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ABSTRACT

The continued interest in public insurance expansions as a means of covering the uninsured highlights the importance of estimates of "crowd-out", or the extent to which such expansions reduce private insurance coverage. Ten years ago, Cutler and Gruber (1996) suggested that such crowd-out might be quite large, but much subsequent research has questioned this conclusion. We revisit this issue by using improved data and incorporating the research approaches that have led to varying estimates. We focus in particular on the public insurance expansions of the 1996-2002 period. Our results clearly show that crowd-out is significant; the central tendency in our results is a crowd-out rate of about 60%. This finding emerges most strongly when we consider family-level measures of public insurance eligibility. We also find that recent anti-crowd-out provisions in public expansions may have had the opposite effect, lowering take-up by the uninsured faster than they lower crowd-out of private insurance.

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The past two decades in the U.S. have seen two striking parallel trends: a rise in the number of uninsured individuals, and a rise in the number of publicly insured individuals. From 1984 through 2004, the share of the non-elderly U.S. population that is uninsured rose from 13.7% to 17.8%. At the same time, the share of non-elderly U.S. population that is publicly insured rose from 13.3% to 17.5%. In other words, despite an enormous expansion in the public health insurance safety net in the U.S., the number of uninsured continues to grow.

There are two possible explanations for this phenomenon. The first is that other factors were occurring over time that put upward pressure on the number of uninsured, so that public insurance increases simply "stemmed the tide" of rising uninsurance (Shore-Sheppard, 2005). The second is that public insurance expansions did not do much towards stemming the tide because most of the rise in public insurance simply came from a fall in private insurance. As is clear from the numbers above, over this same twenty year period the share of the U.S. non-elderly population with private health insurance fell from 70.1% to 62.4%[1].

The notion that public insurance expansions simply erode private insurance coverage, rather than providing coverage to those otherwise uninsured, is known as "crowd-out". This term was first used by Cutler and Gruber (1996) ten years ago, and they proceeded to suggest that crowd-out was sizeable for public insurance expansions over the late 1980s and early 1990s. Their central estimates suggest that the number of uninsured only fell by one-half as much as the number of publicly insured rose, due to offsetting reductions in private insurance.

There has been a large subsequent literature on the crowd-out question, and it has produced results that are mixed, but are generally below those of Cutler and Gruber (1996). At the same time, there has been a large evolution in the policy environment with the introduction of the CHIP program in 1998. This program provided federal financing for new state public insurance expansions to higher income families than were covered by previous expansions. Since crowd-out is more likely in higher income populations (where a higher percentage of eligibles already have private insurance), it is possible that crowd-out could be even larger in recent years. On the other hand, concerned about this issue, a number of states have put in place tools to combat crowd-out that may have reduced this as a policy issue.

In this article, we revisit the important question of effective public insurance expansions are in reducing the number of uninsured. In doing so, we make three innovations relative to past literature. First, we address the criticisms that have been levied against the Cutler and Gruber (1996) method, providing a comprehensive analysis of alternative approaches to the question. Second, we focus on the period from 1996 to 2002, allowing us to model the extent of crowd-out for the more recent public insurance expansions. Finally, we consider in detail the role of anti-crowdout mechanisms such as waiting periods and enrollee costs.

We have three primary findings. First, crowd-out remains a pervasive phenomenon for recent public insurance expansions. Our central estimates suggest crowd-out of about 60%: that is, the number of privately insured falls by about 60% as much as the number of publicly insured rises. These magnitude of crowd-out is, however, fairly sensitive to the various empirical approaches presented below.

Second, it appears quite important to model crowd-out as a *family* phenomenon, not an individual phenomenon. Crowd-out estimates are much larger when family-wide effects of

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[1] Data from Fronstin (1986, 2005). The definition of insurance coverage changed over this period, so we have

eligibility are accounted for, incorporating the spillover onto other family members of eligibility expansions.

Finally, we find suggestive evidence that anti-crowd-out provisions are working to reduce *both* the enrollment of the otherwise uninsured and the otherwise privately insured. On net, we find that if anything these provisions cause crowd-out to rise, not fall, as the number of uninsured joining the program falls faster than the number of privately insured joining the program. This finding, although not statistically precise, is most noticeable for the imposition of enrollee costs under SCHIP.

Our paper proceeds as follows. Part I provides background on both the expansions of the Medicaid program and on previous literature on the crowd-out question. Part II discusses our data and empirical strategy. Part III presents our basic results, while Part IV considers in particular the estimated role of anti-crowdout provisions of recent SCHIP laws. Part V concludes.

Part I: Background

Public Insurance for the Non-Elderly

The Medicaid program was introduced in the late 1960s as a health insurance component for state cash welfare programs which targeted low-income single-parent families. Beginning in the mid-1980s, the Medicaid program was slowly separated from cash welfare programs, first by extending benefits to low-income children in two-parent families, and then by raising the income eligibility thresholds for two groups: children and pregnant women (who were covered only for

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chain-linked the series using 1994 as the reference point.

the costs associated with pregnancy, not other health costs). As a result, by the mid-1990s, most children in America below the poverty line, and all young children below 133% of the poverty line ($24,427 for a family of four), were eligible for Medicaid.[2]

In 1997, the Medicaid program for children was augmented by the Children's Health Insurance Program (CHIP). The goal of CHIP was to expand the eligibility of children for public health insurance beyond the existing limits of the Medicaid program. This program provides $4 billion per year (on average) through 2007 for states to expand their health insurance coverage beyond Medicaid levels, either using expansions of the Medicaid program, or a new program that more closely mimics private health insurance. To provide incentives for states to expand their low-income health care coverage using CHIP funds, the federal government pays a higher share of the state's CHIP costs than it pays of the state's Medicaid costs.

Currently, all children (through age 19) are eligible for Medicaid up to 100% of the poverty line, and children under age 6 and pregnant women are covered to 133% of the poverty line. Many states extended Medicaid eligibility farther for both children and pregnant women. In addition, 38 states and D.C. cover children who are not eligible for Medicaid under SCHIP (which could take the form of a Medicaid expansion or the creation of a new program) up to 200% of the poverty line ($36,800) or higher; children in New Jersey, for example are eligible up to 350% of the poverty line ($64,400).

While federal Medicaid rules require states to cover major services such as physician and hospital coverage, they do not require states to pay for optional services such as prescription

[2]See Gruber (2003) for a review of the institutional features of Medicaid; for more precise details, see Green Book (2004).

drugs or dental care. Despite this, all states have chosen to cover most optional benefits; all states cover prescription drugs and optometrist services, for example, and almost all cover dental services. For the traditional Medicaid population, these services are provided with little or no copayment required (in states that have CHIP, the copayments are allowed to be somewhat higher for those above 150% of the poverty line). This package of services is much more generous than virtually any private insurance plan. Thus, Medicaid is really "the best insurance money can't buy"!

