaid/CHIP threshold are crowded-out of private insurance. This approach allows estimates of crowd-out near the eligibility threshold independent of any expansion. Data from the American Community Survey's yearly survey of American households allows for state-level estimates of crowd-out.

Results: We find considerable heterogeneity in the crowd-out that occurs in each state, ranging from no crowd-out to over 18% in states with similar eligibility thresholds. Additionally, we found that as state eligibility thresholds increase, children are less likely to be crowded-out.

Discussion: This research indicates that national estimates of crowd-out are inappropriate, as state-specific Medicaid and CHIP programs have state-specific crowd-out. Additionally, it indicates that wealthier families that are eligible for public insurance are less likely to switch from private to public coverage than families earning less. Future work should identify reasons for the heterogeneity among states.

Keywords: Children's Health Insurance Program, CHIP, SCHIP, Health Care Financing, Insurance, Premiums, Health Policy, Politics, Law, Regulation, Medicaid, Crowd-Out

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Introduction

The debate on expanding public health insurance coverage to adults has little consensus. Some support exists, though, to provide health insurance to low income children who would lack even basic coverage without government assistance. This coverage is accomplished primarily via the joint federal/state programs of Medicaid and the Children's Health Insurance Program (CHIP).¹ Since the expansion of Medicaid programs, there has been continual debate about the role of "crowd-out" or the movement from private to public insurance coverage, when estimating the effects and costs of these publicly financed programs.

Current law requires states to introduce measures to limit crowd-out, which is primarily achieved by mandating waiting periods before enrollment, requiring asset tests, checking for insurance coverage elsewhere (database searches), and adding premiums and copays (Hoag et al., 2011). The challenge is that efforts to limit crowd-out will simultaneously discourage uninsured children, who these programs are designed to help, from enrolling. An accurate measurement of crowd-out is thus needed to guide policymakers as they design methods to enroll children in public programs.

Crowd-out Explained

Crowd-out occurs when individuals insured by a public program would be covered by private insurance, but for their enrollment in the public program. When this happens, the individuals are said to have been crowded-out of private insurance. In recent years, focus has been on estimating the degree to which children are crowded-out of private insurance, because of the expansion of CHIP eligibility levels.

There are two distinct situations that can result in crowd-out, each of which leads to challenges in estimating total crowd-out. Crowd-out of existing insured children arises when a child who is privately insured switches to a public plan, which is known as substitution crowd-out (Davidson, Blewett, & Call, 2004). The difficulty in estimating this arises, because not every child who is privately insured and switches to public insurance would still be privately insured but for the existence of the public program. For example, many children who are privately insured and switch to public insurance do so because they lost private insurance, such as when their parent changes or loses employment. Retrospectively, analyzing whether children would have maintained private insurance is difficult as methods used to estimate this (surveys, public reporting, enrollment rates and the like) often lack a definitive means of identifying whether a child would still be privately insured if they were not eligible for the public plan.

¹Throughout this paper we refer to the Medicaid, SCHIP (State Children's Health Insurance Program) and CHIP programs under the umbrella term "Medicaid."

The second variety of crowd-out occurs when a child with public coverage remains on that public insurance when a private offer becomes available (Dubay, 1999). We refer to this as “continuation crowd-out,” because children have continued on the public plan after a private option becomes available.² With no evidence of past, private insurance, it is difficult to estimate whether the child would have become newly insured with private insurance, but for the existence of the public plan. Further, it is difficult to estimate this second type of crowd-out using surveys and interviews, because families of many children who are publicly covered cannot conclusively say that, but for the public insurance, they have would enrolled their children in a private plan.

Past Work

Crowd-out has been debated since Cutler and Gruber in 1996 first estimated that fifty percent of newly insured Medicaid children were crowded-out of private plans following an expansion of eligibility (Cutler & Gruber, 1996). Subsequent analysis has suggested varying estimates ranging from values similar to Cutler and Gruber to estimates that there is near zero crowd-out (Gruber & Simon, 2008). These studies primarily relied on three methods: an econometric instrumental variable (IV) approach (Cutler & Gruber, 1996; Lo Sasso & Buchmueller, 2004), comparing children who gained access to expanded Medicaid/CHIP programs to control groups that did not (Blumberg, Dubay, & Norton, 2000; Yazici & Kaestner, 2000), and estimates of substitution using surveys (Sommers, Zuckerman, Dubay, & Kenney, 2007), all of which have weaknesses (Seiber & Sahr, 2011).

The IV approach of Cutler and Gruber analyzes eligibility variability across states, and estimates substitution of private insurance following a change in public insurance eligibility levels. While this does allow for researchers to adjust for policy endogeneity, it does lead to several problems. The first issue is its results are very sensitive to assumptions in the model. Particularly, different ways of treating the same private insurance variable led to overall estimates of crowd-out ranging from 10% to 47% (Lo Sasso & Buchmueller, 2004). A second difficulty, which this paper intends to address, is that the IV approach is not able to estimate state-specific crowd-out, due to its reliance on inter-state variations, to arrive at a national estimate (Seiber & Sahr, 2011). Finally, this approach relies on expansions of the public program.

The second approach evaluates expansions of public programs by comparing children who are newly eligible to individuals who are not, such as non-expansion children or adults, using longitudinal data. These studies have not been able to identify state-specific estimates and are reliant on program expansions.

²An example would be a child who is enrolled in CHIP, because her parents are employed in jobs that do not offer employer-sponsored insurance and, but for the public plan, would have been uninsured. Subsequently, a parent finds new employment that offers health insurance. If the child were uninsured, her parents would have enrolled her privately at this point, but because she is on an existing CHIP plan, they continue CHIP enrollment.

The last approach relies on primary data to estimate the number of individuals who dropped private insurance in exchange for public insurance. The general approach is to interview those who newly enroll in Medicaid, and ask about former insurance coverage to gain an estimate of the number who dropped private coverage to move to a public plan. In addition to the cost and difficulty in acquiring such primary data, this method is limited, because it only focuses on the substitution of private insurance for public insurance, and ignores the children who remain on public insurance plans when private plans become available. None of the approaches have been able to estimate continuation crowd-out.

