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Stemming the Tide?
The Effect of Expanding Medicaid Eligibility
On Health Insurance Coverage

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Abstract

Federal legislation passed in the late 1980s greatly expanded the potential coverage of the Medicaid program. Whereas in 1985 Medicaid was essentially limited to mothers and children on AFDC, by the early 1990s eligibility was expanded to include all children born after 1983 in poor families, regardless of family structure or income sources. In this paper I evaluate the effects of these expansions on Medicaid coverage and overall health insurance coverage of low-income children. Growth in Medicaid enrollment between 1988 and 1993 is decomposed into three underlying sources: changes in the eligibility rules of the program; changes in the eligibility characteristics of the population; and changes in takeup among the eligible. I find that about 68 percent of the 6.7 percentage point rise in coverage rates is attributable to the expanded eligibility rules. While the expansion of Medicaid eligibility may have increased Medicaid enrollment, an important question is whether the increase represented a net gain in health insurance coverage, or a substitution from private to publicly-provided coverage. I employ between-state variation in the impact of the federally-mandated expansions to measure the potential "crowding out" of private health insurance by public insurance. I find little evidence of crowding out: instead, the Medicaid expansions seem to have maintained overall health insurance coverage rates against a backdrop of declining private coverage.

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I. Introduction

Although per capita health care expenditures in the United States are among the highest in the world, a substantial fraction of the U.S. population--mainly from lower-income families--lack health insurance coverage.¹ In 1965, the Medicaid system was established to specifically address the problem of health insurance coverage for the poor. The Medicaid program has grown rapidly in the past three decades and is now the principal source of health care financing for the poor (Wiener and Engel, 1991). Despite this growth, however, the problems of infant mortality and low birth weight have persisted, and a sizeable fraction of children from low-income families remain unenrolled in the program.²

In an effort to address the low levels of health insurance coverage among poor children, Congress passed a series of laws beginning in 1986 that substantially liberalized Medicaid eligibility. By raising the family income threshold for Medicaid coverage and permitting eligibility for children in two-parent families, these laws were intended to raise health care accessibility for pregnant women, infants, and young children. Cost estimates at the time of passage of the laws suggest that legislators expected the laws to have a large effect: the projected cost of the additional coverage was \$498 million in 1988 and \$878 million in 1989.

In this paper, I use Medicaid coverage data from the March Current Population Survey (CPS) to estimate the effects of the expansions on the health insurance coverage rates of low-income children. Although a full assessment of the expansions should include an examination of health

¹In 1993 expenditures on health by the nation as a whole were \$752 billion, or 14.3 percent of GDP (Council of Economic Advisers, 1994).

²In 1993 for example, over 30 percent of children with family incomes below the poverty line were not enrolled in the program.

outcomes,³ a critical step in the evaluation process is an understanding of the impact of the Medicaid expansions on Medicaid coverage and on overall health coverage rates. The large and nationally representative samples available in the CPS provide a uniquely valuable data source for measuring changes in both aspects of health insurance coverage.

Simple tabulations from the CPS data show that the percentage of children in the U.S. covered by the Medicaid program rose from 16.2 percent in 1988 (the first year in which the expansions became effective) to 22.9 percent in 1993. Of course, changes in aggregate enrollment rates may reflect three different underlying factors: changes in the eligibility rules of the program; changes in the eligibility characteristics of the underlying population; or changes in the program takeup rate. To disentangle these three components I impute Medicaid eligibility to individuals observed in each year of the CPS data using the eligibility rules for that year and using the rules that existed prior to the expansions. This analysis suggests that most of the rise in the aggregate Medicaid coverage rate was attributable to the increasing generosity of the eligibility standard.

An important aspect of the Medicaid expansions was their differential impact across states. In fact, prior to the federally-mandated expansions, many individual states had already adopted their own state-specific expansions. In addition, interstate differences in the AFDC eligibility standard (the Medicaid eligibility standard in effect prior to the expansions) imply that the amendments should have raised enrollments much more in some states than others. Comparisons across states show that those states did indeed experience larger increases in the fractions of children enrolled in the Medicaid program.