Just as states can tailor their eligibility requirements to best suit their tastes, they can also regulate the rate at which health service providers are reimbursed. Unlike the case for services covered (in which all states cover basically the same health care services), there is more variability across the states in provider reimbursements. In most states, Medicaid reimburses physicians at a much lower level than the private sector, which often leads physicians to be unwilling to serve Medicaid patients. For childbirth, for example, the reimbursement rate to physicians under Medicaid averages about half of the private sector reimbursement rate. In one survey, one-third of all physicians reported that they serve no Medicaid patients, and another third reported that they limit access of Medicaid patients to their practice. Thus, while the coverage provided by Medicaid is very generous in all states, in a number of states individuals may have trouble availing themselves of that coverage because physicians do not want to accept them as patients.

Theory

The theoretical case for and against crowd-out is developed graphically in Cutler and

Gruber (1996), and we review those arguments here. Since Medicaid is both less expensive and more comprehensive than most private insurance, many individuals will find it attractive to switch to Medicaid when made eligible. At the same time, the fact that providers are less willing to see Medicaid patients may make Medicaid less attractive and mitigate this switching. Medicaid entitlements are also variable, due both to policy changes and the fact that income growth can end eligibility, making this a less attractive alternative to private insurance.

Crowd-out of private insurance should be much more likely for those holding non-group insurance than for those holding insurance through an employer. Non-group insurance is much less comprehensive than employer-provided insurance, and its prices are typically higher and more variable. Moreover, when an individual switches from non-group insurance to public insurance, they see the entire savings of the switch. On the other hand, workers who leave employer-based insurance systems to move to public insurance may not see any of the savings from doing so. While empirical evidence suggests that health insurance costs are passed back to workers (Gruber, 1994; Sheiner, 1994), this research has not established whether this pass back occurs in response to individual or group choices of insurance. If individual workers do not receive the savings from choosing not to purchase insurance, they will perceive moving to Medicaid as a reduction in health insurance but not as an increase in other consumption. Fewer people will drop private insurance coverage in this case.

In the absence of complete wage shifting, employers may encourage workers to drop coverage in other ways. One way to do this is to reduce the generosity of the benefits offered, or in the limit, to simply stop offering insurance to the workers; in either case, these limitations on the private option will make the public option relatively more attractive. Alternatively, employers can reduce the share of the premium that they pay. When employees pay more of the premium, the link between Medicaid receipt and additional income may be more direct (since it does not operate through the veil of shifting to wages). In addition, because there is a tax subsidy for employer spending on insurance but not for individual spending, increasing the share of the premium that employees pay directly effectively raises the price of private insurance relative to Medicaid.

Because of IRS non discrimination rules, however, neither of these actions can be used selectively for those workers eligible for public insurance. If insurance is offered, it must be offered to all full time workers. As a result, all of these actions increase the total cost of insurance for employees that do not qualify for public coverage, since they lose the tax subsidy for some insurance purchases, or (if employers drop coverage) they must purchase insurance in the more expensive individual market.

On net, therefore, the link between health insurance and employment may increase or decrease the amount of crowd-out. If worker specific shifting is not possible, then crowd-out may be reduced, as employees do not realize the savings from moving to the public sector. If employers increase cost sharing or reduce coverage for all workers, however, more workers may decide to drop coverage than are immediately eligible for Medicaid.

Past Research

The initial work on this question was carried out by Cutler and Gruber (1996), who examined crowd-out during the initial Medicaid expansions of the 1987-1992 period. They did so using the Current Population Survey (CPS), the most common source of information on insurance coverage. Their approach was to use state rules to assign each individual eligibility for public insurance based on family income and demographics (marital status, number of children, ages of children). They initially model coverage of any individual as a function of their eligibility, but they recognize that this approach misses spillovers from other family members; for example, when children are made eligible for public insurance, their parents may drop the entire family from coverage. They therefore move to a family-based measure of coverage.

Cutler and Gruber also recognized that eligibility was determined by many of the same factors that drive health insurance coverage; e.g. low income families are both eligible and more likely to be uninsured. They therefore used the "simulated instrument" of Currie and Gruber (1996a,b), whereby each state's eligibility rules is applied to a fixed national population, and the average eligibility by state, year, and age is used as an instrument. This essentially acts as a parameterization of the variation in complicated eligibility rules across states and over time.

As noted, Cutler and Gruber found very high rates of crowd-out. They defined crowd-out in two ways. The first is the reduction in private insurance relative to the growth in public insurance; the second is one minus (the change in uninsurance / the growth of public insurance). If insurance categories were mutually exclusive, these definitions would yield identical results. In fact, however, there is in the CPS a very significant overlap between the private insurance and public insurance categories, and the share of individuals in this overlap group (reporting both private and public coverage) tends to rise as Medicaid expands. The most likely causal interpretation is that these individuals are moving at some point during the measurement period from private to public insurance. In that case, the first definition understates crowd-out, and the second is appropriate.

Looking first directly at children, Cutler and Gruber found that for every 100 children joining Medicaid due to the expansions of the 1987-1992 period, 31 children were losing private health insurance, but the number of uninsured was only going down by 60, so that crowd out was between 31 and 40%. Expanding the analysis to account for family spillovers, their crowd-out estimate overall rises to 50% (using the second definition). This still does not account for any crowd-out due to firm decisions to drop insurance or reduce employer contributions; an earlier version of their paper, work by Shore-Sheppard, Buchmueller, and Jensen (2000) and by Buchmueller, Cooper, Simon and Vistnes (2005), finds a response along the second dimension but not the first.

This article started a sizeable literature devoted to estimating crowd-out effects, as reviewed in Table 1. This literature has produced very mixed results which are sensitive to the methodology, the data set, and the definition of crowd-out (how the overlap population is handled). The first alternative approach was to examine the trends in insurance coverage of children made eligible by expansions. In two articles written shortly after the Cutler-Gruber analysis, Dubay and Kenney (1996, 1997) compared the insurance coverage change for populations eligible for Medicaid expansions to that for populations ineligible for expansions. They used the first definition, the change in private insurance relative to public insurance, and found much smaller crowd-out for those below poverty, but moderate crowd-out above poverty, with comparable estimates to Cutler and Gruber for pregnant women 133-185% of poverty. The problem with this approach, however, is that it assumes that there are no other factors changing over time differentially for children and adult men, which seems unlikely. Thorpe and Florence (1998) took a different approach, assessing the share of children with privately insured parents who move to Medicaid as it expands. They find that only 16% of such children made this move. But this approach does not control for other factors determining such moves, or allow for the fact that Medicaid expansions may also have caused parents to lose private insurance.

A second approach was to more directly compare children made eligible by expansions to those of different ages and incomes who were not made eligible, using longitudinal data to follow individuals over time. The first paper to do so was Yazici and Kaestner (2000), who used the National Longitudinal Survey of Youth (NLSY) to compare the change in insurance coverage of children becoming eligible to those not becoming eligible over the 1988 - 1992 period. Their results are very sensitive to the treatment of the "overlap" population, however: depending on the definition of crowd-out used, crowd-out is either much smaller or larger than the Cutler and Gruber estimates.

