How Do Public Health Expansions Vary by Income Strata? Evidence from Illinois' All Kids Program
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What is This?
This paper examines how income levels affected the substitution of public health insurance for private health coverage under expansions of Illinois’ State Children’s Health Insurance Program (SCHIP). Building on a technique developed by Abadie and Gardeazabal (2003), I estimate that among children whose family incomes are between 200% and 300% of the federal poverty level (FPL), 35% of those covered by SCHIP would have retained private coverage in the absence of SCHIP. Significant substitution also appears between 300% and 400% FPL, but surprisingly I find evidence that the introduction of SCHIP caused an increase in private health insurance coverage for those with family incomes between 400% and 500% FPL.

The question of whether expansions in Medicaid coverage lead to declines in private coverage has emerged as an important issue in the health policy community. As early as 1996 (Currie and Gruber 1996a), economists noted that expanding eligibility for coverage does not necessarily result in full coverage due to uneven program adoption. As public health insurance coverage expands, some individuals with private health insurance may choose to substitute that coverage with public insurance instead. Public expansions therefore can “crowd out” private coverage, offsetting many of the coverage gains expected in the expansion populations. Stimulated by Cutler and Gruber’s (1996) early work on the extent of crowd-out resulting from the Medicaid expansions of the late 1980s and early 1990s, scholars have proceeded to examine the extent of crowd-out in the subsequent State Children’s Health Insurance Program (SCHIP) expansion that provided public health insurance coverage to children with family incomes below 200% of the federal poverty level (FPL). Depending on the research design and data selected, these studies have produced very different results of how many children taking up public health insurance would have had private health insurance in the absence of a public option.

The extent of crowd-out from public insurance is of particular interest in light of the passage of the Children’s Health Insurance Reauthorization Act of 2009 and the Affordable Care Act (ACA) of 2010. The Reauthorization Act expanded health insurance coverage to children with family incomes below 300% FPL, while the Affordable Care Act expanded Medicaid eligibility to all adults with incomes below 133% FPL. In both cases, this will result in the expansion of public health insurance to income thresholds that have not previously been covered. Since earlier research on crowd-out addressed data at lower income thresholds, the applicability of these results at higher income levels is

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unclear. While the coverage expansions slated to take place in 2014 as a result of the Affordable Care Act make it somewhat unlikely that public health insurance expansions will continue in the near term, the trend over the past two decades has seen a continued proliferation of public health insurance options extended to children and the poor—including Aid to Families with Dependent Children (AFDC), the Medicaid expansions of 1990 and 2010, and the SCHIP expansions of 1997 and 2009. Given this long-term trend, the impact of public health insurance expansions is likely to return to the policy agenda at some point in the future.

While the extent of crowd-out has been extensively studied for low-income populations, an important limitation of earlier studies is that they do not estimate substitution that would occur among higher income groups. However, states vary considerably in the income thresholds that are set as eligibility criteria for public insurance. Moreover, there is a theoretical consensus that crowd-out rates are likely to differ significantly depending on the income criteria specified for eligibility. In the few instances where researchers have examined income (notably Dubay and Kenney 1996 and Card and Shore-Sheppard 2004), significant differences have been found in coverage and crowd-out across different income levels. To what extent did SCHIP reduce the number of uninsured children, and to what extent did it crowd out private insurance coverage? And how do answers to these questions vary by the income level targeted by the insurance expansion?

In examining the impact of further expansions of SCHIP, I focus my analysis on the Illinois SCHIP. Illinois represents an ideal test case for three reasons. First, Illinois is unique among the states in extending SCHIP coverage to children of all income levels, while other states continue to restrict SCHIP enrollment based on family income. Illinois’ SCHIP was initially typical of many other public insurance programs, providing health insurance to children living below 185% FPL. This program expanded dramatically in 2006 under then-Gov. Rod Blagojevich’s All Kids program, which extended SCHIP to children of all income levels. Illinois therefore allows examination of the effect of public expansions at income levels not implemented elsewhere in the U.S. Secondly, Illinois’ demographic characteristics and health insurance coverage profile closely approximate the average values found elsewhere in the U.S., a point demonstrated later in my analysis. Thus, patterns found in Illinois might generalize more broadly across the country if SCHIP coverage is expanded elsewhere. Third, by examining SCHIP at different income levels within the same state, I facilitate comparisons across different income levels while holding constant factors that vary across states (i.e., economic performance).

Drawing causal inference from the Illinois experience is complicated by the lack of an obvious counterfactual control region that can approximate Illinois’ coverage levels in the absence of the All Kids intervention. In this paper, I overcome this problem by using “synthetic” controls, an idea demonstrated in Abadie and Gardeazabal’s analysis of Basque political terrorism (Abadie and Gardeazabal 2003), and extended in a recent paper by Abadie, Diamond, and Hainmueller (2010). The key insight of this approach is that a counterfactual synthetic control region can be constructed as a convex combination of multiple “donor” units unaffected by Illinois’ health insurance expansion. In this example, the donor units are other American states that have not extended SCHIP coverage to higher income levels. The synthetic unit is constructed such that its relevant demographic characteristics and health insurance profile closely resemble that of Illinois prior to the introduction of the All Kids program in 2006.

The synthetic control unit thus allows estimation of what Illinois’ health insurance profile would look like after 2006 in the absence of All Kids, and causal inference can be drawn by comparing observations from the real Illinois to those of the synthetic unit in the post-treatment period.

I begin this paper with a discussion of theories about the relationship between crowd-out and income. While the existing literature predominantly argues that expanding public health insurance to higher income populations leads to higher crowd-out, I argue that there are theoretical reasons why
this expectation may not always hold true. Next, I summarize the extensive literature on crowd-out, much of which ignores the impact of the targeted income level on coverage and crowd-out. In particular, I discuss issues involved in applying models that are standard in the crowd-out literature to expansions at higher income levels. I then discuss the synthetic control methodology used in this paper and how this procedure overcomes the problems raised in the earlier literature. This methodology is then applied to examine how All Kids affects insurance coverage and turnout in Illinois for children living between 200% and 500% FPL. Among other findings, my estimates suggest that there may actually be a surprising increase in private coverage among children between 400% and 500% FPL following the expansion of public health insurance. Further examination traces the likely cause of this to a reduction of insurance prices for high-income individuals in Illinois. I conclude with some thoughts on the policy implications of my findings.

Conceptual Framework
Dubay and Kenney (1996) were among the first researchers to theorize a relationship between crowd-out and income. Reflecting the general consensus among health economists, they argued that because private insurance is often unavailable to lower income populations, expansion of public insurance to higher income levels is likely to increase participation in public programs among income groups where private coverage is already available. Consistent with their expectations, Dubay and Kenney found that crowd-out was much higher for near-poor children (those living in families with incomes between 100% and 133% FPL) than for poor children (those living below 100% FPL). However, this research has not been extended to income levels currently covered by SCHIP.

