The Effects of SCHIP Expansion on Family Insurance and Out-of-Pocket Medical Costs

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The Effects of SCHIP Expansion on Family Insurance and Out-Of-Pocket Medical Costs: New Results From the SIPP

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Abstract

Objective: To assess the effects of Medicaid and SCHIP-related crowd-out on out-of-pocket medical expenditures and family premium costs for affected families.

Data Sources: Data are drawn from the 2001 and 2004 panels of the Survey of Income and Program Participation (SIPP), administered by the U.S. Census Bureau. We construct a nationally representative, longitudinal sample of children, ages 0-18, and their families for the period 2001-2005.

Study Design: We hypothesize that child health status is a determinate of crowd-out, and that crowd-out should reduce out-of-pocket and family premium costs. We first estimate the extent of crowd out for 2001-2005. Next we operationalize a definition of crowd-out that exploits the SIPP’s longitudinal design. We use this in a bootstrapped instrumental variable approach to estimate the effects of crowd-out on out-of-pocket and premium costs.

Principal Findings: Estimates suggest there was substantial crowd-out during 2001-2005. Families who crowd out appear relatively vulnerable, and child health status appears highly predictive of crowd-out. Crowd-out appears to provide a cash-equivalent transfer of approximately $2,500 annually for families in the form of reduced out-of-pocket and premium costs.

Conclusions: Contrary to current public policy debates that often assume crowd-out represents a societal cost, our results suggest that it may bring important social benefits to vulnerable families.

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**Introduction**

Public health insurance coverage for children in poor and near-poor families has increased from 18 million in 1987 to 30 million in 2007. This increase is primarily due to eligibility expansions in Medicaid and the State Children’s Health Insurance Programs (SCHIP), which allow states to cover uninsured children in families earning as much as 350 percent of the federal poverty line (FPL). Many have touted SCHIP as a federal-state success story that has successfully expanded coverage to uninsured families (Grogan & Rigby, 2009). The most prominent concern raised about the program, especially during the 2007 reauthorization debate, has focused on *crowd-out*: the possibility that expansions of public health insurance displace private coverage. Findings are mixed as to the amount of crowd-out that has resulted from Medicaid and SCHIP expansions—ranging from as low as zero to as high as 177 percent (see Davidson et al., 2004 and Gruber and Simon, 2007). Still, there is widespread agreement that crowd-out represents a policy problem (see Dingle, 2007).

Despite numerous studies of crowd-out, little is known about its implications for affected families. Hudson, Selden and Banthin (2005) point out this gap in the literature, asserting that debates over crowd-out point estimates “distract policymakers from the larger and more important challenge of weighing various program benefits against program costs” (p. 233). A few studies mention the possible redistributive effects of crowd-out in the form of significant effective income transfers (Cutler and Gruber, 1996a; Hudson, Selden and Banthin, 2005; Davidson et al., 2004; Holahan, 1997; and Ham and Shore-Sheppard, 2005). While these studies suggest the importance of considering the redistributive effects of crowd-out, no one—to our knowledge—has specifically studied these effects. This paper examines two such questions
regarding crowd-out: Who are the children who crowd-out, and what is the impact of crowd-out on out-of-pocket health expenditures and family premium costs?

We begin by estimating the extent of crowd-out using data from the 2001 and 2004 panels of the Survey of Income and Program Participation (SIPP). We draw on Gruber and Simon’s (2007) method for estimating crowd-out. Our estimates suggest high rates of crowd-out during the 2001-2005 period. Consistent with several other studies, though, we find that our point estimates are sensitive to model specification and have large standard errors. We compute bootstrapped 95 percent confidence intervals to illustrate this.

We continue by operationalizing a definition of crowd-out using our longitudinal data, and descriptively comparing those who crowded-out to those who did not. Then, we use an instrumental variable, two-stage-least-squares analysis to estimate the effects of crowd-out on out-of-pocket medical expenditures and family premium costs. We estimate the probability of crowd-out in the first stage and find that parent-reported health status for the child has a large and significant impact on crowd-out. As a child’s health status worsens, she has a much higher probability of crowding-out. In the second stage, the predicted crowd-out variable has a significant impact on out-of-pocket medical expenditures and family premiums. Because sicker children are more likely to shift from private to public insurance, those who crowd-out realize significantly lower out-of-pocket medical expenditures and family premiums. We conclude by considering policy implications.

I. Theory of Crowd-Out and Expected Effects

The theoretical literature converges on the notion that crowd-out will occur when the value of public insurance to families outweighs the value of private coverage. Medicaid is generally considered to be both less expensive and more comprehensive than most private
insurance. This may prove especially true when individuals are in poor health. Because private
(non-group) health insurance premiums are based on actuarial risk, individuals in poor health pay
higher premiums and higher out-of-pocket payments for insurance products in the private
marketplace. However, many health care providers are less willing to serve Medicaid patients
than privately-insured patients. Reduced access to providers may make public coverage less
attractive, and this may mitigate the propensity for families to take up public insurance plans
(Cutler and Gruber, 1996b; Gruber and Simon, 2007). In sum, existing literature suggests crowd-
out will occur when the financial savings of public insurance outweighs the access advantages of
private insurance for families.