Subsequent papers using this approach have turned from the CPS to the Survey of Income and Program Participation (SIPP). The SIPP has a smaller sample and does not uniquely identify all states. At the same time, it is a longitudinal survey which allows researchers to follow insurance status changes over time, and the timing of the insurance question is much clearer than in the CPS.[3] Blumberg, Dubay and Norton (2000) used the 1990 SIPP to show that, of those children made eligible by expansions, only 4% as many lost private coverage as gained public coverage. Their calculation assumes that all those with dual coverage are on Medicaid, providing a lower bound on crowd-out. Card and Shore-Sheppard (2004) pursue a similar analysis in the 1990-1993 SIPP, although they did not follow the same children over time but

[3] The CPS asks respondents in March about their insurance coverage during the previous year, and it is unclear if respondents are actually reporting on current or last year's insurance coverage. The SIPP, in contrast, asks about current insurance coverage.

rather used these surveys as repeated cross-sections. They found no crowd-out for those below poverty, or between 100-133% of poverty, in response to expansions to those populations, but they did find large crowd-out for those below poverty when eligibility was expanded to 133% (perhaps through informational spillovers). An issue with all of these studies, however, is that income is treated as exogenous in assigning children to treatment and control groups, ignoring any possible effects of the expansions on income which may shift children across groups.

The third approach pursued by this literature has been to consider alternative specifications of the Cutler-Gruber (1996) simulated instruments approach. Shore-Sheppard (2005) replicates the Cutler-Gruber findings, but she finds that they are very sensitive to the set of controls in the model. In particular, when she controls for differential time trends by age of child (a full set of age*year interactions), her crowd-out estimate falls to zero. But, as with other CPS analyses, this result is very sensitive to the treatment of the overlap population; using the second definition of crowd-out, her estimates are quite similar to those of Cutler-Gruber even when the extra controls are included. Ham and Shore-Sheppard use the SIPP to replicate the Cutler-Gruber approach, however, and they find no crowd-out. They are able to replicate Cutler-Gruber in the CPS, and they highlight the sensitivity of the findings to the data set used.

Several papers have also considered the effects of the most recent expansions in public insurance. Hudson, Selden and Banthin (2005) use both the Cutler-Gruber approach and the approach of comparing eligible to ineligible children over time with data from the Medical Expenditure Panel Survey (MEPS). They find variable but generally large crowd-out estimates from these approaches. LoSasso and Buchmueller (2004) use a Cutler-Gruber approach with CPS data and estimate a 50% crowd-out of private insurance and also find that the anti-crowdout provisions in the form of a waiting period have been effective in reducing crowd-out. In a paper that focuses on parental expansions under Medicaid, Aizer and Grogger (2003) use CPS data and find that parental expansions increased the coverage of parents as well as their children through a possible spillover effect. Their method is a within-state differences in differences approach using target and control groups within expansion states, before and after expansions. They find that expansions increased public coverage for mothers by 2.7 percent and reduced private coverage by a statistically insignificant 1.3%. For children, it increased public coverage by 5.3% and decreased private coverage by a statistically insignificant 1.2%.

The literature on crowd-out is therefore marked by three eras. The first is the initial Cutler and Gruber study, which finds large crowd-out. The second is further work on the crowd-out effects of expansions in the 1980s and early 1990s, which generally have not corroborated the large crowd-out findings of Cutler and Gruber. These results also suggest that the earlier findings may be driven by data set choice (the CPS) and specification (the omission of age*year interactions). Finally, a recent literature on the late 1990s and early 2000s expansion of public insurance once again finds large crowd-out effects.

This newer literature, however, has not grappled with the criticisms levied against the older literature. None of the new studies have used the SIPP, the data set which is likely most appropriate for this study and in which the earlier crowd-out results were not replicated. None of the studies have addressed differences in results from the group over time comparisons (as in Card and Shore-Sheppard) and the instrumental variables regression method (as in Cutler and Gruber). And none of the studies has explored the robustness to the inclusion of additional controls for changes over time as in the Shore-Sheppard study of the earlier period.

Moreover, there has been relatively little exploration of the unique feature of public insurance expansions in recent years: the increased use of anti-crowdout provisions. The one exception is the LoSasso and Buchmueller paper, which looks at waiting periods. Perhaps more important in the era of the SCHIP program is the imposition of non-trivial costs on enrollees, either in the form of premiums or copayments. These costs can lead both to less take-up by needy uninsured, as well as less crowd-out from those who are insured. Which effect is stronger is an empirical question.

Part II: Data and Empirical Strategy

Data

Given the advantages of the SIPP noted above, and the fact that SIPP-based analyses have been less likely to find sizeable crowd-out, our analysis will focus on this data set. We use the 1996 and 2001 panels of the SIPP: The 1996 panel covers the 1996 to 2000 period, while we use the 2001 panel for 2001 and 2002.

Given the importance of the "overlap" issue raised earlier, we pursue an approach in the SIPP which provides a range of results depending on the interpretation of this overlap. Our key dependent variables measure (a) coverage by Medicaid *only* (no overlap with other insurance), (b) coverage by private insurance *only*, and (c) the extent of overlap between public and private. We can therefore produce two estimates: (i) assuming changes in overlap represents only individuals moving from private insurance to Medicaid (the most likely explanation) and (ii) remaining agnostic about the overlap and simply comparing the groups only on Medicaid and private insurance.

Our sample uses children aged 0-18 years as well as parents aged 19-64 years of age. We use only the 4th reference month observations from each SIPP wave (thus we have upto one observation every 4 months on an individual, picked in a manner that minimizes recall bias). In the 2001 panel of the SIPP, we keep data only through the end of 2002 as this is the end period of our study. We delete observations from states that cannot be uniquely identified in the SIPP (Maine, Vermont, North Dakota, South Dakota, Wyoming). These states together account for 1.3% of the US non-elderly population in 2000 (author calculations using U.S. Census Bureau population data).

Table 2 shows sample means for our data set. There are 405,389 observations on children (where an observation is a person-month). This shows, for example, that 18% of children are on Medicaid alone.

Empirical Methodology

In order to address the various approaches considered in previous studies, we use two empirical methodologies. We begin with descriptive cross-tabulations that follow the approach of Card and Shore-Sheppard (2004), showing the change in insurance coverage in populations made eligible and not made eligible by expansions. Unlike Card and Shore-Sheppard, however, we consider the possibility that income may be endogenous to the expansions, and also show results using a fixed base period income that is not subject to this potential contamination.