While plausible, the previous depiction ignores three countervailing forces that are likely to mitigate or even reverse crowd-out as SCHIP expands to higher income levels. First, there may be stigma attached to SCHIP as a low-income entitlement program. This stigma imposes a private cost to insurance substitution that is likely to be increasingly costly as an individual’s income level increases. Beyond the stigma attached to welfare, SCHIP’s status as a low-income entitlement is likely to produce misinformation about the program’s eligibility rules. For example, Haley and Kenney (1996) found that while large numbers of people have heard of Medicaid and SCHIP, significantly fewer people were aware that children could participate in these programs without receiving welfare. In particular, high-income groups may be more likely to lack familiarity with the enrollment process required for public benefits, and specifically to lack the knowledge that a public insurance program may be accessible to them.

Secondly, at higher income levels the quality of private insurance offered through an employer is likely better than that offered in lower income jobs. In deciding to substitute public for private insurance, individuals must consider not only the quality of the public insurance option, but also the quality of the private insurance plan they are leaving. Even if SCHIP and Medicaid offer comparable coverage to a private plan, they still may be a less attractive option than private coverage. Compensation to care providers is typically lower in Medicaid than private insurance, so providers are often less willing to see publicly insured patients.

Finally, advocates of public insurance argue that the entry of a new competitor in the high-income insurance market has the potential to reduce private insurance prices. This is especially likely in highly concentrated insurance markets like Illinois, where the two largest insurers (HCSC Blue Cross Blue Shield and Coventry) account for 70% of the market share. This level of market concentration is hardly unique to Illinois; in over half of the states the two largest insurers had a combined market share of 70% or more (Emmons, Guardado, and Kane 2011). In particular, Bresnahan and Reiss (1991) found that most of the changes in competitive conduct within oligopolistic markets occur with entry of the second and third firms. Faced with lower costs, some high-income individuals may choose to purchase a private health insurance plan for their children that...
provides better coverage than SCHIP. While the previously discussed mechanisms are only likely to mitigate crowd-out, the effect of lower private insurance rates may actually produce “crowd-in”—that is, an increase in private coverage that accompanies the increase in public coverage (Hacker 2007a,b).

To summarize the previous discussion, there are multiple reasons why one might expect to find a relationship between income and crowd-out. However, these reasons point to different potential relationships, casting doubt on whether crowd-out is positively, negatively, or even non-monotonically related to income. While the posited mechanisms differ considerably, collectively they provide strong reasons that crowd-out rates calculated from low-income populations may differ considerably from those in higher income populations. In the next section, I review the crowd-out literature as applied to low-income populations. While more comprehensive literature reviews on the large crowd-out literature can be found elsewhere (i.e., Gruber and Simon 2008 and Congressional Budget Office 2007), my review focuses primarily on methodology and discusses why the application of previous estimation techniques to high-income populations can produce biased estimates.

Past Research

Any review of the crowd-out literature begins with Cutler and Gruber (1996), who inspired a sizable literature devoted to estimating crowd-out effects. Using individual-level data from the Current Population Survey (CPS), Cutler and Gruber examined crowd-out resulting from the 1987–1992 Medicaid expansions by separately estimating the rate at which public insurance was taken up, and the rate at which private insurance was dropped, as people became eligible for public insurance. These were estimated using two linear probability models:

\[
\text{Private Coverage} = \beta_1 \text{Eligible}_i + \beta X_i \\
+ \sum \alpha_i \text{State}_i \\
+ \sum \alpha_i \text{Time}_i + \varepsilon_i \tag{1}
\]

Public Coverage = \( \beta_2 \text{Eligible}_i + \beta X_i \)

\[+ \sum \alpha_i \text{State}_i \]

\[+ \sum \alpha_i \text{Time}_i + \varepsilon_i \tag{2}\]

where Public Coverage and Private Coverage are dichotomous variables indicating coverage type, Eligible is a dichotomous variable indicating whether individual i is eligible for public health insurance, X is a set of demographic controls, and State and Time are state and year dummy variables. Since \( \beta_1 \) measures marginal take-up for private insurance and is negatively signed, and \( \beta_2 \) measures marginal take-up of public insurance, \( \frac{-\beta_1}{\beta_2} \) is an estimate of the fraction of individuals substituting public for private coverage as eligibility expands.

Cutler and Gruber recognized that \( \beta_1 \) and \( \beta_2 \) were unbiased estimates of marginal insurance take-up only if eligibility for public health insurance was exogenous to the private and public coverage variables. To address this issue, they used a “simulated instrument” for their measure of public insurance eligibility following the work of Currie and Gruber (1996ab). Using their simulated eligibility variable, Cutler and Gruber obtained estimates of \( \beta_1 = -0.074 \) and \( \beta_2 = 0.235 \), which implies a crowd-out rate of 31%. \( \beta_2 \) also implies that 23.5% of those eligible for coverage took up public insurance, while 27% of those who were newly eligible for coverage were uninsured. This implies that in the absence of crowd-out, the take-up rate among the uninsured would have almost reached 90%.

Cutler and Gruber were subsequently challenged by a series of papers, many of which used difference-in-differences (DID) estimators (Ashenfelter and Card 1985). Under simple DID designs, outcomes are observed for two groups over a pre-treatment (or intervention) period and a post-treatment period. While neither group is exposed to treatment during the pre-treatment period, in the post-treatment period one group is exposed to the intervention while the control group is not. Estimation of the treatment effect occurs by subtracting the average
change in the control group from that of the treatment group. This design thus attempts to eliminate biases from comparisons over time in the treatment group (i.e., insurance coverage trends over time unrelated to the treatment), and to fix biases in comparing treatment and control groups resulting from permanent differences between those groups.

A critical assumption underlying DID analysis is that unmeasured, time-varying factors are assumed to have the same effect on treatment and control group members.\textsuperscript{1} When this assumption fails, the estimates are biased. This is particularly likely to be true in cases where the treatment and control groups are drawn from different populations—a situation that is true of every published DID design on crowd-out for children I could find. For example, Dubay and Kenney (1996) conducted a DID analysis comparing changes in insurance coverage of children relative to adult men, an approach criticized for assuming there were no other factors changing over time differentially for the two groups (Cutler and Gruber 1997). Yazici and Kaestner (2000) and Blumberg, Dubay, and Norton (2000) conducted DID analyses comparing changes in insurance coverage of children who became eligible to those who still were ineligible for public health insurance, under the assumption that time-varying factors did not differentially affect the eligible and ineligible populations. Similarly, Hudson, Selden, and Banthin (2005) estimated DID models using never-eligible children of different income levels and married childless women of different income levels as their control group. These DID studies typically estimated lower rates of crowd-out than Cutler and Gruber, ranging from 5\% to 15\% for children in poverty. However, it is known that such estimates are sensitive to somewhat arbitrary changes to the control group, even when the choice of data set is held constant.\textsuperscript{2}

Recognizing the limitations of the original DID designs, Card and Shore-Sheppard (2004) exploited Medicaid eligibility rules in a regression discontinuity design to identify the effect of two separate Medicaid expansions on low-income children—the 1991 expansion to 100\% FPL and the 1990 expansion to children under 6 below 133\% FPL. Following the trend of lower estimates, Card and Shore-Sheppard did not find statistically significant crowd-out in either Medicaid expansion. Card and Shore-Sheppard also estimated that the expansion to 100\% FPL increased Medicaid coverage by 10\% for children born just after the cutoff birth date determining eligibility, while the expansion to 133\% FPL had no effect on health insurance coverage. The null finding between 100\% and 133\% FPL suggests that income can interact with coverage in highly unusual ways, providing additional empirical support for the kinds of unusual income dynamics that I demonstrate later in Illinois' All Kids program.