Building on this general rule, the literature further suggests several potential effects of
crowd-out. First, because public insurance through Medicaid and SCHIP, on average, has fewer
cost-sharing requirements and offers more comprehensive benefit coverage compared to the
typical private insurance plan, one would expect crowd-out to result in lower levels of average
out-of-pocket medical expenses. Consistent with this hypothesis, Kenney (2007) found a
relationship between SCHIP enrollment and fewer financial difficulties associated with meeting
children’s health care needs.

Crowd-out may further result in higher wages for low-income working families.
Economic theory suggests that the costs of employer-subsidized benefits ultimately fall on
workers (Gruber, 1994; Summers, 1989). Several studies have shown that government policies
mandating employers to provide private benefits result in a commensurate wage offset. Gruber
(1994), for example, finds a wage effect associated with mandated maternity benefits. Thus,
workers willing to substitute public for private insurance may be able to obtain higher wages.

Buchmueller et al. (2005) examined the effect of SCHIP expansions on employer health
insurance offerings. While they found no evidence that employers stopped offering health
benefits, they did find that employers induced workers who were eligible for public insurance to
decline private coverage. In particular, employers responded to SCHIP expansions by raising
employee contributions for family coverage, resulting in reduced take-up of private coverage.
Buchmueller et al. observed that by dropping coverage, workers may gain what they would have
paid in premium costs, effectively raising their wages.

In our current analyses, we expect the child’s health status to play an important predictive
role in crowd-out, as a private-to-public transition should be most attractive to these families. We
further expect to see the equivalent of a cash transfer to “crowded-out” families in the form of
reduced out-of-pocket medical expenditures and reduced premium payments.

II: Crowd-Out Estimates

Data and Methods

We begin by estimating the extent of crowd-out during our study timeframe. The SIPP,
collected by the U.S. Census Bureau, offers a longitudinal representation of the civilian non-
institutionalized population in the United States. The survey selects a nationally representative
sample by clustering addresses within cities and counties based on population counts from the
most recent decennial census. Low-income households are sampled with a higher probability.
Interviews are conducted every four months about each individual in the household for each
intervening month, gathering data on demographics, welfare, family income and structure, labor
force participation, and health insurance.

The SIPP’s design is particularly useful for studies of crowd-out because data were
continuously collected during periods of rapid expansion of eligibility for state Medicaid and
SCHIP programs. Gruber and Simon (2007) review the advantages and disadvantages of various
datasets for estimating crowd-out. They make a case for the SIPP because of its longitudinal
design and short periods between interviews. The current analyses use a pooled sample from the
2001 and 2004 panels to create a nationally representative, longitudinal sample of children ages
0-18 and their parents, spanning the start of 2001 through 2005. Our primary data sources for
state Medicaid and SCHIP eligibility levels are annual surveys of state administrations conducted
by the Center for Budget and Policy Priorities (see Cohen Ross & Cox, 2005). Using these data,
we assign Medicaid and SCHIP eligibility to all children using age, family income, other family
demographic data, state of residence, and observation year. Family income takes the form of an
income-to-needs ratio, for which we divide the SIPP’s total family income variable for each
observation by the Census Bureau’s assigned family poverty threshold for that observation.

The Simulated Eligibility Instrument

To address the endogeneity of family health coverage decisions, Gruber and Simon
(2007) adapt the original Cutler and Gruber (1996b) simulated eligibility instrument. We follow
this now-standard strategy, constructing an individual-level eligibility instrument using our
pooled SIPP sample. For each year in our sample, we take a random, nationally representative
sub-sample of children for each age, 0-18 (n=300 per age-year). We apply each state’s eligibility
rules to this nationally representative sub-sample, and calculate the proportion that would be
eligible for public insurance by age-state-year. This provides a “parameterization of the variation
in complicated eligibility rules across states over time” (Gruber and Simon, 2007, p.8). This
procedure assigns to each sample member age 0-18 an exogenous variable in the interval [0,1]
that increases with the overall proportion of eligible children by age and year.

Descriptive statistics are presented in table 1. For descriptive estimates, we utilize Stata’s
SVY routines to adjust for the SIPP’s weighted and stratified survey design. Accounting for such
effects does not change parameter estimates appreciably, but corrects for overly narrow standard 
errors. Only 4th reference month observations are used to counteract seam bias, a problem with 
the SIPP in which reporting is most accurate in the final month of each wave (Levy, 2007; 
Grogger, 2002). We exclude the five states (Maine, Vermont, Wyoming, North Dakota and 
South Dakota) that are not uniquely identifiable in the 2001 panel. This yields a sample of 
348,052 observations for the standard crowd-out analyses. For later analyses of out-of-pocket 
medical expenses and family premium costs, we must rely on a smaller sample because health 
expenditure variables in the SIPP are reported as annualized variables included once a year in 
topical modules. Thus, the second column of table 1 reports weighted averages from this smaller 
subsample of 85,840 observations, which yields nearly identical results.