This paper adds to the existing literature in two primary ways: (1) It demonstrates an additional method to estimate crowd-out independent of a policy change, capturing both substitution and continuation crowd-out, and (2) it produces an estimate of crowd-out levels in individual states. While previous studies focused on estimating the number of children crowded-out before and after a policy change (usually an expansion in Medicaid) we look at the steady-state of crowd-out independent of any policy change, which allows us to estimate all children who were crowded-out, both by substituting private for public and continuing on public after private insurance became available. The large sample size of the American Community Survey (Davern, Quinn, Kenney, & Blewett, 2009), which recently began tracking health insurance status, allows us to estimate crowd-out at the state-level. The regression discontinuity method we employ should not be viewed as a replacement for existing crowd-out estimation methods, but as an additional tool that can help triangulate crowd-out estimates.

Methods

In this analysis we expand on previously published crowd-out estimates based on a regression discontinuity design and data from the American Community Survey. Regression discontinuity (RD) is used to determine the effect of a treatment or policy that is applied at an arbitrary threshold or cutoff point. RD is applied in non-experimental settings where eligibility in a specific program is determined by an arbitrary point along a continuum. The effect of the policy is estimated by comparing the values immediately on each side of the threshold and the difference between them is attributable to the policy (Lee & Lemieux, 2010).

While the RD approach was developed for other disciplines (Thistlethwaite & Campbell, 1960; Schochet, 2008), the externally determined threshold for Medicaid eligibility, where children whose family income is below the cutoff are eligible for Medicaid and those with family incomes just above the threshold are not eligible, allows RD to be used to estimate effects of the program. Previous studies by Card and Shore-Sheppard (Card & Shore-Sheppard, 2004), Koch (Koch, 2013), and De La Mata (De La Mata, 2012) have used this approach to estimate the crowding-out of private health insurance.

Card and Shore-Sheppard compared children whose eligibility was determined by their age, and evaluated children who were eligible for an expansion (those born after September

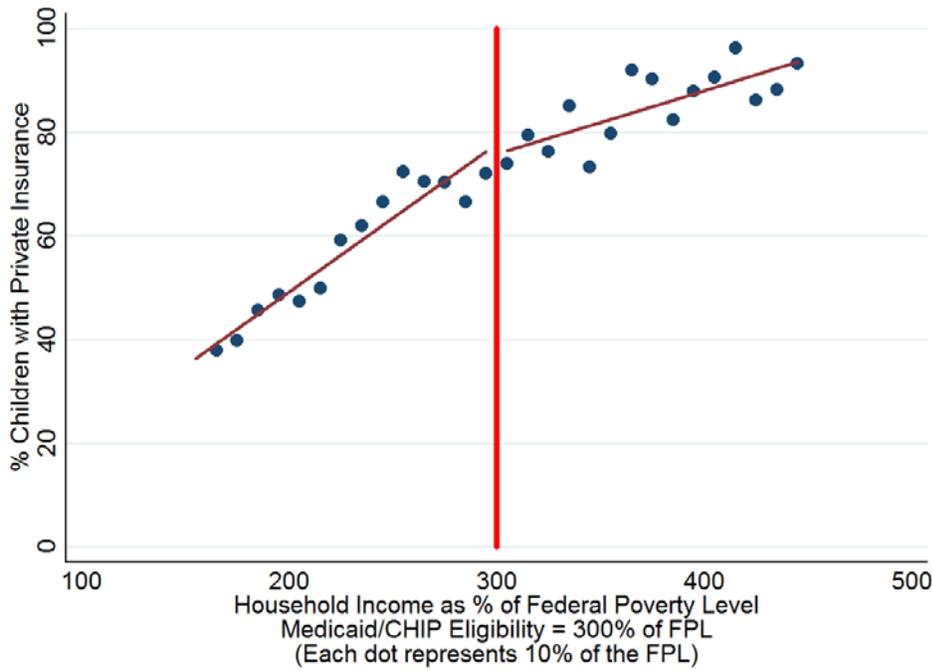
1983) to those who were ineligible (those born September 1983 or earlier). The threshold, then, was the age of children who were eligible. Koch and De La Mata performed a similar analysis to ours, using the income eligibility as the threshold, but due to their smaller sample sizes (using Medical Expenditure Panel Survey, Current Population Survey, and Panel Study of Income Dynamics data), they were forced to combine states together to generate national estimates.³ By taking advantage of the representative national sample of the American Community Survey data, we are able to expand their work and apply this approach at the state level and compare differences in crowd-out between states.

We will illustrate the RD design by looking at two states: one with no estimated crowd-out and one with crowd-out. The basis for estimating crowd-out with RD is that the percent of children with private insurance generally increases as the child's family's income increases (DeNavas-Walt, Proctor, & Smith, 2006). Thus, it is expected that a higher proportion of children whose families earn 150% of the federal poverty level (FPL) will have private health insurance than children whose families earn only 100% of the FPL. When there is no crowd-out, the proportion of children with health insurance is expected to increase gradually until it plateaus at a maximum level. Exhibit 1a shows an example of a state (Maryland) where we found negligible crowd-out as the regressed lines on either side of the eligibility threshold both predict the same number of children having private health insurance. When there is crowd-out we see a break or "discontinuity" in the predicted values as is seen in Exhibit 1b (North Carolina). The expected crowd-out is the discontinuity between the two regressed lines. In other words, but for the existence of Medicaid eligibility (for all children whose families earn less than the FPL eligibility threshold), there would be no discontinuity in the predicted values.

The RD approach has two significant advantages over other methods of estimating crowd-out. The first is that it does not focus on measuring the effect of a specific policy change such as the SCHIP expansions in the 1990s (see Table 1 of Gruber & Simon, 2008). Past approaches relied on difference-in-difference analyses where children who became newly eligible for Medicaid were compared to groups that did not gain eligibility, such as adult men (Dubay & Kenney, 1996) or other children (Yazici & Kaestner, 2000). Such difference-in-difference approaches raise concerns as the comparison group and the treatment group may be different in significant, but unidentified ways (Bertrand, Duflo, & Mullainathan, 2004). The RD approach allows us to look at the "steady-state" of Medicaid enrollment, long after a policy altered enrollment eligibility.