The trend toward lower crowd-out estimates using DID subsequently led researchers to re-examine simulated eligibility models with mixed results. Shore-Sheppard (2008) replicated the original Cutler-Gruber models and found that the inclusion of age*year interaction variables resulted in crowd-out estimates of zero and lower public insurance take-up rates than reported earlier. This finding, confirmed by Ham and Shore-Sheppard (2005) with different data, suggests that omitted trends in insurance coverage by child age and state are correlated with expansions in eligibility.\textsuperscript{3} However, similar models have continued to find significant levels of crowd-out from SCHIP expansions. Using a simulated eligibility design, Lo Sasso and Buchmueller (2004) found a marginal take-up rate for public insurance of 8.1\%, and crowd-out rates between 18\% and 50\% depending on the exact specification used. A similar paper by Gruber and Simon (2008) largely confirmed these results, estimating a low take-up rate of 5.5\% for public insurance accompanied by a direct crowd-out rate of 30\%.

Summarizing the literature, Cutler and Gruber's estimates suggest crowd-out rates of approximately 30\% for the Medicaid expansions of the early 1990s. However, estimates using alternative data and DID have tended to find less crowd-out, and a replication of the original Cutler-Gruber model found no crowd-out once age*year interaction variables were included. More recently, however, researchers applying the
Cutler-Gruber models to the Medicaid expansions of the late 1990s have found lower rates of insurance take-up than before, accompanied by crowd-out rates around 30%. While this crowd-out rate is consistent with the original Cutler-Gruber estimates, the rates cannot be directly compared because the early 1990s expansions primarily targeted children living in poverty, while the late 1990s expansions primarily targeted children with family incomes between 100% and 200% FPL.

Although the Cutler-Gruber models provide an attractive means to estimate crowd-out for children below 200% FPL, their applicability to higher income populations is limited. While Medicaid provides insurance to some high-income children, these children are highly atypical of the general population and are frequently uninsurable by private means. Simulated eligibility models at higher income levels therefore may bias upwardly estimates of public insurance take-up and bias downwardly estimates of crowd-out because eligible high-income individuals are effectively forced to stay in a public insurance plan.

Methodology

In this section, I present a new method to assess the effect of SCHIP using Illinois’ All Kids program as the treatment unit of interest. This exposition closely follows the description in Abadie and Gardeazabal (2003) and Abadie, Diamond, and Hainmueller (2010), and which is implemented subsequently in Abadie, Diamond, and Hainmueller (2011). In this study, I observe $J + 1 = 48$ states, where the first state (Illinois) is exposed to an intervention of interest (All Kids) and the remaining $J$ states are not exposed. Then in state $i$ and time $t$, $Y_{it}^N$ represents the outcome that would be observed in the absence of the intervention for units $i = 1, \ldots, J + 1$ and periods $t = 1, \ldots, T$. Also, $Y_{it}^{T}$ represents the outcome that would be observed for unit $i$ at time $t$ if it were exposed to the intervention in periods $T_0 + 1$ to $T$, where $T_0$ is the number of pre-intervention periods and $l \leq T_0 < T$. In this application, $T = 16$ periods occur between 1995 and 2010; $T_0 = 12$ represents the periods that occur prior to the All Kids intervention in 2006.

Assuming the intervention has no effect on the outcome before the implementation period $t \in T_0$ for all units $i \in T_0$, the effect of exposure to the intervention on unit $i$ at time $t$ is $x_{it} = Y_{it}^T - Y_{it}^N$. For untreated units (i.e., $i \neq I$) or treated units before the intervention (i.e., $i = I$ but $t < T_0$), the effect $x_{it} = 0$. Then more generally, defining $D_{it}$ to be an indicator value that takes the value of one if unit $i$ is exposed to the intervention at time $t$ (which is true if $i = I$ and $t > T_0$) and zero otherwise, the observed outcome for any unit $i$ at time $t$ is $Y_{it} = Y_{it}^N + x_{it}D_{it}$. Estimation of the effect on the exposed unit in each post-treatment time period $t > T_0$ is given by $x_{it} = Y_{it} - Y_{it}^N$, with $Y_{it}$ observed for all time periods. The central issue of estimation therefore centers on how to estimate $Y_{it}^N$, the outcome that would be observed in Illinois in the absence of the All Kids intervention.

Following Abadie, Diamond, and Hainmueller (2010), I approach this problem by estimating $Y_{it}^N$ as a weighted combination of other states, chosen to resemble the demographic characteristics and health insurance profile of Illinois prior to the introduction of All Kids. This “synthetic” Illinois provides estimates of $Y_{it}^N$, the outcome that would be observed in the absence of All Kids. Given $J$ control states (i.e., states not treated with All Kids), I estimate $W = (w_1, \ldots, w_J)^T$, a $(J \times I)$ vector of nonnegative weights that sum to 1. Each single weight $w_j$ represents the weight of state $j$ in the formulation of the synthetic Illinois, and each set of weights $W$ produces a different synthetic Illinois.

To optimize the choice of $W$, I let $X_I$ be a $(K \times I)$ vector of state-level demographic and health insurance coverage variables for Illinois, and I let $X_0$ be a $(K \times J)$ matrix containing the same variables for the $J$ potential control states. Also, I let $V$ be a diagonal matrix of nonnegative components representing the relative importance of the different predictor variables. The vector of weights $W^*$ that defines the combination of control regions best resembling Illinois during the pre-treatment period is chosen such that...
be selected subjectively based on previous knowledge about the relative importance of each predictor, in this application I choose \( V \) such that the path of the synthetic outcome variable \( Y_{it}^N \) best approximates the path of the true observed outcome variable \( Y_{it} \) during the pre-intervention period \( I \leq T_0 < T \).

Model performance is evaluated in three ways. First, one can examine how closely synthetic Illinois’ pre-treatment demographic and health insurance coverage variables \( X_0W \) approximates \( X_I \), the corresponding set of observed variables in the real Illinois. Second, one can also examine how closely the synthetic outcome variable \( Y_{i0}^N \) approximates the observed outcome variable \( Y_{i0} \) during the pre-intervention period. Finally, the out-of-sample performance of the model can be evaluated using a “placebo” treatment. To do so, I choose a placebo treatment period \( T_P \) that occurs before the true implementation period \( T_0 \), and refit the same model, substituting the chosen \( T_P \) for \( T_0 \). Under this condition, note that a crucial difference is that during the placebo “post-treatment” period \( T_P < t \leq T_0 \), \( Y_{it} \approx Y_{it}^N \) and \( x_{it} \approx 0 \). I thus can further validate the model by seeing how closely the estimated \( Y_{it}^N \) tracks the observed \( Y_{it}^N \) in the period between the placebo and actual treatment.