Table 1 shows that approximately one in five children have public health insurance only, 
while nearly 50 percent are eligible for public coverage. Other means for insurance status and 
demographic characteristics match with existing estimates from the 2001-2005 period. 
Importantly, weighted means for the individual simulated eligibility instrument match closely 
with descriptive eligibility estimates.

[Table 1 here]

Crowd-out Results. In table 2, we report on a series of linear probability (LP) models 
that capture associations between children’s health insurance coverage and expansions of 
eligibility for public insurance. Each cell represents an independent LP regression with the 
dependent variable being a dummy variable for the child’s actual insurance coverage. The 
models in table 2 take the following specification

\[
\text{Ins}_{i,j,t} = \beta * IVE_{i,j,t} + \phi X_{i,j,t} + \theta_{j,t} + \epsilon_{i,j,t}
\]  

(1)
Here Ins is a measure of the child’s health insurance coverage for individual i at time t in state j. IVElig is the simulated eligibility instrument discussed above, which increases from 0 to 100 as public health insurance eligibility expands. X is a vector of individual and family characteristics; θ is a vector of state-time dummies, and ε is the error term. Parameter estimates associated with the mutually exclusive binary dependent variables of Public only, private only, both public & private (children reporting both in a reference month), and uninsured add to roughly zero. X draws from Gruber and Simon’s (2007) specifications and includes family income as a percent of the federal poverty line and its square; child’s sex; race; a dummy for Hispanic origin; dummies for 1, 2, 3, 4, and 5+ children; the number of adults in the family working for a large firm; the number of adults working full-time; the number of adults who are a high school graduate and no more; the number with some college and no more; number who are college graduates; and intercepts for single female head; single male head; and single male unemployed head.

Table 2 reports only the point estimates associated with the simulated eligibility instrument (full output available upon request). Regressions are unweighted, but clustered by individual to account for repeated person observations and the SIPP’s stratified survey design. As with descriptive statistics, only 4th reference month observations are used to counteract seam bias. Row one reports on a specification that includes age, state and year fixed effects. Row two reports on a specification with a more exhaustive set of fixed effects, including state*age, state*year, and age*year interactions.

Using just state and year fixed effects, these point estimates suggest that for every 100 children who become eligible, roughly 11 move to public insurance, and roughly 8 leave the private insurance only group. Our results appear sensitive to specification. When only state and
year fixed effects are included, the parameter estimate associated with the uninsured is statistically insignificant from zero. In contrast, when a more exhaustive set of interactions is included (state*year; state*age; age*year), there appears to be a statistically significant effect on the uninsured: for every 100 children who become eligible for public insurance, 8 leave the uninsured category.

[Table 2 here]

The final two columns of table 2 include estimates for crowd-out. Following Cutler and Gruber (1996b) and Gruber and Simon (2007) we calculate two estimates of crowd-out. The first, crowd-out $N$ (for narrow) represents the reduction in private insurance relative to the growth in public insurance. It is calculated from the LP estimates above as: 

$$\text{Crowd-out } N = \frac{\Delta \text{private only}}{\Delta \text{public only}}.$$ 

The second definition, crowd-out $B$ (for broad), is one minus the change in uninsurance divided by the growth of public insurance as captured in the public only group combined with the public and private group. It is calculated as:

$$\text{Crowd-out } B = 1 - \frac{|\Delta \text{uninsured}|}{|\Delta \text{total public}|}.$$ 

If insurance coverage statuses were mutually exclusive, these two crowd-out estimates would yield identical results. However, since some children report both private and public coverage, differences between the two measures arise in this overlap group.

Both sets of estimates reflect the ratio of regression coefficients derived from linear probability models. To address likely non-normality in the associated standard errors, we computed bootstrapped 95% confidence intervals of our crowd-out parameters. In the top row, we performed 100 bootstrap replications. Within each replication, we computed point estimates of our narrow and broad crowd-out measures. We then computed the 95% confidence intervals reported in the table. The bottom, fully-interacted row required more extensive estimation,
requiring approximately four hours per specification. We therefore report confidence intervals based upon 40 bootstrap replications.

As in other studies, our results vary substantially between the two crowd-out calculations—from 77 to 95 percent in the state and year fixed effects model, and from 77 to 43 percent in the interacted fixed effects model. Some authors conceptually prefer the broad definition (crowd-out $B$), which assumes that people in the overlap group transition from dual coverage to public coverage only, and therefore the estimate counts them in the denominator. Cutler and Gruber (1996) and later Gruber and Simon (2007) suggest that most people in the overlap group are transitioning into public coverage. We find mixed evidence to support this. By tracking insurance status for a 12-month period for children in the public and private overlap group, we find that a large majority of them do not transition into the public-only group during that time.

Crowd-out estimates appear sensitive to specification. Changes in fixed effects and other aspects of the model can result in differences in parameter estimates. These changes in turn can have a major effect on the estimates of crowd-out. Despite our large sample at the individual level, we find relatively wide confidence intervals for our crowd-out estimates. In the case of narrow crowd-out, the confidence interval varies by roughly a factor of two, between 0.54 and 1.03.