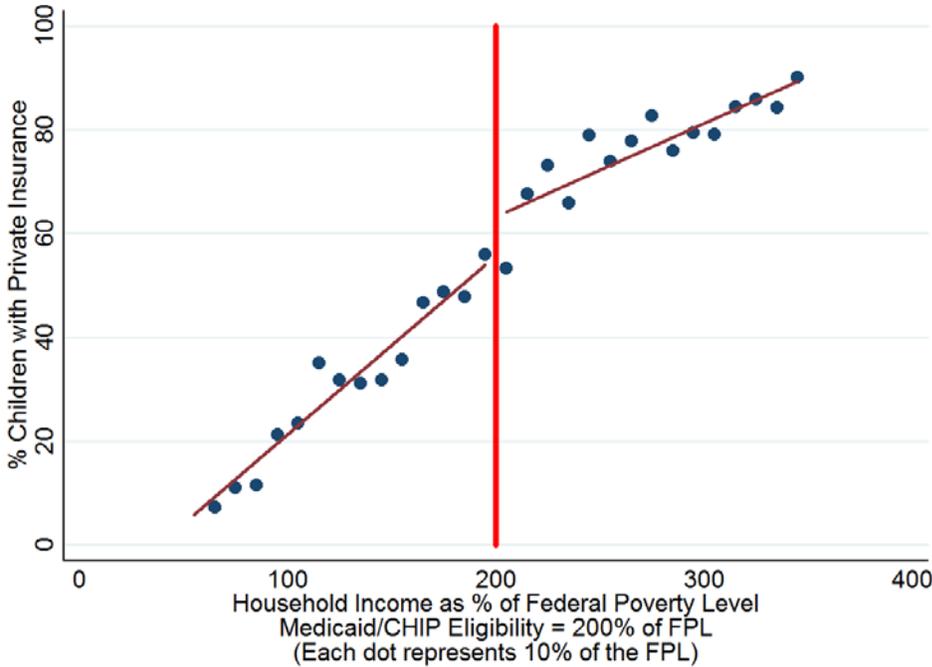
³Since different states have different eligibility thresholds, they combined children based on distance from the eligibility threshold. For example, children whose families earn 290% of the FPL in a state with a 300% eligibility threshold would be combined with children whose families earn 190% of the FPL in a state with a 200% eligibility threshold.

Exhibit 1a. Percent of Maryland Children with Private Insurance as a Function of Federal Poverty Level



SOURCE: Authors' analysis of 2010 American Community Survey data

Exhibit 1b. Percent of North Carolina Children with Private Insurance as a Function of Federal Poverty Level



SOURCE: Authors' analysis of 2010 American Community Survey data

A second advantage of the RD design is that its results can be considered causal. As long as the variation of individuals assigned on each side of the threshold is approximately random, RD can

be used to test the effects of the treatment as if it were a randomized experiment (Lee & Lemieux, 2010). In this case, the “treatment” is whether a child is eligible for Medicaid.

The RD approach also has some known weaknesses. First, it only allows us to evaluate the localized effect of crowd-out; specifically, we can only estimate the rate of children who were crowded out near the eligibility threshold. We are unable to estimate how many total children were crowded-out, because the estimates do not necessarily hold for other income levels. While this makes it impossible to compare all states to each other, it does allow us to compare states that have the same Medicaid cutoff-level.

A second weakness is that RD requires those being measured to be assigned to a treatment independent of their choice. If those who are measured can manipulate whether they are eligible for the treatment, the eligibility threshold is no longer an arbitrary cutoff (Lee & Lemieux, 2010) and the family income is thus endogenous to the eligibility threshold and the results may not be valid (Lee & Lemieux, 2010). We tested for potential endogeneity in two ways: (1) by evaluating whether the population density shifts near the eligibility threshold and (2) by conducting a sensitivity analysis of those near, but not directly next to the threshold.

McCrary (McCrary, 2008) suggests that if individuals do, indeed, modify their income to qualify for the intervention (in this case, eligibility for Medicaid), the population density will change near the eligibility threshold. If families near, but above, the threshold voluntarily choose to lower their incomes to the point of eligibility, there would be an increase in the total population of children immediately below the eligibility threshold and a decrease in children who are immediately above the threshold. To test whether there is a difference, we created histograms of the population density as a function of the FPL and ran linear regressions on those histograms to estimate if the population, near the eligibility threshold, shifted towards the eligibility side. Only one state at $p < .05$ showed evidence of a population shift towards eligibility (Idaho, $p = .039$). Two other states were significant at $p < .10$ (Nevada, $p = .078$ and Texas, $p = .073$). There is thus little evidence of a systematic movement of income towards eligibility.

Under the assumption that only individuals on the margins would alter their income to qualify their children for public insurance, we repeated our regression discontinuity performing a sensitivity analysis. In this case, we excluded data from individuals within 10% of the FPL (those most likely to change their income to affect their eligibility) and found only a modest change in the estimated crowd-out: the median change was 0% (mean of 0.02%) with an interquartile range of -1.45% to 1.27%. To illustrate the magnitude of such a change, a family of four would have to reduce its monthly income by \$220 to decrease its total income by 10% of the FPL. Absent some underlying health concern, it is unlikely that significant numbers of parents would intentionally lower their income to gain Medicaid for their children, particularly when the median price of insuring a child on an individual plan is less than \$100 per month (eHealth, 2011, p. 13). Additionally, there are significant process barriers to enrollment in Medicaid (Stuber & Bradley, 2005) which make enrollment in the program an uncertainty; it is unlikely

that a family would intentionally decrease their income if they were unsure whether, and when, they could enroll their children in Medicaid.

A final weakness of the RD design deals with the discontinuity itself where the eligibility threshold may not clearly divide those eligible from those ineligible for Medicaid. This may occur for multiple reasons. First, since income is self-reported based on memory of the preceding 12 months, there is likely some error with its measurement (U.S. Census Bureau, 2009). Second, some states disregard some forms of income, meaning some children with incomes above the threshold may, in fact, be eligible for the program. Third, more than half of states have a continuous eligibility policy where children who are enrolled in Medicaid can remain enrolled for up to 12 months following a change in income above the eligibility limit (Horner, 2008).