The synthetic control procedure enjoys many advantages over other methods used to estimate effects from comparative case studies. Abadie, Diamond, and Hainmueller (2010) note that the synthetic control procedure generalizes the DID model discussed previously. Additionally, the procedure produces useful estimates in models with time-varying coefficients. This is not true for traditional DID designs, which allow for unobserved confounders but restrict the estimated effects of those confounders to be constant in time. In contrast, the synthetic control model allows the effects of confounding unobserved characteristics to vary with time, thus creating less model dependency.

Furthermore, the procedure directly addresses many of the issues raised in considering how earlier techniques used to estimate crowd-out could be applied to higher income populations. In contrast to the earlier DID designs where the treatment and control groups may not have been comparable (i.e., comparing children to adults), synthetic controls have the advantage of forcing the researcher to demonstrate an affinity between the treatment and control units, in the sense that the predictor values of the synthetic control \( X_0W \) closely approximate those of the observed unit \( X_I \) during the pre-treatment period. This affinity maximizes the chance that time-varying factors have the same effect on the treatment and control groups. In effect, the procedure draws causal inference using exact matching, where the treatment unit is matched not only to the observed donor cases but to all possible convex combinations of those observed cases. Also, the synthetic control procedure addresses the selection issues in the simulated eligibility design, where a direct application of those procedures to higher income populations will yield biased estimates because the treatment units are not representative of the larger population at the income strata of interest. Synthetic controls address this issue by allowing the entire state of Illinois to be used as a treatment unit, because the All Kids treatment covers all children irrespective of their income levels or pre-existing conditions.

Data

Data for these results were obtained from the annual March Supplement to the Current Population Survey (CPS) from the years 1995–2010. I used CPS data for this paper because the synthetic control methodology requires samples designed to be representative within states, a feature that is not true of the Survey of Income and Program Participation or the Panel Study of Income Dynamics (Bureau of Labor Statistics 2010). I begin this analysis using data from 1995 because that was the first year of the CPS following its redesign to improve the quality of its health insurance data (Swartz 1997). All state-level estimates of the total, private, and public coverage variables are Kalman smoothed to reduce measurement error.

My analysis was restricted to children below age 19 with family incomes between
200% and 500% FPL. Although these data are stratified by income, there is sufficient data in the CPS to draw inference. Across the 16 years of data, I average $N = 358.9 \ (s = 62.1)$, $N = 301.9 \ (s = 55.1)$, and $N = 215.3 \ (s = 37.4)$ observations each year, respectively, for the three income strata of interest (200% to 300% FPL, 300% to 400% FPL, and 400% to 500% FPL). Summary statistics of the key variables of interest in Illinois and the contiguous U.S. are presented in Table 1.

### Results

In this section, I present an application of the synthetic control method to Illinois’ All Kids program. I begin by describing the application of this method to insurance coverage at the 400% to 500% FPL population in greater detail, focusing on the diagnostics used to assess the fit of my model. I then apply the same procedure to coverage between 200% and 400% FPL to determine the net increase in child health insurance coverage resulting from All Kids. Next, I apply the same procedure to determine changes in public versus private coverage across the 200% to 500% FPL income level. These results facilitate subsequent estimates of crowd-out.8

I begin by constructing a synthetic control for Illinois using CPS data from 1995–2006, the pre-treatment period before the enactment of All Kids. Recall that the objective is to approximate Illinois’ predictors of child health insurance coverage between 400% and 500% FPL using a convex combination of donor states. For predictor variables, I use the percentage of children covered with health insurance below the federal poverty level, at 100% to 200% FPL, 200% to 300% FPL, 300% to 400% FPL, and 400% to 500% FPL, along with a standard set of demographic controls including race, income, income distribution, unemployment rate, and education. Donor states include all states except for Alaska, Hawaii, and the District of Columbia, though my results are robust to the inclusion of those states and the District of Columbia as well.9 This control group allows estimates of children’s health insurance coverage in the post-intervention period, 2007–2010, because they did not enact public health expansions at that income level during the post-treatment period.

Table 1 summarizes the predictor values for the real Illinois and its synthetic counterpart, averaged across the 1995–2006 pre-treatment period. Comparing the predictor values in columns 2 and 3, the synthetic control closely reproduces the values from Illinois during that period, suggesting a strong fit for the synthetic unit. Column 4 shows the same values calculated for the 47 states included in the donor pool, which largely represents the predictor values across the rest of the U.S. In comparing predictor values between Illinois and the U.S., we see some minor differences, most notably a $3,005 difference in mean income. This is significant because it suggests that Illinois is
not particularly unusual among states; hence the results of this study may potentially generalize to the U.S. at large.10 Also note that for all variables, the synthetic control more closely approximates the predictor values of Illinois than the nation at large, especially with regard to income. This suggests that the synthetic unit serves as a better control unit than simply using all other states as a control. Finally, the standard deviations of the predictor variables for the 47 control states are shown in column 5. The relatively large deviations for all variables suggest that some combinations of control states will produce extremely poor synthetic controls that fail to reproduce the predictor values shown.11

Table 2 explores the construction of the synthetic control unit more closely. While the estimated weights defining the combination of states used to construct the synthetic unit only approximately sum to 1 because of rounding, 94% of the total weight is accounted for by five states: Delaware, Maryland, Michigan, Oregon, and Rhode Island. These weights can be used to generate the synthetic control, which then can be used to estimate the effect of All Kids on Illinois’ child health insurance coverage rates between 400% and 500% FPL.

Figure 1 displays the percentage of children with family incomes between 400% and 500% FPL covered by either private or public health insurance in Illinois from 1995 through 2010, along with its synthetic counterpart. Prior to the introduction of the All Kids policy treatment, synthetic Illinois largely replicates the slight downward trend in total health insurance coverage that is actually observed in Illinois. Combined with the high balance on all predictors shown previously in Table 1, this suggests that synthetic Illinois provides a reasonable counterfactual approximation to the coverage that would have been observed between 2007 and 2010 in the absence of the All Kids expansion.12 However, coverage in real Illinois diverges from coverage in synthetic Illinois after the 2006

### Table 2. State weights in synthetic Illinois

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<td>0</td>
<td>Texas</td>
<td>0</td>
</tr>
<tr>
<td>Maine</td>
<td>0</td>
<td>Utah</td>
<td>0</td>
</tr>
<tr>
<td>Maryland</td>
<td>.19</td>
<td>Vermont</td>
<td>0</td>
</tr>
<tr>
<td>Massachusetts</td>
<td>0</td>
<td>Virginia</td>
<td>0</td>
</tr>
<tr>
<td>Michigan</td>
<td>.12</td>
<td>Washington</td>
<td>0</td>
</tr>
<tr>
<td>Minnesota</td>
<td>0</td>
<td>West Virginia</td>
<td>0</td>
</tr>
<tr>
<td>Mississippi</td>
<td>0</td>
<td>Wisconsin</td>
<td>0</td>
</tr>
<tr>
<td>Missouri</td>
<td>0</td>
<td>Wyoming</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: All weights were rounded to two significant digits, so they may not sum exactly to 1 as presented here. The results suggest that a synthetic Illinois is best fitted using largely a convex combination of Delaware, Maryland, Michigan, Oregon, and Rhode Island.