**Who Crowds Out and Why?**

While the estimates presented above explore the extent of crowd-out, there is more to learn about who crowds out and why. This brief section offers a descriptive discussion of this before turning to the instrumental variable regression analyses of medical expenditure outcomes. For this study, we consider a child to have crowded-out if she reported only private health
insurance in the first month of the person-year, and subsequently reported public health
insurance coverage at some later point during that year. This should create a conservative
estimate for effects associated with medical expenditure outcomes because it includes transitions
from private to public insurance lasting as little as one month. Table 3 provides a profile of
children who have crowded-out, compared to the overall sample means and children who
remained on private insurance all year.

Children who crowded-out were less likely to be white, non-Hispanic. While three-
fourths of the group remaining on private insurance all year were white non-Hispanic, just over
50 percent of the crowd-out group were the same. As might be expected, the annual family
income of the crowd-out group was lower than the comparison groups, with a yearly income at
250 percent FPL.

Children in crowd-out families were slightly less likely to have an adult working full-
time, although the average was close to one. The crowd-out group was also less likely to have a
college graduate in the family. About one-quarter of children who crowded-out lived in
households headed by a single woman, while only 11 percent of the private insurance group
lived in such households. Children in the private insurance group all year were in better health
overall. In fact, 63 percent of these children were reported by parents to be in excellent health,
while the same was true of only about half of the crowd-out group. Over all, the average child
who crowds-out has a relatively low-income (though still above poverty), is disproportionately
likely to live in a single-mother household, is more likely to be Black or of Hispanic origin, and
is less likely than the comparison group to be in excellent health.

[Table 3 here]

III. Effects of Crowd-Out on Family Health Expenditures
To test our hypotheses about the effects of crowd-out, we utilize variables from the SIPP’s topical modules on medical expenses and health care utilization. Available topical modules were included in the 4th reference month: in the 2001 panel during waves 3, 6 and 9, and in the 2004 panel in wave 3. These topical modules provide annualized data on out-of-pocket medical experiences, family health insurance premiums, and medical care utilization, among other things. Analyses below are restricted to observations with responses included in the topical module. This yields a sample of n=85,840 children, ages 0-18. Out-of-pocket costs are individual medical expenses for children in the subsample, and have been recoded by the U.S. Census Bureau to account for reported reimbursements. (We recode negative out-of-pocket expenses as zero.) For the *family premium* variable, we cluster by subfamily to generate the family’s total annual cost of health insurance premiums during the person-year. In table 3 we report descriptive means for out-of-pocket expenses and family premium costs. Children who crowd-out have lower average health care costs than the comparison groups of children.

*Instrumental variable two-stage least squares results*

We next explore the effects of crowd-out on out-of-pocket medical expenditures and family premium costs using an instrumental variable, two-stage least squares approach. This methodology is necessary given the endogeneity of family coverage decisions, especially the binary nature of an endogenous transition from private to public coverage. In the first stage, we estimate a probit specification in which the dependent variable is the dummy—transitioned from private to public insurance during the person-year observation. We use the Gruber and Simon (2007) individual simulated eligibility instrument as one variable in estimating this probability of this crowd-out transition. The simulated eligibility instrument is excluded from the second stage. Our specification for the probit model is as follows in (2).
\[ \hat{P} = \Pr[X_\beta + IVElig_\theta + \epsilon_{i,j,t} > 0] \]  \hspace{1cm} (2)

Here \( IVElig \) represents our simulated eligibility instrument, discussed in part II. Other independent variables included in \( X \) are measures of the child’s health status, family size and income, education, race and ethnicity, age, the state-month unemployment rate, the state-month number of families on TANF, and state and year fixed effects. We then use these probit results to construct a predicted probability of crowd-out, \( \hat{P} \), for each observation in each year. This approach addresses the binary nature of the endogenous crowd-out variable.

We then use this predicted probability of crowd-out as an instrument in a second-stage equation, as specified in (3).

\[ ME_{i,j,t} = \hat{P}_{i,j,t} \gamma_{i,j,t} + \phi X_{i,j,t} + \theta_{j,t} + \epsilon_{i,j,t} \]  \hspace{1cm} (3)

Here \( ME \) represents medical expenditures for individual \( i \) in state \( j \) at time \( t \). \( \hat{P} \) is the instrument for crowd-out, using the predicted probability generated from equation (2). \( X \) includes the same independent variables included in (2), with the exception of the excluded simulated eligibility instrument (child’s health status, family size and income, education, race and ethnicity, age, the state-month unemployment rate, the state-month number of families on TANF, and state-and-year fixed effects).

As presented in the first two columns of table 4, the first stage probit model performs well. Our simulated eligibility variable is large and highly significant (\( p<0.001 \)). By standard metrics, our simulated eligibility variable is a strong instrument. In addition to providing a useful first-stage, this analysis also produces substantive results. Children of color were more likely to crowd-out than white, non-Hispanic children. Increases in the unemployment rate led to increases in the probability that a child would crowd-out. Perhaps most important to the current
analysis, after controlling for other factors, children in poor health were significantly more likely to shift from private to public health coverage during a person-year than other children who began the year on private insurance. These children may encounter the largest out-of-pocket expenditures, creating the maximum incentive for families to complete the enrollment process. Alternatively, these children may have more frequent contact with healthcare providers who can inform families of their eligibility for public health insurance and assist in enrollment.