For a *sharp RD*, the probability of being eligible for Medicaid must go from 1 to 0 immediately at the eligibility threshold as income increases. In a *fuzzy RD*, the probability of being eligible for Medicaid will decrease at the eligibility threshold by an amount less than 1 (for example, if only 80% of children lose eligibility at the threshold, then the probability of being eligible for Medicaid decreases from 1 to 0.2 as income increases). To interpret the fuzzy RD, the effect of the eligibility on private insurance must be divided by the change in the probability of being eligible for Medicaid (Lee & Lemieux, 2010). Since we do not know, with certainty, the proportion of children at the threshold truly losing eligibility, we estimate this as a sharp RD (i.e., divide our estimates by 1 rather than a value less than 1). This biases our results towards zero, so our estimates should be viewed as *conservative estimates* of crowd-out at the eligibility threshold. If the probability of losing eligibility at the threshold is indeed less than 1, the actual estimates for crowd-out would be higher.

Data

All data came from the Public Use Microdata Sample (PUMS) from the 2010 American Community Survey (ACS). The ACS is a yearly survey performed by the U.S. Census Bureau that collects a variety of demographic information from a randomized sample of households in the United States (Griffin & Waite, 2006). Household information is broken down by individual within the home and then each individual is weighted to allow estimates for the entire population. The 2010 ACS PUMS file contained information from 1,235,126 households and 3,013,142 individuals. After eliminating all individuals over the age of 18, our sample size was 732,906 unique records representing a weighted total of 78,661,704 children.

The large sample size allows for more accurate estimates of the percent of children who are insured in any income level compared to other datasets. Further, the large sample size allows us to look at the state-specific crowd-out levels. This state-by-state comparison, in particular, is a desirable approach, as Medicaid and SCHIP are state-run programs and what is true in one state may not hold in another.

Data for the ACS is collected throughout the year with monthly surveys that are aggregated to create yearly estimates of the population (U.S. Census Bureau, 2009). Each survey provides information on numerous demographic variables including, of interest in this study, income and insurance status. The insurance status variable refers to insurance status at the time of the survey. Income refers to income earned during the prior 12-month period (Noss, 2011). The Census Bureau then creates an estimate of each individual's poverty level based on family income from the previous 12 months, family size, and age of family members (U.S. Census Bureau, 2011). We use this income-to-poverty ratio recode variable as the basis for the federal poverty level of the children in our sample.

Medicaid or CHIP eligibility is determined by household income relative to the FPL established by the Department of Health and Human Services (HHS). In 2010, this was \$10,830 for a single-person home and an additional \$3,740 for each subsequent person in the household (Department of Health and Human Services, 2010). To calculate the HHS poverty level, we utilized the Census Bureau's income-to-poverty ratio recode variable multiplied by the HHS poverty level and then divided by the Census Bureau's income level. For example, with a family of two, we multiply the Census Bureau's poverty level by \$14,570 (100% of the HHS poverty income for a family of two) / \$14,676 (100% of the Census Bureau's weighted average poverty income for a family of two). This gives us the change between ACS poverty level and HHS poverty level. This makes a relatively small difference for most children in our sample, but makes a large difference for children in families with more than 9 people.

A second analysis that we performed was based on income disregards where some states allow families to exclude a portion of their income when determining eligibility for Medicaid. In early 2008, the Kaiser Family Foundation conducted a survey of all states and compiled their income disregard rules (Ross, Horn, Rudowitz, & Marks, 2008).⁴ We used the rules that were in place in early 2008 and applied them to our 2010 data and estimated the new income, given the disregards. There were two challenges with this. The first is that we are only able to apply the disregards that are applicable to everyone (those based on worker income) and we were not able to estimate other disregards (such as amount paid or received in child support). The second challenge is that some states significantly changed their Medicaid/CHIP programs between early 2008 and 2010.⁵ Because we were unable to accurately estimate income, given the sometimes significant changes to the Medicaid/CHIP plans in some states, we primarily focus on the results that were derived without the disregards, but we do provide these estimates.

⁴The disregard rules were thus applicable, primarily, to 2007 year data. The ACS did not begin tracking health insurance until 2008.

⁵In particular, 11 states (Alabama, Colorado, Indiana, Iowa, Louisiana, Montana, New York, Pennsylvania, South Carolina, Washington and Wisconsin) increased their eligibility thresholds by at least 50% of the FPL. Additionally, 4 more states (Kansas, Nebraska, North Dakota and West Virginia) increased their eligibility threshold to a lesser extent. It is unknown how income disregard rules changed during this time.

Analytic Strategy

For the RD estimates, we first grouped children, by state, into blocks based on their household income as a percent of the FPL. For example, children whose families earn from 0–10 percent of the FPL are in one block, children who earn from 11–20 percent are in another block, and so on. The width of the blocks was chosen based on the need to balance having sufficient observations within each block while maximizing the number of blocks to increase the power of our regression. Wider blocks result in a larger sample of children within each block, but fewer total blocks to regress, and smaller blocks result in the opposite. A block size of 10% of the FPL was chosen as a balance between these two competing interests.

Within each block we then calculated the percent of children in each block who have private insurance using weights provided by the ACS.⁶ We then plotted the blocks of data as a function of the FPL. The result is that we have created histograms with a width of 10% of the FPL that represent the percent of children with private insurance at each poverty level. We created these blocks of children, because the RD design depends on looking at the effect of the Medicaid eligibility threshold on the *proportion* of children with private insurance; the blocks allow us to estimate the proportion of children at a given FPL that have private health insurance. The unit of analysis, then, is the proportion of children with private insurance at different income levels, not the individual child.