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policy intervention. The gap between the observed and synthetic coverage represents the estimate of All Kids’ effect on the total insurance rate at this income level. While the gap is negligible during the pre-treatment period, the large positive gap suggests that All Kids significantly increased health insurance coverage among children of this income group.

To evaluate the statistical significance of this gap, I conduct a permutation test to determine how likely a gap of this magnitude is likely to occur by chance under the null hypothesis. More specifically, I generate the distribution of mean squared prediction errors (MSPE) under the null hypothesis when no intervention has occurred, and compare this distribution to the observed MSPE of 9.03 from the post-treatment observations. In the original model, I use 12 pre-treatment observations between 1995 and 2006 to fit a model that is then used to estimate four counterfactual cases in the 2007–2010 post-treatment period. To simulate a null distribution, I instead use a random selection of eight of the 12 pre-treatment observations to fit the model (i.e., observations from the 1995–2002 period). This model also allows me to generate four counterfactual cases for the remaining four pre-treatment cases (i.e., for 2003–2006). Of the 495 possible permutations, I test 100 such permutations at random, calculating the average out-of-sample MSPE of the remaining four observations for each trial. None of the control trials achieves such a large MSPE, and the inclusion of 100 trials in this sampling distribution suggests that one can reject the possibility of a null result at the $\sigma = .01$ level of significance. This procedure can be generalized to apply the logic of the jackknife to generate standard errors (Tukey 1958).13

Figure 1. Coverage in true vs. synthetic Illinois, 1995-2010 (Results shown are for children with family incomes between 400% and 500% FPL. Synthetic Illinois coverage was generated by taking a convex combination of coverage rates from different states using the weights shown in Table 2)
As an additional check on this hypothesis test, I implement the placebo treatment discussed in the methods section, where I refit the model using a fake treatment period timed before the actual treatment takes place. I conduct this test by using a placebo treatment in the year 2000. This test proceeds by fitting the model using only the first six observations (1995–2000), and comparing the predicted values of that model to the observed values in the period for the post-placebo period prior to the actual treatment (2001–2006). These out-of-sample predictions should closely approximate the observed values since the real treatment in 2006 has not yet occurred. In contrast to the jackknife, this procedure tests for the possibility that there is always divergence between the synthetic and observed results after even a fake treatment, however unlikely that may be. Figure 2 displays the observed and synthetic approximation of the placebo test. As expected, the placebo treatment does not cause the true and synthetic coverage rates to diverge between 2001 and 2006, providing additional evidence that the coverage gaps in the post-treatment period shown earlier in Figure 1 are unlikely to occur by chance.

I repeat this analysis for the 200% to 300% FPL and 300% to 400% FPL income levels, but discard some control states that expanded SCHIP above 200% FPL. Results between 100% and 200% FPL cannot be obtained because there are no control states that did not enact an SCHIP expansion at that income level; however, coverage and crowd-out at this level have been analyzed using the methods discussed in the literature review.

Figure 2. Placebo in time: true vs. synthetic Illinois, 1995-2006 (Results shown are for children with family incomes between 400% and 500% FPL. Here we falsely assume that the All Kids treatment occurred in 2000 rather than 2006, and refit the model. The synthetic control still closely tracks the observed coverage rates in Illinois following the placebo treatment, providing further evidence that the coverage gaps in the post-treatment period shown earlier in Figure 1 are unlikely to occur by chance)
In both cases, the synthetic unit accurately reproduces the observed coverage values during the pre-treatment period. However, estimates in the post-treatment period differ substantially. Between 200% and 300% FPL, the synthetic unit suggests that insurance coverage would have increased slightly in the post-treatment period even in the absence of All Kids. Nevertheless, All Kids appears to have increased health insurance coverage above and beyond the expected increase. At the 300% to 400% FPL level, however, the story is quite different. All Kids appears to have had no net effect on health insurance coverage above and beyond the expected increase. At the 300% to 400% FPL level, however, the synthetic unit suggests that insurance coverage would have increased slightly in the post-treatment period even in the absence of All Kids. Nevertheless, All Kids appears to have increased health insurance coverage above and beyond the expected increase. At the 300% to 400% FPL level, however, the story is quite different. All Kids appears to have no net effect on health insurance coverage at this income level, and the increase in coverage shown in the synthetic unit at the 200% to 300% FPL level resulting from factors other than All Kids also appears to be absent.

Table 3 summarizes the net effect of SCHIP on insurance coverage, tabulating the net increase in health insurance coverage by year and income strata. Following the logic outlined in the resampling test, I estimate standard errors using the jackknife by calculating the out-of-sample prediction errors for each observation in the pre-treatment period. Between 200% and 300% FPL, total coverage increased after four years by 2.7 percentage points above what would have been expected in the absence of any policy intervention. This increase covered 28.3% of the uninsured population at the income level, so extension of coverage to the uninsured is substantively large. Between 300% and 400% FPL, increases in coverage were not statistically significant. However, between 400% and 500% FPL, the 3.36 percentage-point increase in net coverage had an enormous effect, covering 49.9% of the uninsured. My results therefore suggest that the marginal impact of public health insurance on coverage does not change monotonically with the income level of the expansion.

I extend the analysis presented previously, estimating the same models separately for private and public health insurance coverage from 200% to 500% FPL with two changes. First, I replace the original coverage control variables for private or public versions of those same variables, as appropriate. Secondly, following Cutler and Gruber (1996) and Gruber and Simon (2008), I treat cases in which an individual claims to have both private and public coverage together as situations where an individual is making a transition from private insurance to public insurance. While there are generally few cases where an individual claims both forms of insurance, this assumption will generally produce higher estimates of crowd-out than the alternative of discarding the cases altogether.

Figure 3 plots observed and synthetic coverage rates for private and public insurance between 1995 and 2010. Private insurance coverage is shown along the top, while public insurance coverage appears on the bottom. In five of the six cases, the synthetic control unit continues to closely reproduce the corresponding coverage rates observed in Illinois, providing evidence of good model fits. However, even without looking at the post-treatment period, there is strong evidence pointing to substitution in the pre-treatment period; all income levels show some decrease in private coverage accompanied by some increase in public coverage during that time. Another notable trend in the data is that net private and public coverage are strongly related to income—as income increases, private coverage rates increase and public coverage rates decrease.