Second stage results

Equation (3) contains the predicted probability \( \hat{P} \) from equation (2). Straightforward estimation would thus provide misspecified standard errors. Given our complex econometric specification, we again use bootstrapping as a robustness check, using 200 replications. Within each replication, we estimate equation (2) and an accompanying \( \hat{P} \). We then estimate equation (3). This procedure allows us to compute 95 percent confidence intervals for all variables.

Table 4 reports the results, as specified in equation 3. Here we show the 95 percent confidence intervals for our crowd-out variable—the key variable of policy interest. The full set of bootstrapped confidence intervals are available from the authors. Given our large sample size, virtually all coefficients are highly significant (p<0.01 or less).

In these models, the independent variables for medical expenses are continuous variables for the total annual amount of these expenses. Our instrumented crowd-out variable has a large and statistically significant effect on both out-of-pocket expenditures and insurance premiums. Crowded-out families realize large savings by shifting to public insurance.

As reported in the second part of table 4, crowd-out reduces out-of-pocket expenditures by $318 and family health insurance premiums by $2,242. Together, this represents an average
total annual savings of $2,560. Bootstrapped confidence intervals are relatively tight, consistent with our tight parametric standard errors (p<0.0001).

These point estimates are large, given the mean out-of-pocket and health insurance premiums paid in our sample. These large point estimates suggest that the marginal crowded-out individual is on average relatively sick and a relatively high-cost user of health care services. The parameter estimates associated with the health status variables support this conclusion. After controlling for other factors, including crowd-out, poor health status is associated with an average annual increase of $1,200 in out-of-pocket medical expenses and almost $500 in annual premium costs, relative to excellent health status. We again computed bootstrapped 95 percent confidence intervals with 200 replications to address our complex econometric specification. For simplicity, we report only the bootstrapped confidence intervals for our estimated crowd-out variable and health status variables. (Results for all coefficients are available from the authors.)

Discussion

We find relatively high levels of crowd-out related to expansions of Medicaid and SCHIP between 2001 and 2005. During this period, expanded SCHIP income eligibility thresholds reached higher income groups than did expansions during the early 1990s. Rates of private health insurance coverage in these later, moderate-income groups were somewhat higher, leading to greater possibilities of crowd-out as public coverage expanded. Consistent with several other crowd-out studies, our estimates are highly sensitive to model specification. Despite our large sample size, our bootstrap analysis implies large confidence intervals. In the case of our narrow crowd-out measure, our confidence interval ranges by almost a factor of two, from 0.54 to 1.03. While the evidence is strong that crowd-out occurs, it is difficult to draw precise conclusions as to its exact extent, and researchers and policymakers should be cautious in drawing conclusions
based on a favored set of point estimates. We suspect that the same bootstrapped analysis of
previous crowd-out data would also yield wide confidence intervals. This raises a simple but
important point: Arguments about competing crowd-out point estimates are uninterpretable in
the absence of associated confidence intervals.

A key contribution of our study is to develop an initial descriptive understanding of who
the crowd-out group actually is, and what the effects of crowd-out might be for affected families.
Our statistical modeling suggests that children in families who transition from private to public
insurance are a relatively vulnerable group. Crowded-out children are more likely to be non-
white and in poor health.

Our second stage 2sls results suggest that crowd-out provides large financial benefits to
affected families in the form of reduced medical expenses. We estimate that SCHIP provides a
cash-equivalent transfer of more than $2,500 to affected families. This estimate does not include
any additional offsets families may receive in the form of higher cash wages in positions that do
not provide health coverage. For a family of 3 with a $30,000 income (roughly 170 percent
FPL), the estimated reduction in medical costs is comparable to the value of the federal Earned
Income Tax Credit (EITC). However, rather than targeting families according to earned income,
this crowd-out transfer effectively targets families with high medical expenditures relative to
their income. In essence, for the marginally effected crowd-out family, SCHIP acts akin to
Medicaid’s medically needy eligibility program.

These findings have policy implications. During the SCHIP reauthorization debate, many
policy experts pointed out that only about 60 percent of children in families earning less than 200
percent FPL were enrolled in state SCHIP programs (Congressional Budget Office, 2007). This
statistic caused some concern that states had been too quick to expand coverage to higher-income
families before uninsured children in lower-income families are adequately covered (The Kaiser Commission on Medicaid and the Uninsured, 2007). Gruber and Simon (2007) argue that families in the 300 percent FPL range have a much higher likelihood of dropping private coverage for public than families under 200 percent FPL. This income effect leads to the concern expressed by numerous policymakers that expanded public insurance for children may be inefficient because it expends resources on higher-income families who already have private coverage, perhaps at the expense of support targeted at lower-income, uninsured families.