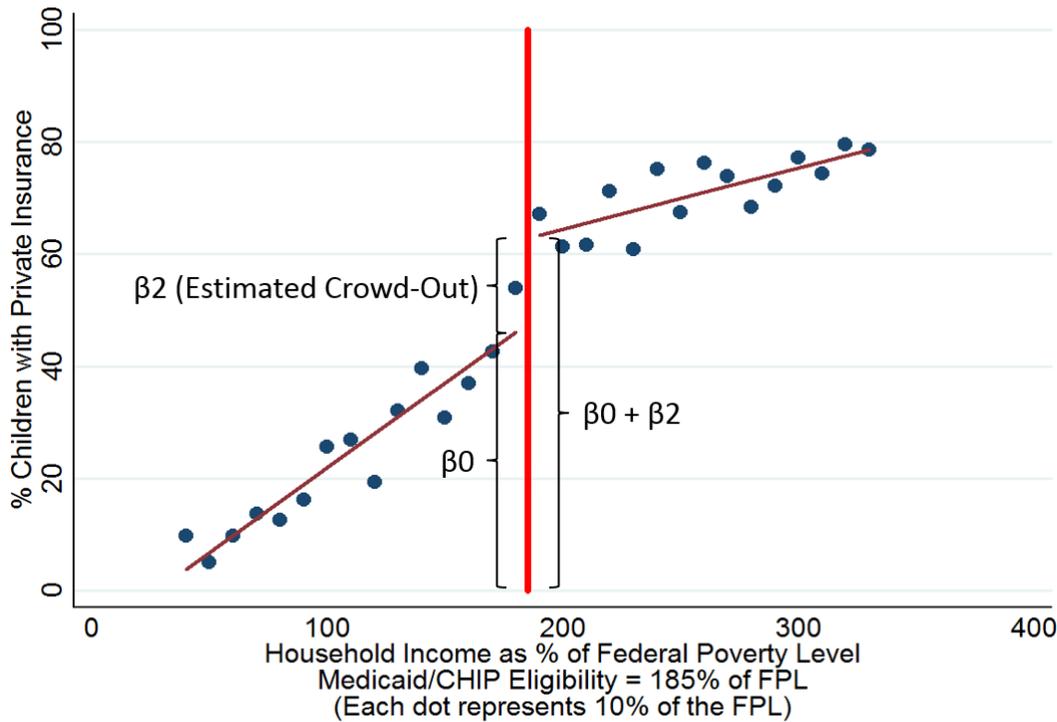
Using state Medicaid/CHIP income eligibility from the Kaiser Foundation (Heberlein, Brooks, Guyer, Artiga, & Stephens, 2011), we centered the blocks for each state around that state's eligibility threshold, and evaluated the blocks plus or minus 150% from the eligibility threshold.^{7,8} In Exhibit 2, for example, of children in Oklahoma whose families earned from 125–135% of the FPL (50% of the FPL less than the cutoff level of 185%), approximately 32% had private insurance, and of children whose families earned from 235–245% of the FPL (50% of the FPL more than the cutoff level), approximately 75% had private insurance.

By regressing the blocks of the percent of children with private insurance who are eligible for Medicaid, we are able to predict the percent of children who are privately insured at the eligibility cutoff if the child is Medicaid eligible. Then, by regressing the blocks of the percent of children with private insurance who are not eligible for Medicaid, we are able to predict how many children are privately insured at the eligibility cutoff if they are not eligible for Medicaid.

⁶The median weighting for each data point was 86 with an interquartile range of 63 to 127. The median subject from the ACS survey, then, represented 86 actual children.

⁷This reduction in total blocks to those nearest the threshold allows us to linearly regress the data points closest to the threshold value.

⁸We also excluded any blocks of data that were based on fewer than eight observations (16 total blocks, primarily in the District of Columbia).

Exhibit 2. Percent of Oklahoma Children with Private Insurance as a Function of Federal Poverty Level

SOURCE: Authors' analysis of 2010 American Community Survey data

The general form of the regression model we estimated is as follows:⁹

$$Y = \beta_0 + \beta_1 * Poverty_Level + \beta_2 * Ineligible + \beta_3 * (Poverty_Level * Ineligible)$$

The dependent variable, Y , is the estimated percent of children at any $Poverty_Level$ with private insurance. With the blocks of data centered around the eligibility threshold, β_0 is the expected percent of children at the threshold with private insurance based on those eligible for Medicaid; $\beta_0 + \beta_2$ equals the expected percent of children with private insurance at the threshold based on those ineligible for Medicaid; β_1 is the slope of the line predicting the percent of children with private insurance and are eligible for Medicaid; $\beta_1 + \beta_3$ equals the slope of the line predicting the percent of children with private insurance and are ineligible for Medicaid. *Ineligible* is a dummy variable with 1=ineligible for Medicaid and 0 otherwise. For an example of this strategy applied to the state of Oklahoma, refer to Exhibit 2.

The estimated number of children crowded out is represented by β_2 , which is the difference between the estimated percent of children with private insurance at the threshold who are ineligible for Medicaid ($\beta_0 + \beta_2$) and the estimated percent of children at the threshold with

⁹We used linear regression to estimate crowd-out for each state. We experimented with non-linear regression, but linear provided the most consistent fit of the data between states, particularly when considering the small number of blocks that we had to work with (approximately 15 blocks on each side of the eligibility threshold).

private insurance who are eligible for Medicaid (β_0). P-values are calculated based on the significance of β_2 .

Findings

Exhibit 3 shows the estimated crowd-out for each of the states and the District of Columbia and Exhibit 4 includes this same information in graphical form with a linear trend line indicating the estimated localized crowding-out of children as a percent of the FPL. The primary finding is that there is considerable variation between the states' crowd-out at specific eligibility thresholds. Because the RD design does not permit us to estimate total crowd out, we are limited to comparing the *localized* effect of crowd-out near the eligibility threshold. Nineteen states use 200% of the FPL as their threshold for Medicaid eligibility and the estimated crowd-out ranges from 6.9% to 10.61% ($p < .05$ $n=5$; range of -8.77% to 16.94% for all p-values). Of the eight states that use 250% of the FPL as their threshold, only one has a significant crowd-out estimate (California at 3.27%; range of -6.2% to 6.89% for all p-values). Of the 14 states that use 300% of the FPL as their threshold, none had significant estimates of crowd-out (ranges of -4.51% to 16.20% for all p-values). The heterogeneity of estimated crowd-out is indicative of the heterogeneous approach to implementing Medicaid programs. Though jointly funded by the Federal and State governments, Medicaid and SCHIP programs are implemented individually by the states, with different approaches to managing the Medicaid population (Kaiser Family Foundation, 2010) and with different approaches to limiting crowd-out (Hoag et al., 2011).