My estimates of public coverage rates highlight a limitation of the approach because I am unable to construct a synthetic estimate for public coverage between 400% and 500% FPL. This is not surprising, as public health

![Table 3. Summary of percentage point changes in total insurance coverage in Illinois after All Kids expansion](image-url)

<table>
<thead>
<tr>
<th>FPL</th>
<th>Changes (percentage point)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2007</td>
</tr>
<tr>
<td>200%–300%</td>
<td>2.06</td>
</tr>
<tr>
<td></td>
<td>(.64)</td>
</tr>
<tr>
<td>300%–400%</td>
<td>1.31</td>
</tr>
<tr>
<td></td>
<td>(.35)</td>
</tr>
<tr>
<td>400%–500%</td>
<td>2.11</td>
</tr>
<tr>
<td></td>
<td>(.29)</td>
</tr>
</tbody>
</table>

Notes: Jackknife standard errors are in parentheses. Numbers represent percentage point increases in net coverage by year, calculated as the difference in coverage between the observed and synthetic control.
Figure 3. Private/public coverage in true vs. synthetic Illinois, 1995-2010 (From left to right, top panels show results for private coverage ranging from 200% to 500% FPL, while lower panels show corresponding results for public coverage by income. No synthetic unit could be constructed for Illinois' public coverage between 400% and 500% FPL. Note also that results for public coverage between 400% and 500% FPL are not presented on a comparable scale)
insurance coverage rates for high-income populations are generally quite low, fluctuating between 2% to 4% in Illinois during the pre-treatment period. In these cases, construction of a synthetic unit can be very difficult because such units are typically interpolated as convex combinations of states. Some of these donor states will have higher public coverage rates than Illinois during the pre-treatment period, but these are typically balanced by the inclusion of some donor states with public coverage rates lower than those in Illinois. Since Illinois’ public coverage rate is already quite low for this income group, there are insufficient donor states with low public coverage that are able to reproduce both Illinois’ public coverage pattern and predictor values. Despite my inability to produce a synthetic replicate of Illinois at the 400% to 500% FPL, the time series plot in Figure 3 clearly suggests that there is a significant take-up of public health insurance following the passage of All Kids. However, this pattern diverges significantly at 400% to 500% FPL, where one can see an increase in private coverage instead. This is likely accompanied by an increase in public coverage as well, though the determination of this is complicated by the lack of a synthetic Illinois to approximate the counterfactual.

Tables 4 and 5 present the effects numerically for public and private insurance respectively during the entire post-treatment period. These values are needed to calculate crowd-out estimates in relative (percentage) terms, but they are also of interest because they also produce estimates of crowd-out in absolute terms as a proportion of the entire population. Between 200% and 300% FPL, public coverage increased by 6.54 percentage points in 2010, a large amount that is more than 1.5 times larger than a standard deviation of child health insurance coverage across the U.S. as reported earlier in Table 1. Take-up of public insurance is lower at other income levels, varying between 1.58 to 3.58 percentage points. In most cases, the observed shifts are significant at standard levels. The change in public and private insurance rates also suggests that the full impact of the All Kids intervention unfolds over many years—coverage rates for both types of insurance still do not appear to have stabilized four years after the intervention. The length of time that public health care expansions require for full effect, and the measurement of crowd-out rates over different periods of that

### Table 4. Summary of changes in public insurance coverage in Illinois after All Kids expansion

<table>
<thead>
<tr>
<th>FPL</th>
<th>Changes (percentage point)</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>200%–300%</td>
<td></td>
<td>2.57</td>
<td>4.72</td>
<td>5.94</td>
<td>6.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.68)</td>
<td>(1.68)</td>
<td>(1.68)</td>
<td>(1.68)</td>
</tr>
<tr>
<td>300%–400%</td>
<td></td>
<td>.29</td>
<td>1.61</td>
<td>2.43</td>
<td>3.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.66)</td>
<td>(.66)</td>
<td>(.66)</td>
<td>(.66)</td>
</tr>
<tr>
<td>400%–500%</td>
<td></td>
<td>.69</td>
<td>1.31</td>
<td>1.64</td>
<td>1.58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
<td>(—)</td>
</tr>
</tbody>
</table>

**Notes:** Jackknife standard errors are in parentheses. Numbers represent percentage point increases in public coverage by year, calculated as the difference in coverage between the observed and synthetic control. Estimates for 400% and 500% FPL are derived naively by assuming that 2006 coverage levels remain constant.

### Table 5. Summary of changes in private insurance coverage in Illinois after All Kids expansion

<table>
<thead>
<tr>
<th>FPL</th>
<th>Changes (percentage point)</th>
<th>2007</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
</tr>
</thead>
<tbody>
<tr>
<td>200%–300%</td>
<td></td>
<td>.43</td>
<td>−1.27</td>
<td>−2.13</td>
<td>−2.27</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.24)</td>
<td>(1.24)</td>
<td>(1.24)</td>
<td>(1.24)</td>
</tr>
<tr>
<td>300%–400%</td>
<td></td>
<td>−.35</td>
<td>−1.76</td>
<td>−2.52</td>
<td>−3.72</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.68)</td>
<td>(.68)</td>
<td>(.68)</td>
<td>(.68)</td>
</tr>
<tr>
<td>400%–500%</td>
<td></td>
<td>.67</td>
<td>1.48</td>
<td>1.96</td>
<td>2.62</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.78)</td>
<td>(.78)</td>
<td>(.78)</td>
<td>(.78)</td>
</tr>
</tbody>
</table>

**Notes:** Jackknife standard errors are in parentheses. Numbers represent percentage point increases in private coverage by year, calculated as the difference in coverage between the observed and synthetic control.
expansion, may provide a partial explanation why estimates of crowd-out vary so dramatically, even when the estimation strategy remains constant.19

The crowd-out rate is defined as the fraction of children taking up public health insurance who, in the absence of a public health insurance option, would have taken up private health insurance instead. I calculate it using the formula:

\[
\text{Crowd-out} = \frac{-\Delta Private}{\Delta Public}
\]

where \(\Delta Public\) and \(\Delta Private\) are the entries found in Tables 4 and 5 respectively. Applying this equation, I calculate the coverage and crowd-out rates shown in Table 6. Three results emerge from this analysis. Between 200% and 300% FPL, crowd-out reached 35% by 2010—an estimate that is consistent with the magnitude of the effect found by Cutler and Gruber (1996) for Medicaid below 200% FPL. Between 300% and 400% FPL, I observe no effect on net coverage, suggesting that every marginal person taking up public health insurance would have otherwise been covered by private health insurance. Finally, between 400% and 500% FPL, total coverage increased by 3.36 percentage points, aided by a 2.62-percentage-point increase in private coverage shown earlier in Table 5. Stated differently, we actually observe “crowd-in”—an increase in private coverage rather than substitution away from it. No standard errors are provided for crowd-out estimates, so it is important to note the potential effect of this omission on the interpretation of the results:

as Hudson, Selden, and Banthin (2005) have noted, standard errors for crowd-out estimates can be much larger than the standard errors for the individual coefficients used to estimate them.