Several studies, however, highlight the financial burdens faced by middle-income families bearing substantial medical expenses associated with care for a child in poor health. For these families, crowding-out may provide important and well-targeted social benefits (e.g. Shattuck and Parish, 2008). Obviously, for the marginal crowded-out family, SCHIP does not reduce uninsurance. However, our findings suggest that substitution of public for private insurance results in a substantial cash transfer, and such a transfer may serve important social goals, such as more financial stability (and perhaps more stable labor force attachment) for low and middle-income families with sick children.
Table 1: Health Insurance and Other Characteristics of U.S. Children, Ages 0-18, 2001-2005
Selected Descriptive Statistics

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</tbody>
</table>

Source: Authors’ calculation from a pooled sample of the 2001 and 2004 panels of the Survey of Income and Program Participation.

Notes: Weighted means using Stata’s SVY routine. Unidentifiable states in the 2001 panel (Maine, Vermont, Wyoming, North Dakota, and South Dakota) are dropped from both panels.
Table 2: Effects of Increased Eligibility for Public Insurance on Insurance Status of Children Ages 0-18, 2001-2005
n= 348,052
(Linear Probability Models)

<table>
<thead>
<tr>
<th>Model Variation</th>
<th>Public Only</th>
<th>Both Public &amp; Private</th>
<th>Private Only</th>
<th>Employer Only</th>
<th>Not Employer Based</th>
<th>Uninsured</th>
<th>Crowd-out N [95% CI]</th>
<th>Crowd-out B [95% CI]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, state, and year</td>
<td>.107***</td>
<td>-.021*</td>
<td>-.082***</td>
<td>-.044*</td>
<td>-.038***</td>
<td>-.004</td>
<td>.77 [.54, 1.03]</td>
<td>.95 [.62, 1.00]</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>(.023)</td>
<td>(.012)</td>
<td>(.024)</td>
<td>(.024)</td>
<td>(.014)</td>
<td>(.016)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>State<em>age, state</em>year, age*year</td>
<td>.096**</td>
<td>.059***</td>
<td>-.074*</td>
<td>-.032</td>
<td>-.042*</td>
<td>-.082**</td>
<td>.77 [.35, 1.28]</td>
<td>.43 [.21, 1.21]</td>
</tr>
<tr>
<td>Fixed Effects</td>
<td>(.039)</td>
<td>(.022)</td>
<td>(.041)</td>
<td>(.041)</td>
<td>(.023)</td>
<td>(.033)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*** stat sig .01 level; ** sig .05 level; * sig .10 level

Notes: Unidentifiable states in the 2001 panel (Maine, Vermont, Wyoming, North Dakota, and South Dakota) are dropped. Regressions utilize 4th reference month observations. Controls variables include family income as percent of FPL and square, state-month-year unemployment rate, state-month-year number of families on TANF, sex, race, Hispanic origin, dummies for 1, 2, 3, 4, and 5+ children, number of adults in family working for a large firm, number of adults working full-time, number of adults who are HS grad and no more, number with some college & no more, number who are college graduates, and intercepts for single female head, single male head, and single male unemployed head.

Crowd-out N = (∆private/ ∆public).
Crowd-out B = 1- (|∆uninsured|/ |∆public|). Public is considered public only and both public & private.
Table 3: Demographic Characteristics of U.S. Children, Ages 0-18  
(Means)

<table>
<thead>
<tr>
<th>Mean</th>
<th>All Children</th>
<th>Crowded-Out</th>
<th>Private Insurance All Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>9.12</td>
<td>9.14*</td>
<td>9.53</td>
</tr>
<tr>
<td>Female</td>
<td>.489</td>
<td>.497</td>
<td>.491</td>
</tr>
<tr>
<td>White, non-Hispanic</td>
<td>.606</td>
<td>.536*</td>
<td>.753</td>
</tr>
<tr>
<td>Black, non-Hispanic</td>
<td>.152</td>
<td>.203*</td>
<td>.094</td>
</tr>
<tr>
<td>Hispanic Origin</td>
<td>.185</td>
<td>.193*</td>
<td>.099</td>
</tr>
<tr>
<td>Poverty level</td>
<td>303.6</td>
<td>249.9*</td>
<td>414.4</td>
</tr>
<tr>
<td>Total in family</td>
<td>4.03</td>
<td>3.99</td>
<td>4.07</td>
</tr>
<tr>
<td>Total children</td>
<td>2.35</td>
<td>2.37</td>
<td>2.21</td>
</tr>
<tr>
<td>Total adults working full-time</td>
<td>1.03</td>
<td>.899*</td>
<td>1.28</td>
</tr>
<tr>
<td>Head is single female</td>
<td>.212</td>
<td>.246*</td>
<td>.109</td>
</tr>
<tr>
<td>Total college grad.</td>
<td>.438</td>
<td>.315*</td>
<td>.681</td>
</tr>
<tr>
<td>In excellent health</td>
<td>.562</td>
<td>.527*</td>
<td>.628</td>
</tr>
<tr>
<td>Out of pocket costs</td>
<td>$163</td>
<td>$134*</td>
<td>$219</td>
</tr>
<tr>
<td>Family premium costs</td>
<td>$1,068</td>
<td>$891*</td>
<td>$1,592</td>
</tr>
<tr>
<td>Observations</td>
<td>85,840</td>
<td>3,460</td>
<td>44,363</td>
</tr>
</tbody>
</table>