While the large sample size of the ACS allowed us to estimate crowd-out in every state, the states with smaller populations generally had larger p-values and smaller adjusted R^2 values as there were more outliers in the blocks of data. We generally found more modest estimates of crowd-out from states with larger populations as seen in Exhibit 5 where only the states with more than 5000 observations were used to estimate the crowd-out.

Of the 50 states and the District of Columbia, seventeen were estimated to have negative crowd-out. Of these, most had smaller sample sizes, which lead to more variability and more outliers when we plotted blocks of data. For example, the state with the most negative estimated crowd-out, Wyoming, only had 793 observations with which to base our estimate. Of these seventeen with negative estimated crowd-out, all of them had p-values greater than 0.18. It is unlikely that Medicaid eligibility would lead to "crowding-in" of private insurance and these data do not support that proposition.

The second finding is that the local crowd-out effects tend to decrease as the eligibility threshold increases. As viewed in Exhibit 5, the trend line predicts no crowd-out at 301% of the FPL,¹⁰ indicating that there is no expected crowd-out with eligibility thresholds above this point.

¹⁰Excluding New York and New Jersey, the two states with the highest income thresholds, changes our estimate of no crowd-out to 280% of the FPL, effectively making the slope steeper.

Exhibit 3. State-Level Estimates of Crowd-Out

State	Cutoff	n	No Disregarded Income			Disregarded Income based on 2008 Rules		
			Estimated Crowd-Out	Standard Error	P-Value	Estimated Crowd-Out	Standard Error	P-Value
Alabama	300	4627	-1.09%	3.62%	0.765	-0.09%	4.00%	0.982
Alaska	175	951	15.25%	12.63%	0.238	-6.17%	10.76%	0.571
Arizona	200	9217	6.56%	3.43%	0.067*	5.65%	3.39%	0.108
Arkansas	200	4212	-0.40%	6.51%	0.951	-7.57%	5.76%	0.200
California	250	42368	3.27%	1.51%	0.040**	3.04%	1.62%	0.072*
Colorado	250	5724	1.53%	3.54%	0.669	-0.44%	3.29%	0.893
Connecticut	300	3143	2.82%	4.82%	0.564	0.53%	4.82%	0.912
Delaware	200	974	16.94%	9.21%	0.077*	11.28%	10.18%	0.278
Washington, DC	300	204 [#]	7.80%	26.98%	0.778	-24.99%	10.90%	0.042**
Florida	200	22309	6.19%	2.32%	0.013**	6.94%	2.14%	0.003***
Georgia	235	12491	3.86%	2.62%	0.152	3.36%	3.00%	0.273
Hawaii	300	1394	-0.10%	8.75%	0.990	-0.51%	4.87%	0.917
Idaho	185	3092	7.84%	4.85%	0.117	7.09%	5.19%	0.183
Illinois	200	15873	4.92%	2.62%	0.071*	6.18%	2.81%	0.037**
Indiana	250	8868	-0.51%	3.42%	0.882	-2.86%	3.45%	0.414
Iowa	300	4082	-4.08%	3.41%	0.242	0.10%	3.23%	0.974
Kansas	241	3978	2.97%	3.92%	0.455	3.28%	3.69%	0.381
Kentucky	200	5559	2.71%	5.18%	0.604	5.43%	4.77%	0.265
Louisiana	250	5304	-2.61%	5.16%	0.618	-0.35%	3.27%	0.914
Maine	200	1572	14.26%	7.33%	0.062*	19.71%	7.19%	0.011**
Maryland	300	5425	0.29%	3.18%	0.927	0.37%	3.65%	0.920
Massachusetts	300	5611	-1.44%	3.08%	0.644	1.28%	3.60%	0.725
Michigan	200	13221	5.89%	2.72%	0.039**	7.13%	2.62%	0.011**
Minnesota	275	6986	-0.17%	3.27%	0.958	-0.59%	3.11%	0.850
Mississippi	200	4349	-0.24%	5.10%	0.962	8.09%	6.32%	0.212
Missouri	300	6604	-0.82%	2.63%	0.756	2.35%	3.27%	0.478
Montana	250	1258	-6.72%	9.73%	0.495	-13.31%	7.62%	0.093*
Nebraska	200	2549	1.32%	5.26%	0.804	-1.11%	3.69%	0.766
Nevada	200	3892	9.22%	5.07%	0.080*	8.72%	3.92%	0.035**
New Hampshire	300	1260	7.60%	8.98%	0.405	6.00%	6.37%	0.355
New Jersey	350	13417	-3.36%	2.45%	0.182	-4.34%	2.75%	0.126
New Mexico	235	2580	11.71%	5.50%	0.043**	11.96%	5.32%	0.033**
New York	400	23428	0.70%	2.15%	0.746	2.56%	2.35%	0.288
North Carolina	200	12589	9.91%	3.08%	0.003***	12.15%	2.82%	0.000***
North Dakota	160	836	7.98%	10.90%	0.471	2.16%	11.79%	0.856
Ohio	200	15223	5.23%	2.70%	0.064*	4.53%	2.39%	0.069*
Oklahoma	185	5907	18.23%	3.10%	0.000***	11.93%	3.91%	0.005***

Exhibit 3. (cont.)