Our second empirical methodology follows the original approach of Cutler and Gruber (1996), assigning eligibility to individuals, and then instrumenting with "simulated eligibility". Thus, our basic approach is to run regressions of the form

1) $Ins_{ijt} = \alpha + \beta ELIG_{ijt} + \phi X_{ijt} + \upsilon_j + \rho_t + \varepsilon_{ijt}$

where the subscript i denotes individuals, j denotes states, and t denotes time (year by month); INS is a measure of insurance coverage; ELIG is individual i's eligibility for insurance; X is a set of individual and state level characteristics; and ρ_t and υ_j are a set of year by month (t) and state (j) dummies, respectively. We include controls for the following characteristics: number of families on cash assistance by month by state, state unemployment rate by month, family monthly income as a percent of the FPL and its square, an indicator for being female, a set of indicators for the number of children in the family (one, two, three, fours, five or more),the number of adults in the family who work for a firm with over 100 workers, the number in the family who work full time, the number in the family who have only high school completion, the number in the family who have some college completion, who have college completion or more, whether family is headed by a single female, single male, whether male head is unemployed in a two parent household, indicators for race and ethnicity (White, Black, Hispanic vs others) and fixed effects for each age 0-18 for kids. In specifications that consider the impact of family level eligibility, we also include a set of additional controls for family composition by age categories: dummy variables for having one, or more than two, family members of a given age in the interval 0-18 (36 dummy variables) and dummy variables for total family size (up to 14). Standard errors are clustered by state.

There are two major threats to the validity of this estimate of the effect of eligibility on insurance coverage. The first is the fact that eligibility is determined by many of the same factors that determine insurance coverage. In principle, we can control for these factors in the X vector, but in practice eligibility is a complicated non-linear combination of these factors that is difficult to capture in the control set. Currie and Gruber (1996a,b) introduced an instrumental variables approach to solving this problem, by taking a fixed national population in each year and applying each state's rules to that population. In this way, the only feature that differs across states is the rules and not other factors in the X vector.

A second threat is omitted variables that affect both eligibility rules and insurance coverage. As discussed above in the context of Shore-Sheppard (2005), there may be omitted trends in insurance coverage by child age or state that are correlated with expansions in eligibility. Following Shore-Sheppard, we consider the robustness of our results to controls for such omitted factors.

Part III: Results

Cross-Tabulations

We begin our analysis with cross-tabulations that clearly show the patterns of insurance coverage over time. To do so, we take just the starting and ending years of our data (1996 and 2002, respectively) and tabulate public only, private only, and overlap between private and public insurance by age group and income group. We begin with simple tabulations by income group, considering children in families with incomes below the poverty line, between 100 and 200% of the poverty line, between 200 and 300% of the poverty line, and between 300 and 400% of the poverty line. As Table 3 shows, for those broad income groups, the change in eligibility from 1996 to 2002 was 10.3%, 72.2%, and 29.1%, and 7.6%, respectively. There is clearly important variation along the income distribution in changes in eligibility, particularly for the group of children between 100 and 200% of the poverty line.

The next three columns of Table 3 show the associated change in Medicaid coverage, private insurance coverage, and the overlap (both public and private). As would be expected, the rise in Medicaid coverage is largest for the group between 100 and 200% of poverty. And, consistent with crowd-out, this is also the group that sees the largest decline in private coverage.

To evaluate these changes, Table 4 takes the data from Table 3 and computes some difference-in-difference tabulations of private and public coverage. There are two columns of results, corresponding to (a) assuming that the individuals who report both private and public coverage are moving from private to public insurance coverage, (b) excluding from the calculation the set of individuals who report both private and public coverage. As discussed earlier, we find approach (a) to be the most plausible given the expansion of public insurance over this period, but it is important to assess the sensitivity to this assumption.

Each row in the top panel computes the three difference in difference comparisons available from the income group data, comparing the treatment group of 100-200% of poverty to three different control groups. The estimates in the table show the ratio of the change in private insurance to the change in public insurance for each case. As is clear, these estimates imply very large crowd-out, and are not particularly sensitive to the use of the overlap group. The lowest crowd-out estimate here is 58%, and the largest is over 100%.

The second panel of Table 3, and the corresponding second panel of Table 4, perform this same exercise but with one important change: we use the base income (as of the start of the SIPP panel) of respondents to categorize them, rather than using current income. This approach controls for any potential income endogeneity to public insurance eligibility, which is not accounted for by using current income. Base period income is inflated to actual year and month using the national monthly Consumer Price Index.

As Table 3 shows, using this approach yields much less sharp distinctions in eligibility change over time across income groups, as is to be expected from the fact that the treatment is noisier since incomes change over time. Nevertheless, Table 4 shows that the crowd-out estimates implied by these changes are fairly similar, albeit somewhat lower, than those using current income. The range of crowd-out estimates here is from 47% to 92%. Thus, in contrast to the earlier findings from Card and Shore-Sheppard (2004), the evidence of crowd-out from this approach is quite strong.

Instrumental Variables Regressions

We next move from these cross-tabulations to instrumental variables regressions of the type described in the previous section. The instrument is created by first taking a random sample of 300 children of each age (and their families) from each year of the SIPP. This national sample is used for each of the 12 months in each of the years, with the eligibility rules in each state (in each year and month) to calculate the fraction of the national sample of a given age who are eligible for public insurance (and also for Medicaid and SCHIP forms separately). Table 5 shows estimates from (1) above estimated using different dependent variables for insurance status, and different measures of eligibility (based on own eligibility or the eligibility of the family). We also distinguish between models that include two-way interactions between age, year and state (“All interactions”) and ones without these interactions (“Baseline”). We show only the coefficient (and standard error) of interest in a regression that includes all of the controls described above. Each row represents a different specification; each column represents a different dependent variable. The two columns labeled "Crowd" are the exceptions, where we calculate the implied crowd-out magnitude in the two ways discussed earlier.

The first row shows the estimates on the eligibility variable from our base IV specification. For example, the coefficient of 0.072 in the first row, first column, implies that, for every 100 children made eligible for insurance through the expansions of the 1996-2002 period, 7.2 children gain Medicaid coverage (and no other type of coverage). This is a very low marginal take-up rate, but it is consistent with the fact that most children in the income ranges made eligible for insurance already had insurance coverage. Indeed, among children made newly eligible over this period, 80% had other insurance coverage before they became eligible. Thus, if take-up were restricted to the previously uninsured, then over one-third of the newly eligible uninsured would be taking up.

The second column of the first row shows the effect of eligibility on private insurance coverage (with no overlap with other coverage). The estimate here suggests a small and insignificant effect: for each 100 children being made eligible, only 1.7 children lose private insurance. The third column shows the impact of eligibility on being recorded as having both public and private coverage; this is marginally significant and suggests that for each 100 children made eligible, 1.5 are coded as having both types of coverage.

The implications for crowd-out estimates are shown in the next two columns. As before, we consider two measures of crowd-out, depending on how the overlap population is treated. Crowd1 refers to the first method, assuming that the overlap group move from private to public, while Crowd2 ignores the overlap group. The estimates here suggest modest crowd-out of 24-37%.