As a robustness check, I also compare results derived from the synthetic model against those using a simple DID model in Table 6. Using individual-level CPS data from Illinois and its neighboring states between 2003 and 2010, I estimate linear probability models of the form

\[
\text{Coverage}_i = \beta_0 + \beta_1 \times IL + \beta_2 \times Treatment + \beta_3 \times Treatment \times IL,
\]

where \(\text{Coverage}_i\) is a binary variable indicating whether individual \(i\) is covered by public or private health insurance, \(IL\) is a dichotomous variable for an Illinois resident, and \(Treatment\) indicates whether the respondent was surveyed after the introduction of All Kids in 2006.20 Each cell in columns 4 and 5 reports an estimate of \(\hat{\beta}_3\), the estimated effect of All Kids on public or private coverage at the specified income strata. The sum of public and private coverage, shown in column 6, represents the DID estimate of All Kids’ overall effect on health insurance coverage in Illinois. Although there is significant uncertainty associated with these estimates, the DID results are broadly consistent with the patterns obtained via the synthetic model in suggesting that net coverage increased between 200% and 300% FPL and between 400% and 500% FPL. In particular, although the estimate for coverage between 400% and 500% FPL fails to achieve statistical significance, it is similar in magnitude to the synthetic estimate, and the unusual

---

### Table 6. Summary of crowd-out estimates in Illinois after All Kids expansion

<table>
<thead>
<tr>
<th>FPL</th>
<th>Synthetic estimates (%)</th>
<th>Using DID approach (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(\Delta)Coverage</td>
<td>Crowd-out</td>
</tr>
<tr>
<td>200%–300%</td>
<td>2.7</td>
<td>34.8</td>
</tr>
<tr>
<td>300%–400%</td>
<td>-0.63</td>
<td>~100</td>
</tr>
<tr>
<td>400%–500%</td>
<td>3.36</td>
<td>Crowd-in</td>
</tr>
</tbody>
</table>

Notes: Standard errors are in parentheses. For synthetic results, change in coverage is calculated as percentage point differences between observed and synthetic unit in 2010. Crowd-out calculated as \(-\text{Private}/\text{Public}\). Each private and public coverage estimate comes from a separate DID (difference in differences) regression, using data from 2003 to 2010, and states adjacent to Illinois as a control group. Net coverage results under DID are the sum of the changes in private and public coverage. Results between the synthetic estimate and DID are largely consistent with each other.
increase in private coverage at this income level that is estimated by the synthetic model enjoys similar supporting evidence. Crowd-out estimates are 15% higher between 200% and 300% FPL when derived using DID, though previous caveats about the uncertainty surrounding such estimates also apply here.21

Why Does Crowd-in Occur?

Estimates from the previous section suggest that at high-income levels above 400% FPL, the expansion of public health insurance may actually cause crowd-in—an increase in private coverage rather than substitution away from it. Why might this occur? My key hypothesis is that the entry of a new public competitor in the high-income insurance market has the potential to reduce private insurance prices, or at least slow their growth considerably. This is especially likely to be true in insurance markets that are highly concentrated with few competitors—a characterization that is largely true of both Illinois and the U.S. at large. Faced with lower costs, some high-income individuals may choose to purchase a private health insurance plan for their children that provides better coverage than SCHIP.

Before proceeding further, note that other researchers have also uncovered evidence for crowd-in. In particular, there is growing evidence that despite expanding eligibility for public health insurance, the Massachusetts health reform simultaneously increased both public and private health insurance coverage. Using data from a household survey, Long (2008) reported that employer-based coverage and public insurance each expanded by 2.9 percentage points, while Long, Stockley, and Yemane (2009) found a 5.6-percentage-point increase in employer-sponsored insurance accompanied by an 11.7-percentage-point increase in public coverage, using a DID design with CPS data. These findings were largely confirmed by Gabel et al. (2008), who found evidence of crowd-in using employer surveys. Between 2007 and 2008, they found that the percentage of firms offering health benefits increased from 73% to 79%, while the percentage of firms offering coverage nationally was statistically unchanged. Firms with 11 to 50 workers also increased coverage significantly, from 88% to 92%, and were no more likely than firms nationally to consider dropping coverage or restricting eligibility (Gabel et al. 2008). These earlier results, coupled with the supporting evidence that I present here, jointly point to the empirical plausibility of crowd-in.

In this section, I use publicly available data from the Medical Expenditure Panel Survey—Insurance Component (MEPS-IC) to investigate this issue.22 I tabulate the growth of total family premiums per enrolled employee in the private sector between 2004 and 2008, covering the two years before and after the introduction of All Kids, for both Illinois and the U.S. at the fourth payroll quartile. I estimate the effect of All Kids on premium growth as the difference in premium growth between Illinois and the U.S. for the years 2006–2008, over and above the difference in premium growth for the period 2004–2006. This analysis allows me to control for pre-existing differences in premium growth that jointly affect both Illinois and the U.S., but are unrelated to the All Kids reform.

My analysis is subject to two important caveats. First, note that publicly available MEPS-IC data do not contain sufficient information to calculate standard errors for my estimates. Secondly, the MEPS-IC does not contain income data directly, but instead provides data on the wage distribution of firms providing coverage. The fourth payroll quartile thus refers to the quartile of the Illinois workforce in the group of establishments with the highest average payroll, not to the top 25% of income earners in Illinois. Nevertheless, the MEPS-IC remains the best source of publicly available information on insurance premiums, and both the direction and substantive magnitude of the changes I estimate are largely consistent with expectations.

Table 7 presents my analysis of family premium growth rates. The second column shows that premiums for the 2006–2008 period for employees in high-payroll establishments grew 3.8% in Illinois after All Kids, compared to 7.1% across the U.S. A simple estimate of the effect of All Kids would be the difference...
between the two, or a 3.3% decrease that is consistent with my expectation that All Kids reduced insurance premiums. This simple calculation, however, does not account for the possibility that Illinois may have had a different pre-existing trend in premiums from the rest of the country. I examine this in the first column of Table 7, which shows that Illinois’ premium rates were actually growing 1.5% faster than the rest of the country. The differential growth in Illinois versus the U.S. between 2006 and 2008, compared to the premium growth rate between 2004 and 2006, yields −4.8% as my estimate of the effect of All Kids on premiums in high-payroll establishments. With an average family premium rate of $12,475 in 2008, this effect amounts to $599 in reduced costs for a family in the fourth payroll quartile in Illinois.

In the third and fourth rows of Table 7, I also tabulate premium growth rates across the same periods for residents at all payroll percentiles. While both Illinois and the U.S. show a substantial slowing in the growth of premium rates after 2006, they still grow faster than what was found earlier for high-payroll establishments in Illinois. The reduction in premium rates caused by All Kids thus appears to have a highly localized effect, focused primarily on premiums in high-payroll establishments. This is consistent with my finding of crowd-in only at high-income levels. Overall, I find evidence that All Kids lowered family premiums considerably at high-payroll establishments, which may partially explain why I observe crowd-in.

### Conclusion

This paper examines the impact of SCHIP expansions on insurance coverage across higher income populations. Health economists widely believe that as eligibility levels for public health insurance programs are expanded to cover higher incomes, the possibility of substitution from private to public insurance rises because the expansions increasingly target those with access to private insurance. However, there are many reasons why this relationship may not be so simple—a conclusion that previously drew empirical support from the work of Card and Shore-Sheppard (2004). In examining Illinois’ All Kids program, I find additional evidence that the relationship between income and crowd-out is much more complex. More specifically, I find that for children with family incomes between 200% and 300% FPL, the All Kids program produced an increase in health insurance coverage of two percentage points with 35% crowd-out. For children with family incomes between 300% and 400% of FPL, All Kids produced no increase in overall coverage with significant crowd-out. Finally, I find that for children with family incomes between 400% and 500% FPL, SCHIP produced a 3.4-percentage-point increase in coverage with crowd-in. These findings are of substantive interest because there is clearly a desire by some legislators to continue expanding SCHIP eligibility to higher income populations.