**Source:** Author’s calculation from a pooled sample of the 2001 and 2004 SIPP.

**Notes:** Sub-sample includes all respondents included in medical expenses/utilization of health care topical module. Unidentifiable states in the 2001 panel (Maine, Vermont, Wyoming, North Dakota, and South Dakota) are dropped from both panels. Standard errors are adjusted using Stata’s svy routine for stratified samples. (*p<0.05)
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Robust Standard Error</th>
<th>Stage 2: Effects of Crowd-out on Medical Expenditures and Family Premiums</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simulated Eligibility</td>
<td>0.976***</td>
<td>(0.235)</td>
<td>-317.8***</td>
</tr>
<tr>
<td>Health Status</td>
<td></td>
<td></td>
<td>-2242***</td>
</tr>
<tr>
<td>“Excellent” Referent</td>
<td></td>
<td>[.422, 1.503]</td>
<td>[bootstrapped 95% CI] -169, -464]</td>
</tr>
<tr>
<td>Health Status “Good”</td>
<td>0.195***</td>
<td>(0.0290)</td>
<td>168.2***</td>
</tr>
<tr>
<td>Health Status “Fair”</td>
<td>0.380***</td>
<td>(0.0712)</td>
<td>542.1***</td>
</tr>
<tr>
<td>Health Status “Poor”</td>
<td>0.861***</td>
<td>(0.130)</td>
<td>1206***</td>
</tr>
<tr>
<td>State Unemployment Rate</td>
<td>0.161***</td>
<td>(0.0327)</td>
<td>20.37**</td>
</tr>
<tr>
<td>State families on TANF</td>
<td>0.000000278**</td>
<td>(0.00000117)</td>
<td>0.00000880</td>
</tr>
<tr>
<td>Family Poverty Level</td>
<td>-0.00136***</td>
<td>(0.000100)</td>
<td>0.126***</td>
</tr>
<tr>
<td>Family Poverty Level, Sqr</td>
<td>0.000000394***</td>
<td>(4.53e-08)</td>
<td>-0.0000317***</td>
</tr>
<tr>
<td>Female</td>
<td>0.000803</td>
<td>(0.0195)</td>
<td>-2.476</td>
</tr>
<tr>
<td>Num of Children 1 Referent</td>
<td></td>
<td></td>
<td>-27.84***</td>
</tr>
<tr>
<td>Num of Children 2</td>
<td>0.0257</td>
<td>(0.0274)</td>
<td>-9.513</td>
</tr>
<tr>
<td>Num of Children 3</td>
<td>0.0955***</td>
<td></td>
<td>199.3***</td>
</tr>
</tbody>
</table>

Table 4: Effects of Crowd-out on Out-of-Pocket Medical Expenditures and Family Premiums Costs

Two-Stage Least Squares Results
<table>
<thead>
<tr>
<th>Variable</th>
<th>Estimate</th>
<th>Std. Error</th>
<th>z value</th>
<th>p value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Num of Children 4</td>
<td>0.232***</td>
<td>(0.0407)</td>
<td>-37.10***</td>
<td>461.5***</td>
</tr>
<tr>
<td>Num of Children 5</td>
<td>0.123**</td>
<td>(0.0580)</td>
<td>-63.88***</td>
<td>783.3***</td>
</tr>
<tr>
<td>Num in fam working for a large firm</td>
<td>-0.103***</td>
<td>(0.0158)</td>
<td>-20.78***</td>
<td>-207.6***</td>
</tr>
<tr>
<td>Num in fam working full-time</td>
<td>-0.222***</td>
<td>(0.0193)</td>
<td>-13.78**</td>
<td>105.0***</td>
</tr>
<tr>
<td>Num in fam who did not graduate from high school</td>
<td>Referent</td>
<td>Referent</td>
<td>Referent</td>
<td>Referent</td>
</tr>
<tr>
<td>Num in fam who are high school graduates and no more</td>
<td>0.0338*</td>
<td>(0.0189)</td>
<td>-4.251</td>
<td>338.0***</td>
</tr>
<tr>
<td>Num in fam who have some college and no more</td>
<td>-0.0520***</td>
<td>(0.0189)</td>
<td>18.04***</td>
<td>416.8***</td>
</tr>
<tr>
<td>Num in fam who are college graduates</td>
<td>0.173***</td>
<td>(0.0292)</td>
<td>20.63***</td>
<td>486.6***</td>
</tr>
<tr>
<td>Head of fam single female</td>
<td>0.0779*</td>
<td>(0.0447)</td>
<td>5.329</td>
<td>17.87</td>
</tr>
<tr>
<td>Head of fam single male</td>
<td>0.334***</td>
<td>(0.0547)</td>
<td>15.44</td>
<td>-23.64</td>
</tr>
<tr>
<td>Head of fam unemployed male</td>
<td>0.303***</td>
<td>(0.0325)</td>
<td>25.34</td>
<td>284.4***</td>
</tr>
<tr>
<td>Hispanic Origin</td>
<td>0.173***</td>
<td>(0.0292)</td>
<td>-39.63***</td>
<td>-60.66*</td>
</tr>
<tr>
<td>White, Non-Hispanic</td>
<td>Referent</td>
<td>Referent</td>
<td>Referent</td>
<td>Referent</td>
</tr>
<tr>
<td>Black, Non-Hispanic</td>
<td>0.363***</td>
<td>(0.0289)</td>
<td>-78.81***</td>
<td>-179.3***</td>
</tr>
<tr>
<td>Amer. Ind, Aleut, Eskimo</td>
<td>0.383***</td>
<td>(0.0318)</td>
<td>-31.28</td>
<td>20.38</td>
</tr>
</tbody>
</table>