The next two columns of the table divide the sample of privately insured into those with employer insurance and non-group insurance exclusively. The effects on both types of insurance are insignificant, although there are significant overlap effects in each case (see last two columns).

As emphasized by Cutler and Gruber (1996), it seems likely that the entire family's eligibility for Medicaid is relevant to both take-up and crowd-out. On the take-up side, parents may be more likely to enroll their children if other children, or the parents themselves, are eligible for coverage as well. Indeed, Sommers (forthcoming) finds that Medicaid enrollment among eligible children is higher if siblings are also eligible. On the crowd-outside, insurance is often purchased for the entire family, so it would not be surprising that as more family members are eligible for public insurance it increases the pressure to drop private insurance.

To investigate this issue, we replace our measure of individual eligibility with a measure of family eligibility: the % of the family (including the focal member) that is eligible for public insurance, which varies from zero for no eligibility to 100% for family eligibility. The family includes children aged 0-18 and their parents aged 19-64.[4] We create an instrument in the same way, using the family mean of simulated eligibility rather than the simulated eligibility for that child. Since the regression includes the detailed demographic controls discussed earlier, we are not identifying the model from demographic differences across families but rather solely from variation in simulated eligibility.

The results of this exercise are shown in the second set of rows of Table 5 (family eligibility). As expected, we find somewhat higher take-up; making the entire family eligible raises the odds that a child takes up Medicaid by 10.9% (although this is not significantly different from the 7.2% take-up rate for own eligibility). The larger difference is for private insurance, where there is now a sizeable and statistically significant negative coefficient of -0.066; there is also an increase in the overlap coefficient to 0.027. As a result, the estimated crowd-out is sizeable for this specification, ranging from 61% to 68%. This is comparable to the difference-in-difference tabulations from the previous table, which is sensible since those were comparing broad income groups which would incorporate family eligibility rather than own eligibility.

This significant reduction in private insurance reflects a reduction in employer-provided insurance, with no effect on non-group insurance (although some effect on the group that overlaps between non-group insurance and public insurance). For each 10 percentage point increase in the share of the family made eligible for Medicaid, there is a 0.66 to 0.9% reduction in employer-provided coverage, depending on the treatment of the overlap group. This amounts to a 1 to 1.36 percent reduction in the level of employer-provided health insurance for each 10 percentage point increase in the share of the family made eligible for Medicaid.

Controlling for Other Omitted Factors

As emphasized by Shore-Sheppard (2005), a key assumption of models such as these is that there are no omitted factors correlated with legislative patterns of eligibility. For example, there could be differential trends in insurance coverage by age that are correlated with, but not caused by, the Medicaid expansion. Shore-Sheppard found that Cutler-Gruber type models were

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[4] There are some children in the children's regression who were not matched to parents in the data set-these children

very sensitive to the inclusion of controls for these factors.

To address this point, we have re-estimated our models controlling for the full set of second-order interactions: state*age; age*year; and state*year. The first controls for the fact that state fixed factors may operate differently at different ages; while children may be the same on average in state A and state B, there could be large differences by age that just average out. The second and third terms address Shore-Sheppard's concern that other factors are changing over time differentially by age groups of children or by state. These results are shown in rows 2 and 4 of the table.

In the case of own eligibility, in rows 1 and 2, columns 1 and 2, there is a weakening of the effects on both take-up and crowd-out. In the case of family eligibility (rows 3 and 4), however, both get stronger – in particular the reduction in private insurance. In this case, there is a fairly tightly estimated crowd-out of 78% to 81%. Once again, however, this comes primarily from those with employer-based insurance, suggesting little crowd-out of non-group insurance.

Summary

To summarize, our results suggest that crowd-out is not sizeable if the individual's own eligibility alone is considered, but that once family eligibility is considered crowd-out grows in importance. This conclusion is robust to all of the methods employed in the previous literature, such as examining group trends over time, using instrumental variables regression, and controlling for possible omitted time trends.

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are included in the family regressions with the same information as in the individual regressions.

Part IV: The Role of Anti-Crowd-Out Provisions

A major difference between recent expansions of insurance for children and previous rounds of expansion is the attention that has been paid to crowd-out and the use by states of anti-crowd-out provisions in their SCHIP programs. The most prominent of these is waiting periods, whereby individuals have to show their lack of health insurance coverage for some period before enrolling in SCHIP. 34 states have waiting periods in their SCHIP programs as of 2000: the most common waiting period is 6 months (15 states), and the longest is 12 months (in the states of Alaska, New Mexico and Virginia). The results of LoSasso and Buchmueller (2004) suggest that such waiting periods might be important, as they show significant crowd-out without waiting periods that disappears when waiting periods increase up to 5 months.

We revisit that analysis here using our SIPP data and specifications. We first divide our variable for eligibility into eligibility for traditional Medicaid, which has no waiting period, and eligibility for SCHIP, which can have a waiting period in some states. We then add an interaction of the SCHIP eligibility term with the state's waiting period. Our instruments are adjusted accordingly: we use a simulated eligibility measure for SCHIP and Medicaid separately, and interact the former with months of waiting period in the state/year cell. This specification parallels that of LoSasso and Buchmueller (2004), except that we allow for separate direct effects of Medicaid and SCHIP, while they impose the same direct effect.

The results of this analysis are shown in Table 6, both for own eligibility (the first half of the Table) and family eligibility (the second half of the table). There are three sets of rows under each part. The first set shows the impact of eligibility for Medicaid; the second set shows the impact of eligibility for SCHIP and the third shows the interaction between eligibility for SCHIP and the waiting period in the state. The crowd-out calculations are presented for Medicaid coverage, SCHIP coverage (assuming no waiting period), and for SCHIP with the standard deviation of waiting periods among states that have a waiting period (2 months). For example, the value of 0.36 for "Crowd1" (which assumes that the overlap between private and public coverage represents a movement from private to public coverage) in the baseline specification row corresponding to "Medicaid" in the first panel indicates 36% crowd-out, The value of 0.54 for "Crowd1" corresponding to the "SCHIP" line indicates 54% crowdout for SCHIP eligibility, assuming a 0 month waiting period. The value of 0.59 in the row below that indicates 59% crowd-out for SCHIP eligibility using a 2 month waiting period.

Unfortunately, many of our estimates here are imprecise. But the results suggest that crowd-out is at least as great for the SCHIP program, with no waiting period, as it is for the Medicaid program. Most strikingly, we find little evidence that waiting periods reduce crowdout. This is contrary to findings published in LoSasso and Buchmueller (2004).[5] Crowd-out is almost as large for states with waiting period as for those without in the specification using the child's own eligibility; and crowd-out is much *larger* when family eligibility is used. For example, using the Crowd1 definition and including all interactions, crowd-out is 60% for SCHIP if no waiting period, and 110% when using a two month waiting period. This reflects the fact that take-up of Medicaid coverage is declining faster than is crowd-out of private coverage as waiting periods are introduced. The imprecision of these results makes strong conclusions inappropriate, but there is certainly no reason to conclude that waiting periods are lowering the crowd-out rate.