State	Cutoff	n	No Disregarded Income			Disregarded Income based on 2008 Rules		
			Estimated Crowd-Out	Standard Error	P-Value	Estimated Crowd-Out	Standard Error	P-Value
Pennsylvania	300	12990	0.61%	2.23%	0.787	0.07%	2.47%	0.976
Rhode Island	250	993	6.89%	8.05%	0.400	2.89%	8.00%	0.720
South Dakota	200	1236	3.74%	4.08%	0.368	-2.58%	4.60%	0.580
South Carolina	200	6140	8.55%	7.73%	0.278	11.14%	8.81%	0.217
Tennessee	250	7532	-2.13%	3.65%	0.563	-3.30%	3.39%	0.338
Texas	200	37133	7.44%	1.90%	0.000***	9.28%	2.37%	0.000***
Utah	200	6050	10.61%	2.92%	0.001***	8.01%	3.97%	0.054*
Vermont	300	659	16.20%	10.54%	0.136	17.56%	10.77%	0.116
Virginia	200	8273	1.51%	3.77%	0.692	-0.23%	2.87%	0.937
Washington	300	6995	4.59%	3.56%	0.209	1.45%	3.89%	0.713
West Virginia	250	2001	-2.36%	6.62%	0.724	-8.07%	5.49%	0.154
Wisconsin	300	6876	-4.51%	3.55%	0.216	1.84%	3.03%	0.548
Wyoming	200	793	-8.77%	11.26%	0.443	-4.41%	11.46%	0.703

* p<.10

** p<.05

#Due to the very small sample size used to calculate Washington, DCs estimated crowd-out, its estimates should be evaluated with caution.

** p<.01

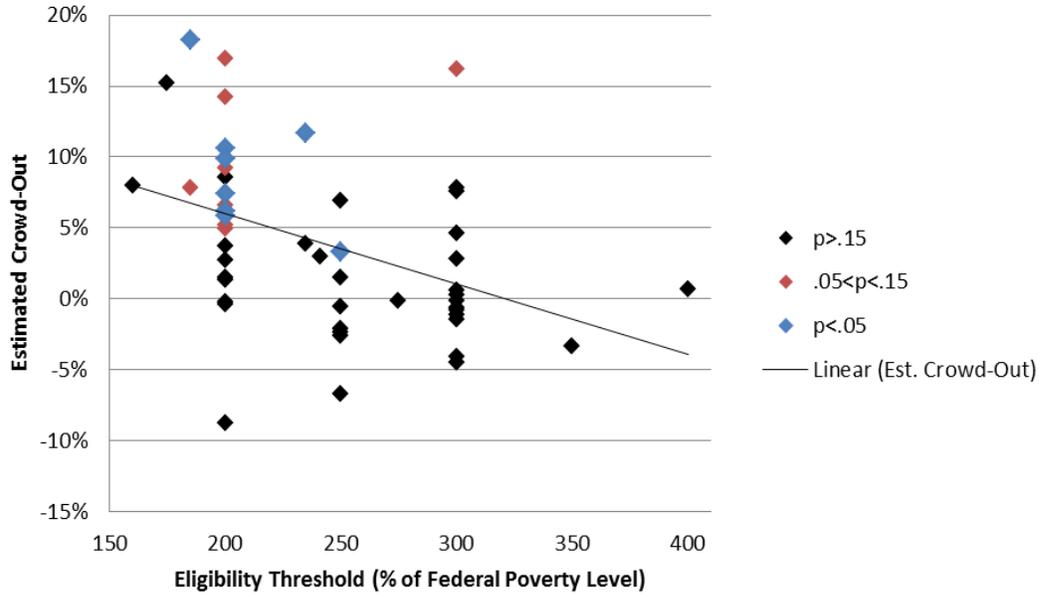
SOURCE: Authors' analysis of 2010 American Community Survey data

Similarly, if we only chart the states with significant levels of crowd-out ($p < .10$), then the expected point at which there is no crowd-out is 300%. Previous work has identified a decrease in crowd-out as income increases (Koch, 2013), and our work confirms this effect at the state eligibility threshold. This finding calls into question the common perception that crowd-out is higher among children with higher family incomes (Winfrey & D'Angelo, 2007). It is unclear if the type of crowd-out (switching from private insurance to public insurance, or remaining on public insurance when private insurance becomes available) changes as income levels increase.

This does not support a finding that overall crowd-out is less in states with higher eligibility thresholds; the effect is local and only suggests that higher eligibility thresholds are associated with lower crowd-out at that income level. This finding indicates that proportionately fewer high income children are expected to be crowded out than low-income children. For example, we estimate that, overall, approximately 3% of all children who are eligible for Medicaid and whose families make 250% of the FPL would be crowded out, while 6% of all children who are eligible for Medicaid and whose families make 200% of the FPL would be crowded out, and no children would be crowded-out if their families earn 300% of the FPL. This general finding does not account for program differences, such as copays or premiums in states

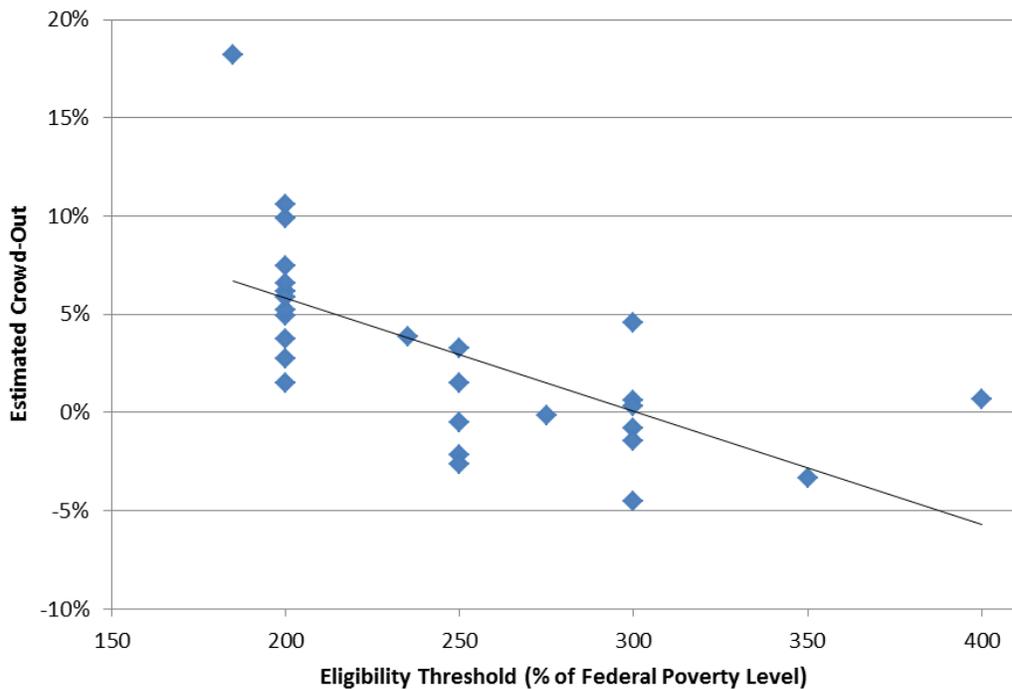
with higher eligibility thresholds, or income volatility, which may vary by income level. These may reduce the comparability of these estimates.