* indicates significance at the 10% level, ** at 5%, *** at 1%.
<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>t-Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asian, Pac. Islander</td>
<td>0.190***</td>
<td>(0.0636)</td>
<td>(22.53)</td>
<td>(71.98)</td>
</tr>
<tr>
<td>Age 0 Referent</td>
<td>-55.11***</td>
<td>(13.89)</td>
<td>(44.37)</td>
<td></td>
</tr>
<tr>
<td>Age 0 Referent Age 1</td>
<td>0.231***</td>
<td>(0.0700)</td>
<td>(20.22)</td>
<td>(64.61)</td>
</tr>
<tr>
<td>Age 0 Referent Age 2</td>
<td>0.318***</td>
<td>(0.0684)</td>
<td>(19.75)</td>
<td>(63.10)</td>
</tr>
<tr>
<td>Age 0 Referent Age 3</td>
<td>0.227***</td>
<td>(0.0678)</td>
<td>(19.64)</td>
<td>(62.74)</td>
</tr>
<tr>
<td>Age 0 Referent Age 4</td>
<td>0.149**</td>
<td>(0.0676)</td>
<td>(19.35)</td>
<td>(61.84)</td>
</tr>
<tr>
<td>Age 0 Referent Age 5</td>
<td>0.217***</td>
<td>(0.0674)</td>
<td>(19.36)</td>
<td>(61.87)</td>
</tr>
<tr>
<td>Age 0 Referent Age 6</td>
<td>0.172**</td>
<td>(0.0688)</td>
<td>(19.49)</td>
<td>(62.27)</td>
</tr>
<tr>
<td>Age 0 Referent Age 7</td>
<td>0.144**</td>
<td>(0.0683)</td>
<td>(19.41)</td>
<td>(62.00)</td>
</tr>
<tr>
<td>Age 0 Referent Age 8</td>
<td>0.146**</td>
<td>(0.0688)</td>
<td>(19.35)</td>
<td>(61.83)</td>
</tr>
<tr>
<td>Age 0 Referent Age 9</td>
<td>0.134*</td>
<td>(0.0688)</td>
<td>(19.24)</td>
<td>(61.49)</td>
</tr>
<tr>
<td>Age 0 Referent Age 10</td>
<td>0.0872</td>
<td>(0.0699)</td>
<td>(19.22)</td>
<td>(61.42)</td>
</tr>
<tr>
<td>Age 0 Referent Age 11</td>
<td>0.0997</td>
<td>(0.0690)</td>
<td>(19.10)</td>
<td>(61.03)</td>
</tr>
<tr>
<td>Age 0 Referent Age 12</td>
<td>0.0865</td>
<td>(0.0701)</td>
<td>(19.00)</td>
<td>(60.71)</td>
</tr>
<tr>
<td>Age 0 Referent Age 13</td>
<td>0.0861</td>
<td>(0.0709)</td>
<td>(19.01)</td>
<td>(60.73)</td>
</tr>
<tr>
<td>Age 0 Referent Age 14</td>
<td>0.0791</td>
<td>(0.0724)</td>
<td>(18.88)</td>
<td>(60.33)</td>
</tr>
<tr>
<td>Age 0 Referent Age 15</td>
<td>0.131*</td>
<td>(0.0718)</td>
<td>(18.89)</td>
<td>(60.36)</td>
</tr>
<tr>
<td>Age 0 Referent Age 16</td>
<td>0.175**</td>
<td>(0.0718)</td>
<td>(18.67)</td>
<td>(59.66)</td>
</tr>
<tr>
<td>Age 0 Referent Age 17</td>
<td>0.0873</td>
<td>(0.0753)</td>
<td>(18.78)</td>
<td>(60.02)</td>
</tr>
<tr>
<td>Age 0 Referent Age 18</td>
<td>0.0624</td>
<td>(0.0772)</td>
<td>(19.24)</td>
<td>(61.49)</td>
</tr>
</tbody>
</table>

State and year fixed effects omitted

Constant -2.695*** (0.259) 88.07 (64.08) 705.5*** (204.7)
Observation 47,823 Observations 47823 47823
Pseudo R-sqr .14 R-sqr 0.031 0.054

Source: Authors’ calculation from a pooled sample of the 2001 and 2004 panels of the SIPP.
Notes: Sub-sample includes all respondents included in medical expenses/utilization of health care topical module who report only private insurance at the beginning of a person-year observation and either crowd-out, or remain on private insurance all year. Unidentifiable states in the 2001 panel (Maine, Vermont, Wyoming, North Dakota, and South Dakota) are dropped from both panels. Standard errors are clustered at the person-level.

*p<0.05, **p<0.01, ***p<0.001
References