SCHIP Costs

Another important new feature of SCHIP programs was the increase in costs that enrollees could bear. Medicaid is free and imposes only nominal copayments on enrollees. SCHIP enrollment, however, can be subject to premiums, and copayments for services can be nontrivial for those above 150% of poverty (but premiums and copayments can not add up to more than 5% of income). In principle, these charges can also serve as anti-crowd-out provisions, deterring those with private insurance from dropping that coverage. But they may also deter individuals who are eligible for signing up for the program as well.

To investigate this issue, we have created a variable for each child which is the expected cost sharing faced during the year in dollars. To construct this, we assign each SCHIP-eligible child in the SIPP their expected usage of health care (dollars by category, number of visits by category, as well as total cost in dollars) during the year from the MEPS by age categories and gender. The health care services we consider are doctor visits, hospital stays, and prescription drugs. We use the cost sharing rules that apply to children by the type of insurance for which they are eligible (Medicaid or SCHIP), their age, family structure and income which are often used to determine whether cost sharing will apply to a certain child. By dividing the estimated out of pocket costs by the estimated total costs for health care, we calculate the expected cost sharing fraction. The instrument is created in a similar way as for eligibility (at the state/age/year level) except here we limit the sample to just the children who are estimated to be eligible for SCHIP. We then use the same regression framework just described, breaking out

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[5] LoSasso and Buchmueller have kindly replicated our specification in their data and continue to find evidence that

separately Medicaid and SCHIP eligibility, and interacting this cost-sharing variable with the latter.

The results of this exercise are shown in Table 7 (which is arranged in a manner similar to Table 6) and are quite striking. There is a negative and significant interaction of the cost-sharing variable with SCHIP eligibility in the Medicaid take-up equation, indicating that although making someone eligible for SCHIP has a positive but statistically significant effect on take-up, the incremental impact on take-up of requiring cost sharing decreases take-up in a statistically significant manner. The 0.105 (standard error 0.03) coefficient on the Medicaid variable in the first column indicates a statistically significant increase in public coverage of 10.5 percentage points as a result of Medicaid expansions. The 0.052 coefficient on the SCHIP eligibility variable (standard error 0.04) in the first column indicates a statistically insignificant increase of public coverage by 5.2 percentage points from an SCHIP expansion with no cost sharing. In contrast, the statistically significant coefficient of -0.383 indicates that as cost sharing increases, the effect of SCHIP expansion on increases in public coverage decreases. As the total expected amount a child pays out of pocket under SCHIP as fraction of their expected total costs rises from zero to one, the take-up of SCHIP reduces by 38.8 percentage points. On the other hand, there are positive interactions in both the private insurance and overlap equations, although neither is statistically significant.

We interpret these results by showing coverage effects implied by a 0.08 (one standard deviation) cost-sharing percentage, relative to a state with an SCHIP program with no cost-sharing. The results imply that crowd-out is higher for Medicaid than for SCHIP with no cost-

waiting periods reduce crowd-out. Thus, the main difference between our results appears to be the data set used.

sharing– but it is highest (depending on the inclusion of interactions) for SCHIP with cost-sharing at the median of states that have cost-sharing. For example, for family eligibility and the Crowd1 definition, crowd-out is 64% for Medicaid, 30% for SCHIP with no costs, and 80% for SCHIP with one standard deviation higher costs. Once interactions are included, however, the crowd-out effects are comparable on all three coefficients.

Once again, our findings in Table 7 suggest that state efforts to increase financial barriers to public programs may deter the use of those programs by those who need them at a faster rate than it is deterring the use of those programs by those who are crowded out. While the conclusion imprecise, there is certainly no evidence that imposing costs on beneficiaries is reducing crowd-out of private insurance.

Part V: Conclusions

Despite large increases in eligibility of children for public insurance over the past two decades, continued increases in eligibility remain a popular option for expansions of insurance coverage in the U.S. Central to evaluating such policy initiatives is understanding the degree to which expanded public insurance entitlements will reduce private insurance coverage. This "crowd-out" problem has become the subject of a large literature over the past decade. The purpose of this paper was to bring to bear the improved methods and data from this literature to draw conclusions about the ultimate magnitude of crowd-out.

We have three primary conclusions. First, crowd-out is significant. Our central estimates suggest that crowd-out is on the order of 60%: private insurance coverage is reduced by 60% as much as public insurance coverage rises when there are public eligibility expansions. This result is not statistically precise, but emerges from several different approaches, in particular both changes in cohorts over time and instrumental variables regression models.

Central to this finding is our second conclusion: family eligibility matters. Crowd-out is only about half as large when we consider individuals only, but this higher magnitude emerges when we consider the entire family's eligibility for Medicaid. Making more of the family eligible for public insurance lowers private insurance coverage at a much more rapid rate than it raises public insurance take-up.

Finally, and perhaps most interestingly, our findings suggest that the anti-crowdout efforts that have accompanied the SCHIP program have probably raised crowd-out more than lowering it. The imprecision of our results in Section IV limit the power of these conclusions, but they certainly suggest that features such as waiting periods and especially cost-sharing lower take-up by the uninsured faster than they deter crowd-out from private insurance.

Despite our ability to synthesize many of the issues raised in previous research, there is more work to be done on this important topic. The highest priority should clearly be to explore further the issues raised in Section IV about how the design of public insurance expansions affects take-up and crowd-out. More generally, as states experiment more broadly with alternatives such as private purchasing pools, understanding the degree of substitutability between private and publicly subsidized insurance, and how that features with the nature of the publicly-subsidized insurance, becomes a critical area for future research.

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Table 1
Literature on Crowd-Out

Article	Data Source	Methodology	Crowd-Out Definition	Results
Cutler and Gruber (1996)	1987-1992 CPS	Instrument eligibility with simulated eligibility based on entire nation; control for state, year, age; consider family-level spillovers	γPrivate Insurance / Public Insurance) or (1 – {Uninsured / Public Insurance})	Children 31% or Children: 40% Family Level: 50%
Dubay and Kenney (1996)	1988 & 1993 CPS	Change in insurance coverage of children relative to change for adult men	γPrivate Insurance / Public Insurance)	Below poverty: 15% 100-133%: 22%
Dubay and Kenney (1997)	1988 & 1992 CPS	Change in insurance coverage of pregnant women relative to change for men	γPrivate Insurance / Public Insurance)	Below poverty: 0% 100-133%: 27% 133-185%: 59%
Thorpe and Florence (1998)	1989-1994 NLSY	Measure movement from private insurance onto Medicaid among children with privately insured parents	% of those entering Medicaid with privately insured parents	16%
Blumberg, Dubay and Norton (2000)	1990 SIPP Panel	Compare change in insurance coverage of children made eligible by expansions to those not made eligible	% of children made eligible losing private relative to gaining public	4%
Yazici and Kaestner (2000)	1988 & 1992 NLSY	Compare change in insurance coverage of children becoming eligible to those not becoming eligible	(1 – {Uninsured / Public Insurance}) or γPrivate Insurance / Public Insurance)	55-59% 5-24%
Aizer and Grogger (2003)	1995-2002 CPS	Compare change in insurance, for those above AFDC eligibility vs below, in states with adult expansion, before vs after expansion	Coefficient on private coverage equation (no crowd-out calculations)	Statistically insignificant effect on private coverage for mothers and for children
Card and Shore-Sheppard (2004)	1990-1993 SIPP Panels	Compare changes in insurance coverage of children around income and age limits for eligibility	γPrivate Insurance / Public Insurance)	Below poverty, eligible for <100: 0 Below poverty, eligible for 100-133: 50% 100-133: 0