Although comparisons at higher income levels are difficult to make because of the
scarcity of published high-income studies, the 35% crowd-out estimate at 200% to 300% FPL is largely in line with other estimates. My estimate is similar to those at lower income levels found by Cutler and Gruber (1996), and tends to be higher than estimates derived using DID (see, for example, Dubay and Kenney 1996; Blumberg, Dubay, and Norton 2000; Yazici and Kaestner 2000; Card and Shore-Sheppard 2004). Most notably, the crowd-out estimate is consistent with the Congressional Budget Office’s (CBO) projection of 33% crowd-out for the Children’s Health Insurance Program Reauthorization Act. The CBO projection is particularly important not only because of its budgetary implications, but also because the Reauthorization Act expanded coverage to 300% FPL; hence, it provides the most comparable estimate by income level. This level of crowd-out is seen by some as acceptable; in describing the projection of the House-passed SCHIP reauthorization in 2007, former CBO Director Peter Orszag stated that he “has not seen another plan that adds 5 million kids to SCHIP with a 33% crowd-out rate. This is pretty much as good as it is going to get” (BNA Health Care Daily 2007).

Finally, my research also has implications for implementation of the Affordable Care Act and its coverage expansions slated to take place in 2014. At its core, the Affordable Care Act requires individuals not already covered with health insurance to purchase private insurance or pay a penalty. Moderate-income individuals will be eligible to meet this requirement by purchasing private insurance on government-operated health insurance exchanges at government-subsidized rates. While my paper focuses on the crowding out of private insurance by public insurance, the Affordable Care act may potentially produce some crowd-out of unsubsidized private insurance by subsidized private insurance in a manner similar to what I describe in this paper. My results suggest that predicting future crowd-out rates resulting from the ACA may be difficult, in part because subsidized insurance exchanges will affect income strata much higher than what has typically been observed in previous studies of Medicaid and SCHIP.

Notes

1 Note that time-varying characteristics can be added to DID models, and many researchers (e.g., Hudson, Selden, and Banthin 2005; Shore-Sheppard, 2008) have acknowledged the need to do this.

2 A prominent example is Hudson, Selden, and Banthin (2005), who compared SCHIP crowd-out estimates using a difference-in-trends approach with data from the 1996–2002 Medical Expenditure Panel Survey. Using children with family incomes between 300% and 400% FPL as a control group produced a crowd-out estimate of 56%, while using children with family incomes between 400% and 600% FPL produced a crowd-out estimate of 19%.

3 Take-up and crowd-out rates were estimated to be 13.6% and 0% respectively.

4 A notable example is Tennessee’s TennCare Medicaid program, which insures more than 500,000 individuals who are uninsurable by private insurance due to pre-existing conditions (Chang 2007).

5 A similar point was made by Hudson, Selden, and Banthin (2005), who argue that high-income families have different insurance options than children targeted by SCHIP and Medicaid.

6 These results, of course, will not hold for $t > T_0$, since the real treatment will have occurred.

7 Proof of this claim under standard conditions is shown in Appendix B of Abadie, Diamond, and Hainmueller (2010).

8 For most SCHIP programs, stratifying data in this manner is potentially problematic because it may be endogenous with respect to income (i.e., individuals might alter their income to become eligible for public insurance). However, this is unlikely to be true in Illinois, since there are no income-eligibility levels in the All Kids program.

9 I remove Alaska and Hawaii because the FPL in these states is different from those of the 48 contiguous states.

10 Gruber (2008), for example, has argued that the health reform introduced by former Gov. Mitt Romney in Massachusetts would be unlikely to produce near-universal coverage if
implemented in other states because of its unusually high-income and coverage rates.

11 Note that although Illinois is similar to the average of the other states, the large standard deviations also suggest that Illinois cannot be generalized to many other individual states with characteristics that deviate unusually from the country at large.

12 As an additional test validating the value of the synthetic control unit, I calculated the mean squared prediction error in the pre-treatment period using each donor state as the sole control unit. Only one state, Utah, produced a pre-treatment MSPE lower than the synthetic unit, and a quick check shows that Utah has a set of predictor variables that differ significantly from those of Illinois. Hence, no single control state can produce a set of coverage patterns and covariates comparable to that of the synthetic unit.

13 Under the jackknife, I discard one pre-treatment observation and fit a model using the remaining 11 pre-treatment observations, then calculate the deviation between the predicted value and the discarded out-of-sample value. This can be done 12 times, using each of my 12 pre-treatment observations as testing data. The standard deviation of this distribution represents my approximation of the standard error.

14 Predictor values are also well reproduced; however, to save space I omit weight and predictor value tables for the remaining models in the paper. Plots comparable to Figure 1 are also omitted but available upon request.

15 The 2010 observation is marginally significant at \( p = .1 \), but this is likely due to chance. As an additional check, I evaluated the statistical significance of the average effect over the entire post-treatment period from 300\% to 400\% FPL of \(-.21\%\) by generating sampling distributions over four observations as done earlier during the resampling test for 400\% to 500\% FPL, and estimate a standard error of \(.28\% \ (t = .75)\) for full-period effects. Hence, I reject the possibility of a coverage effect across the entire post-treatment period at the 300\% to 400\% FPL income level at standard levels of significance testing. In repeating this test across all estimates (i.e., full, private, and public coverage rates at all income levels), I typically find that the standard errors for the full period are 50\% to 100\% smaller than those estimated for single observations alone. Standard errors averaged over four post-treatment observations are available upon request.

16 I also note that my inability to generate a public coverage estimate for 400\% to 500\% FPL does not invalidate estimates of total coverage at that income level, shown earlier in Figure 1. For example, both the Survey of Income and Program Participation and the Panel Study of Income Dynamics are not representative within states, but are nationally representative survey samples commonly used in health economics research.

17 For public coverage between 400\% and 500\% FPL, I present estimates assuming coverage stayed constant at 2006 levels after treatment. Most likely, this estimate of the magnitude of the effect of coverage is overestimated, as the trajectory of public coverage shown in Figure 3 was already trending upwards even before the introduction of All Kids.

18 With the exception of 2010, the private coverage reductions estimated for 200\% to 300\% FPL are not individually significant. However, in testing the joint significance of the average change over the full post-treatment period, I find that the average post-treatment estimate of \(-1.31\) percentage points is marginally significant \((t = -1.88)\).


20 Neighboring states for the control group include Indiana, Iowa, Kentucky, Missouri, and Wisconsin. Only data from these states and Illinois were used in the DID regressions.

21 Although DID using adjacent states as a control group yields similar estimates to the synthetic model, it is worth noting that the predictors of child health insurance coverage shown in Table 1 in the five adjacent states deviate somewhat from Illinois. In general, the averages of these five states have slightly higher rates of pre-2006 health insurance coverage, moderately lower rates of education, significantly fewer minorities, and lower income than Illinois.


References