While the expansion of Medicaid eligibility may have increased Medicaid enrollment, an important question is whether the increase represented a net gain in health insurance coverage, or a

³Currie and Gruber (1995) address the issue of improvements in child health using data from the National Health Interview Survey.

substitution from private to publicly-provided coverage. Here, comparisons across states in the impact of the expansions provide an obvious method for measuring the potential "crowding out" of private insurance by public insurance. I find little evidence of crowding out: rather, the expansions seem to have increased total coverage as well as Medicaid coverage.

II. Expansions of the Medicaid Program⁴

Medicaid is a joint state-federal program financed by state contributions and federal matching funds.⁵ Program participants fall into three groups: low-income aged and disabled people; the "medically needy"--people who have recently incurred large medical expenses; and low-income families with dependent children. Members of the third group were the main focus of the 1986-1990 legislative changes, and in this paper I concentrate exclusively on them. Historically, this group has been comprised of families receiving cash assistance through the Aid to Families with Dependent Children (AFDC) program. Thus, Medicaid eligibility and participation were directly linked to the eligibility standards for AFDC. Generally, to qualify for AFDC a family must be either headed by a single parent or have an unemployed primary earner. The family must also pass two income tests and a resource test. First, the family's countable income (gross income less certain deductions) cannot exceed the state-established "need standard" (the income deemed necessary for a family of a given size to purchase basic necessities). Second, the family's gross income cannot exceed 185 percent of the state's need standard. Finally, the value of the family's resources (excluding some necessities) cannot exceed \$1,000.

⁴This section draws heavily on Green Book (1984-1993), Congressional Research Service, (1988, 1993), Health Care Financing Administration (1988, 1990), and Altman and Beatrice (1990).

⁵The matching formula varies by state and is based primarily on the state's per capita income, with 50 percent being the minimum matching rate. It should also be noted that the services provided under Medicaid vary significantly across states, subject to federally imposed minimum standards.

Starting in the late 1980's, a series of federal law changes substantially diminished the link between Medicaid eligibility and AFDC eligibility by extending Medicaid coverage to families with incomes above the AFDC thresholds.⁶ Figure 1 presents a timeline showing legislative changes between 1986 and 1990 that expanded Medicaid eligibility for infants, children, and pregnant women.⁷ In the Omnibus Budget Reconciliation Acts (OBRA) of 1986 and 1987, Congress gave states the authority to raise the income thresholds for Medicaid coverage of certain groups above the AFDC level. In addition, OBRA 1987 required states to cover all children born after September 30, 1983 who met AFDC income standards, regardless of their family composition. The Medicare Catastrophic Coverage Act (MCCA) and Family Support Act (FSA), both of 1988, required states to extend Medicaid eligibility even further. The MCCA required coverage of pregnant women and infants and permitted coverage of children up to 8 years of age with family incomes below 75 percent of the poverty level. Coverage of eligible two-parent families where the principal earner was unemployed was mandated by the FSA. Even broader expansions took place as a result of OBRA 1989 and OBRA 1990. OBRA 1989 required coverage of pregnant women and children up to age 6 with family incomes up to 133 percent of the federal poverty level, and OBRA 1990 required states to cover children born after September 30, 1983 with family incomes below 100 percent of the federal poverty level. In total, expansions enacted in the late 1980s raised the eligibility threshold from the AFDC level to at least 100 percent of the poverty line and possibly higher, depending on age and

⁶Until the recent expansions, the primary group eligible for Medicaid but ineligible for AFDC has been "Ribicoff children." These are children who are financially eligible for AFDC but do not qualify due to family structure--e.g., they are from two-parent families or they are in privately subsidized foster care.