LoSasso and Buchmueller (2004)	1996-2000 CPS	Instrument eligibility with simulated eligibility based on entire nation; control for state, year, age, state*year; interact with state waiting periods	γPrivate Insurance / Public Insurance)	Average: 50% Varies with state waiting periods
Shore-Sheppard (2005)	1987-1995 CPS	Same as Cutler-Gruber, but add additional controls - children only	(1 – {Uninsured / Public Insurance}) or γPrivate Insurance / Public Insurance)	33% (age/year controls) - 59% (all controls) 0
Ham and Shore-Sheppard (2005)	1985-1995 SIPP	Instrument eligibility with simulated eligibility based on all other states; control for state, year, age	γPrivate Insurance / Public Insurance)	No Crowdout
Hudson, Selden and Banthin (2005)	1996-2002 MEPS	Compare changes in children made eligible and remaining ineligible; instrument with simulated eligibility	γPrivate Insurance / Public Insurance)	Comparison: 25-55% IV: 39-70%

Table 2
Descriptive Statistics of Selected Variables

Variable	*Mean*	*St. Dev*
Medicaid only	0.18	0.39
Private insurance only	0.63	0.48
Both Medicaid and private insurance	0.02	0.14
Employer insurance only	0.59	0.49
Non-group insurance only	0.03	0.18
Uninsured	0.15	0.36
Both non-group insurance and Medicaid	0.00	0.04
Both employer insurance and Medicaid	0.02	0.14
Eligible for public insurance (any)	0.43	0.50
Instrument for above	0.43	0.16
Eligible for SCHIP	0.08	0.26
Instrument for above	0.08	0.11
Eligible for Medicaid (as opposed to SCHIP)	0.36	0.48
Instrument for above	0.36	0.15
Family level eligibility (any)	0.34	0.41
Instrument for above	0.32	0.14
Family level eligibility for Medicaid	0.30	0.41
instrument for above	0.27	0.13
Family level eligibility for SCHIP	0.04	0.16
Instrument for above	0.04	0.06
Waiting period in months	1.53	2.48
Waiting period, conditional on not being zero	4.48	2.19
Cost sharing (fraction of expected costs paid out of pocket through premiums and other means)	0.04	0.08
The above, conditional on not being zero	0.12	0.08
Age in years	9.08	5.33
Female (1=yes, 0=no)	0.49	0.50
White	0.64	0.48
Black	0.16	0.37
Hispanic	0.15	0.36
Family income as % FPL	275.20	314.00
Single female headed family	0.26	0.44
Single male headed family	0.04	0.20
Unemployed married male headed family	0.06	0.23
Welfare caseload (families by month/state)	163566	211445
Unemployment rate (month/state)	4.93	1.08
Observations	405,389	

Notes: Unweighted data from the SIPP 1996 and 2001 panels. From the 2001 panel, we exclude data after December 2002. Children are aged 0-18 years. Only 4th reference month observations are kept (one response per wave). States that are unidentified in the SIPP include North Dakota, South Dakota, Maine, Wyoming, and Vermont.

Table 3
Tabulations

Tabulations Using Actual Income				
Income Group	Change in Eligibility	Change in Medicaid	Change in Private	Overlap
<100% FPL	0.103	0.023	-0.007	0.002
100-200% FPL	0.722	0.126	-0.123	0.021
200-300% FPL	0.291	0.052	-0.08	0.014
300-400% FPL	0.076	0.019	-0.047	-0.001

Tabulations Using Base Period Income				
Income Group	Change in Eligibility	Change in Medicaid	Change in Private	Overlap
<100% FPL	0.101	0.007	0	0.012
100-200% FPL	0.478	0.14	-0.122	0.016
200-300% FPL	0.38	0.057	-0.083	0.008
300-400% FPL	0.21	0.024	-0.06	0.001

Note: Calculations are based on authors' tabulations of 1996 and 2002 SIPP data.

Table 4
Crowd-out Calculations from Tabulations in Table 3

Tabulations Using Actual Income		
Income Group	Crowd1	Crowd2
DD1: 100-200% relative to <100%	1.11	1.13
DD2: 100-200% relative to 200-300%	0.62	0.58
DD3: 100-200% relative to 300-400%	0.76	0.71

Tabulations Using Base Period Income		
Income Group	Crowd1	Crowd2
DD1: 100-200% relative to <100%	0.92	0.92
DD2: 100-200% relative to 200-300%	0.52	0.47
DD3: 100-200% relative to 300-400%	0.59	0.53

Notes: Crowd1 assumes that the overlap is a move from private to public coverage; Crowd2 ignores the overlap.

Table 5
Effect of Eligibility for Any Public Insurance on Insurance Status

		Public only	Private only	Both Public and private	Crowd 1	Crowd 2	Employer coverage only	Non group coverage only	Both Public and non group	Both Public and employer coverage
Own eligibility	Baseline	0.072*** (0.02)	-0.017 (0.02)	0.015** (0.01)	0.37	0.24	-0.011 (0.02)	-0.006 (0.01)	0.003*** (0.001)	0.013** (0.01)
	All interactions	0.055*** (0.02)	-0.011 (0.02)	0.008 (0.01)	0.30	0.20	0.004 (0.03)	-0.012 (0.02)	0.003 (0.004)	0.005 (0.01)
Family eligibility	Baseline	0.109*** (0.03)	-0.066** (0.03)	0.027** (0.01)	0.68	0.61	-0.066** (0.03)	0.0004 (0.01)	0.004* (0.002)	0.024** (0.01)
	All interactions	0.156*** (0.05)	-0.122*** (0.04)	0.027* (0.01)	0.81	0.78	-0.121** (0.05)	-0.001 (0.02)	0.004 (0.003)	0.025* (0.02)

Notes: Standard errors are in parentheses. Each estimate is from a separate regression. * indicates statistical significance at the 10% level; ** indicates significance at the 5% level; and *** indicates significance at the 1% level. Number of observations is 405,389. All interactions refer to state*age, state*year and age*year.