Exhibit 4. Local Crowd-Out of Private Children's Health Insurance at Eligibility Threshold, by State (2010)



SOURCE: Authors' analysis of 2010 American Community Survey data

Exhibit 5. Local Crowd-Out of Private Children's Health Insurance at Eligibility Threshold, by State (2010; States where $n > 5000$)



SOURCE: Authors' analysis of 2010 American Community Survey data

Discussion and Policy Implications

The extreme variability in crowd-out estimates indicates substantive differences between states. While previous work has adjusted for state-specific differences (Cutler & Gruber, 1996) to estimate national crowd-out, this extreme heterogeneity indicates a need to evaluate total crowd-out on a state by state basis. It is not sufficient to simply adjust for state residency or use other statistical methods to estimate state-level effects, because crowd-out is a function of the state of residency. The disparate state programs and their individual effect on crowd-out must be estimated and then national models can be developed based on these state-specific estimates.

The differences between how states implement their Medicaid programs is the variable that should be of interest to policy makers as crowd-out is a function of how these programs are implemented. Acting within the concept of states acting as laboratories of democracy, states that have successfully reduced the number of uninsured while limiting crowd-out should be evaluated and emulated by other states.

One reason that children may not move to public coverage is due to a preference for private coverage. While state plans may be cheaper for some eligible children, there are clear reasons that families might choose the private option such as, for example, a preference for providers who do not accept Medicaid, or a perceived stigma associated with Medicaid (Stuber & Kronebusch, 2004). When deciding in which insurance plan to enroll children, more than just finances factor in; access to preferred providers, and the effort required to disenroll from employer-sponsored coverage to enroll in a public plan also have a role in decision making.

There may also be some state policies that effectively discourage crowd-out, such as by adding premiums and co-pays at higher income levels (Heberlein et al., 2011). There was no difference in crowd-out for states with Medicaid/CHIP premiums versus states without premiums ($p=.49$), but states with copays had significantly lower average crowd-out rates ($2.3\% < 5.9\%$, $p=.019$). Copays, then, may be a deterrent to dropping private insurance in exchange for public. Identifying which factors drive decisions to drop private insurance will aid policymakers' decisions about structuring public insurance plans going forward.

Another policy issue involves the decreasing local crowd-out effect as the eligibility threshold increases. Critics of Medicaid expansion have claimed that higher eligibility thresholds will cause greater percentages of children to be crowded out at the higher eligibility levels (Winfrey & D'Angelo, 2007). This directly counters that assumption, implying that wealthier children are less likely to be crowded-out than ones from poorer families. This may be due to the premiums charged for wealthier families or because Medicaid is not a perfect substitute for private insurance.

From a policy perspective, concerns of families with higher incomes dropping private insurance and moving to public plans appear to be unfounded. Our results indicate that the majority of children who obtain Medicaid and come from families with higher incomes do so because they otherwise lacked private insurance.

From a state and national perspective, less concern of crowding-out at higher income levels should lead to a reevaluation of the eligibility threshold for Medicaid and SCHIP programs. States should compare the risk of crowd-out at higher eligibility levels to the transaction-costs of assuring the continued eligibility of children, which may reduce take-up of public insurance by children who otherwise would be uninsured (see also Dick, Allison, Haber, Brach, & Shenkman, 2002).

Finally, the relatively small crowd-out at all income levels suggests that the discourse on children's health insurance programs should shift away from crowd-out towards the merits of public programs. Arguments for and against public children's health insurance programs should be based on benefits of publicly insuring children who otherwise would be uninsured, not on whether previously insured children drop private insurance and move to the public's payrolls.

From a research perspective, the RD approach should be viewed as one more tool to help triangulate estimates of crowd-out. It is limited to local estimates of crowd-out effects, but is relatively simple to calculate and can be combined with other approaches for a more robust estimate of total crowd-out. There is significant work still to be done to accurately calculate levels of crowd-out at the state level, but this does provide one more arrow in the quiver of researchers.

Future Work

There is no consensus as to the overall effect of public insurance plans crowding out private plans and further estimates of crowd-out should be pursued. While this work provides localized estimates of crowd-out, it does not provide estimates of total crowd-out within a state. Therefore, state-level estimates of total crowd-out still need to be determined. National estimates of crowd-out can then be calculated as the sum of the state-level estimates.

Along with estimating state-specific crowd-out levels, there is a need to determine why there are such differences in crowd-out between states. There is scant evidence as to which specific policies lead to increases or decreases in crowd-out and such research will be pivotal for policymakers' decisions. Also, factors such as state economies, demand for insurance, and the political environment within a state may affect the levels of crowd-out. These factors need to be identified and further explored. Additionally, different state approaches to Medicaid and CHIP should be evaluated on their effect on uninsured children taking up Medicaid.

To further understand the dynamics of the effect of state policies and external factors on crowd-out is to estimate how crowd-out changes over time. Repeated measures of crowd-out within a state, coupled with a close, qualitative analysis of state policies and external economic and political factors, may shed light into what drives crowd-out.

A second area of work is to learn why children who are eligible for public insurance, particularly at higher incomes, do not leave their private plans. There are many potential reasons for lower levels of crowd-out at higher income levels, and we suggest studying the relative

desirability of private insurance at different income levels and the effect of premiums and copays on demand for public insurance.

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