⁷Note that because of the timing of the legal changes and the CPS surveys, there is a two-year difference between the date of the legislation and the date of the survey. For example, the 1988 CPS should demonstrate the effect of OBRA 1986.

state of residence, while relaxing the restrictions on two-parent families and those with earned income.

III. Measuring the Effect of the Medicaid Expansions

In principle, the legislative changes described in Figure 1 would have had a profound effect on medical insurance coverage. Nevertheless, several other considerations suggest that coverage may not have expanded as rapidly as an examination of the laws would indicate. First, although Congress passed the laws, the states had to implement them and pay for a large portion of the increased cost. Thus states may have been slow to implement the changes, particularly if they had difficulty finding the funds to pay for the increased cost. Second, the newly eligible children had to enroll in the program. Since takeup is less than full for most government programs, it is important to examine takeup as well as eligibility. This is particularly true for a program such as Medicaid, since eligible children may not actually be enrolled until they become sick.⁸ Finally, expansions in Medicaid may not lead to increases in total health coverage if government coverage has a "crowding out" effect on private coverage. I examine the first two issues in the following sections, and I examine the issue of crowding out in the final section.

The data used in this paper to measure Medicaid eligibility are from the CPS March supplements for 1988-1993. In addition to the usual demographic and labor force data, the March supplements provide information on respondents' income sources, household composition, and participation in government programs, including government health programs. The detailed family income and family structure data in the March CPS make it possible to impute eligibility for the Medicaid program.

⁸Technically, a child who requires medical services and is potentially eligible for Medicaid can apply for coverage after the fact. For example, hospitals may enroll eligible children who come to the emergency room for care.

Despite the advantages of the CPS data, several researchers have called into question the March CPS measure of health insurance coverage (see e.g. Swartz, 1986, 1988; Office of Technology Assessment, 1988; Ku, et al., 1990). In particular, CPS estimates of Medicaid enrollment have been found to be too low when compared with the estimates from other data sources. For example, Ku, et al. (1990) note that comparisons with administrative data often suggest that Medicaid participation is under-reported in the CPS. It is important to note that the administrative enrollment counts may themselves be inflated, since states have strong economic incentives to over-report coverage and thus obtain federal matching funds. Nevertheless, comparisons with other person-level data sets have also yielded evidence of an undercount in the CPS (Swartz 1986).

In light of these concerns I conducted a comparison of Medicaid coverage rates in the March 1988 CPS and Round 4 of the 1987 National Medical Expenditure Survey (NMES). The main results are summarized in Appendix A. A critical issue in this comparison is the interpretation of the Medicaid coverage questions in the CPS. Although the wording of the question is intended to elicit an estimate of coverage over the previous calendar year, some researchers have argued that respondents answer as if the question referred to a point in time for a period just prior to the survey (e.g. Swartz (1986)). Consistent with this interpretation, I find that reported health insurance coverage in the March 1993 CPS is very similar to reported coverage for the same individuals in the April 1993 "Benefits Supplement," which asks directly about health insurance coverage as of the survey week (see Appendix A). In light of this finding, I adopt the assumption that the March CPS Medicaid coverage responses refer to coverage as of a point in time sometime between the end of the previous year and the survey date.

In 1988 the Census Bureau changed both the questionnaire and the processing system used for the March CPS. The revised questionnaire incorporated more questions about health insurance coverage of children in an attempt to improve the accuracy of the coverage estimates. The Census

Bureau processed the 1988 data twice, with and without incorporating the new questions, and I compare the results from both data files to the results from the NMES. The comparison of coverage rates in Appendix Tables A1 and A2 shows little indication of an undercount in the CPS. For example, the fraction of all children covered by Medicaid is 14.0 percent using the NMES data, 14.3 percent using the CPS data processed under the old system, and 16.2 percent using the revised 1988 data. Similarly, the fraction of children under 10 years of age covered by Medicaid is 15.4 percent using the NMES data, 15.5 percent using the old CPS data, and 17.6 percent using the revised file. The difference between the results using the old CPS data and the NMES data is not statistically significant, whereas the results using the revised version of the CPS are significantly higher. Based on this evidence, I conclude that the March CPS surveys provide a reasonable source of Medicaid coverage rates, and that the coverage measures in the March CPS can be interpreted as point-in-time coverage rates as of a window between December and March. Throughout the rest of the paper I use the revised 1988 data, since these are more consistent with the data in the following years.