Table 6
Effect of Eligibility for Medicaid and SCHIP on Insurance Status (Months interaction)

		Public only	Private only	Both public and private	Crowd 1	Crowd 2	Employer coverage only	Non group coverage only	Both public and non group	Both public and employer coverage
Own eligibility										
Baseline	Medicaid	0.101***	-0.026	0.016**	0.36	0.26	-0.025	-0.002	0.002*	0.014*
		(0.03)	(0.02)	(0.01)			(0.02)	(0.01)	(0.001)	(0.01)
	SCHIP	0.054*	-0.023	0.013	0.54	0.43	-0.009	-0.014	0.006***	0.006
		(0.03)	(0.03)	(0.01)			(0.03)	(0.01)	(0.001)	(0.01)
	SCHIP*months	-0.011**	0.006	0.003	0.59	0.34	0.006	0.001	0.0001	0.004
		(0.01)	(0.01)	(0.003)			(0.01)	(0.003)	0.0002	(0.002)
All interactions	Medicaid	0.078	-0.025	-0.021	0.36	0.26	-0.024	-0.001	0.005	-0.024
		(0.11)	(0.03)	(0.28)			(0.03)	(0.02)	(0.01)	(0.28)
	SCHIP	0.011	0.02	-0.002	0.54	0.43	0.052	-0.032*	0.007**	-0.01
		(0.06)	(0.05)	(0.14)			(0.04)	(0.02)	(0.003)	(0.14)
	SCHIP*months	-0.004	-0.007	0.001	0.59	0.34	-0.01	0.003	-0.001***	0.003
		(0.01)	(0.01)	(0.02)			(0.01)	(0.004)	(0.001)	(0.02)
Family eligibility										
Baseline	Medicaid	0.145***	-0.086***	0.029**	0.7	0.59	-0.086***	0.0002	0.003	0.027**
		(0.04)	(0.03)	(0.01)			(0.03)	(0.02)	(0.002)	(0.01)
	SCHIP	0.051	-0.027	0.01	0.6	0.53	-0.028	0.001	0.008**	0.002
		(0.05)	(0.05)	(0.01)			(0.06)	(0.02)	(0.003)	(0.01)
	SCHIP*months	-0.017	0.003	0.008**	1.1	1.24	0.002	0.001	0.0003	0.009**
		(0.01)	(0.01)	(0.004)			(0.01)	(0.004)	(0.001)	(0.004)
All interactions	Medicaid	0.217***	-0.163***	0.028	0.7	0.59	-0.156**	-0.008	0.004	0.026
		(0.06)	(0.05)	(0.02)			(0.06)	(0.02)	(0.004)	(0.02)
	SCHIP	0.009	0.049	-0.009	0.6	0.53	0.024	0.025	0.006	-0.015
		(0.04)	(0.06)	(0.02)			(0.07)	(0.03)	(0.01)	(0.02)
	SCHIP*months	-0.009	-0.018	0.012***	1.1	1.24	-0.019	0.0004	-0.001	0.014***
		(0.01)	(0.02)	(0.004)			(0.02)	(0.01)	(0.001)	(0.004)

Notes: Standard errors are in parentheses. Each set of estimates (Medicaid, SCHIP and SCHIP*months) is from a separate regression. * indicates statistical significance at the 10% level; ** indicates significance at the 5% level; and *** indicates significance at the 1% level. Number of observations is 405,389. All interactions refer to state*age, state*year and age*year.

Table 7
Effect of Eligibility for Medicaid and SCHIP on Insurance Status (Cost Sharing Interactions)

		Public only	Private only	Both Public and private	Crowd 1	Crowd 2	Employer coverage only	Non group coverage only	Both Public and non group	Both Public and employer coverage
Own eligibility										
Baseline	Medicaid	0.105***	-0.03	0.015*	0.39	0.30	-0.028	-0.001	0.002	0.014*
		(0.03)	(0.02)	(0.01)			(0.02)	(0.01)	(0.001)	(0.01)
	SCHIP	0.052	-0.005	0.008	0.22	0.10	0.015	-0.021	0.004**	0.003
		(0.04)	(0.03)	(0.01)			(0.03)	(0.01)	(0.002)	(0.01)
	SCHIP*%costs	-0.383**	0.148	0.054	0.87	0.79	0.091	0.058	0.011	0.055
		(0.19)	(0.15)	(0.03)			(0.15)	(0.08)	(0.01)	(0.04)
All interactions	Medicaid	0.094***	-0.023	0.004	0.36	0.26	-0.02	-0.002	0.004	0.001
		(0.03)	(0.03)	(0.01)			(0.03)	(0.02)	(0.002)	(0.01)
	SCHIP	0.015	-0.01	0.018	0.54	0.43	0.02	-0.03	0.003	0.016
		(0.03)	(0.04)	(0.01)			(0.03)	(0.02)	(0.003)	(0.01)
	SCHIP*%costs	-0.233	0.285	-0.005	0.54	0.42	0.179	0.106	0.01	-0.019
		(0.18)	(0.28)	(0.06)			(0.25)	(0.12)	(0.01)	(0.06)
Family eligibility										
Baseline	Medicaid	0.154***	-0.088***	0.027**	0.64	0.57	-0.085***	-0.003	0.003	0.026*
		(0.04)	(0.03)	(0.01)			(0.03)	(0.02)	(0.002)	(0.01)
	SCHIP	0.072	-0.015	0.01	0.30	0.21	0.006	-0.021	0.005	0.005
		(0.06)	(0.05)	(0.01)			(0.05)	(0.02)	(0.003)	(0.01)
	SCHIP*%costs	-0.838**	0.182	0.102	0.80	0.09	-0.073	0.256*	0.02	0.104
		(0.33)	(0.22)	(0.08)			(0.22)	(0.14)	(0.02)	(0.08)
All interactions	Medicaid	0.222***	-0.168***	0.027	0.66	0.59	-0.156***	-0.012	0.004	0.025
		(0.06)	(0.05)	(0.02)			(0.06)	(0.02)	(0.004)	(0.02)
	SCHIP	0.034	0.011	0.013	0.61	0.53	0.023	-0.012	0.0004	0.012
		(0.06)	(0.05)	(0.02)			(0.06)	(0.02)	(0.01)	(0.02)
	SCHIP*%costs	-0.635	-0.122	0.132	0.62	0.54	-0.572**	0.449***	0.02	0.123
		(0.50)	(0.27)	(0.15)			(0.27)	(0.16)	(0.03)	(0.15)

Notes: Standard errors are in parentheses. Each set of estimates (Medicaid, SCHIP and SCHIP*%costs) is from a separate regression. * indicates statistical significance at the 10% level; ** indicates significance at the 5% level; and *** indicates significance at the 1% level. Number of observations is 405,389. All interactions refer to state*age, state*year and age*year.