In the bulk of my analysis I use person-level Medicaid coverage and eligibility data for all children under age 15 from the 1988-1993 March CPS.⁹ Descriptive statistics for this sample are presented in Table 1. Basic characteristics of the children such as age and region of residence change little over the period, as would be expected. The fraction of children in poverty, the fraction on Medicaid, and the fraction in single-parent families rises over the period, however. The statistics in Table 1 lead to two main conclusions. First, as suggested by the rise in the percentage of children in female-headed families and the rising fraction of children in families with incomes below the poverty line, children in the U.S. suffered a modest worsening in family circumstances between 1988 and

⁹Age 15 is used as a cut-off age primarily because children under 15 and adolescents aged 15 to 18 are treated differently by the Census Bureau. Any respondent 15 or older is treated as an adult; thus the Medicaid enrollment variable is obtained differently from that of younger children. In addition, no child as old as 15 is affected by the law changes studied in this paper.

1993. Second, the percentage of children covered by Medicaid rose sharply over the period, and substantially faster than the fraction on AFDC.

IV. Analysis of the Effect of Changes in the Medicaid Program

At first glance, it may seem obvious from Figure 2 that the Medicaid expansions increased Medicaid enrollment over the late 1980s and early 1990s, but a closer look raises questions about the cause of the enrollment increase. Although enrollments increased throughout the period, they did not increase steadily. Rather, the period can be divided into two sub-periods. From 1988 to 1990, enrollments rose by 0.5 percentage points, while from 1990 to 1993 enrollments rose 6.2 percentage points. This division is significant, since during the 1990-1992 sub-period the economy experienced a severe recession, and it is possible that the increase in enrollment was driven by macroeconomic factors, rather than legislated expansions of income thresholds. Since the true source of the increase is likely to be a combination of the broadening of eligibility and the change in the characteristics of the population, it is important to disentangle the effects of the recession from the effects of the law change. In addition, changes in the takeup rate (the rate at which those who are eligible for the program actually enroll) may have played an important part in the increase in enrollment. In the following sections, I use three methods to analyze the relative effects of these changes.

A. Do the Changes in the Enrolled Population Correspond to the Changes in the Rules?

Since the legislative actions taken in OBRA 1986-OBRA 1990 affected some children but not others, a comparison of the characteristics of the enrolled and unenrolled populations provides a simple test of whether the legislation has had an effect. For example, the laws affected younger children more than older children, so the probability of Medicaid receipt should differ by age. To some extent this relationship does hold (see Table 2). In general, younger children have a higher probability of receiving Medicaid than older children. The divisions by age do not fall exactly where

the laws place them, however. For example, since OBRA 1989 required that states cover all children below age 6 with family incomes up to 133 percent of the poverty level, one would expect to see little difference in the probability of receipt within the group of children 0 to 6 years old after 1990. In addition, one would expect a sharper dividing line between children age 9 and under, whose family income need only be below 100 percent of the poverty level, and older children, who must meet AFDC income standards in order to qualify for Medicaid.¹⁰

Besides age, the other characteristics to which the laws referred were family structure, poverty level, and AFDC reciprocity. The legal changes diminished the importance of the link between AFDC reciprocity and Medicaid. Therefore, one would expect to see an increase in the fraction of children in families that are not headed by a single female and are not receiving AFDC but are receiving Medicaid. An examination of Table 2 shows that to some degree this expectation is borne out. The change in the probability of Medicaid coverage given that the family does not receive AFDC is greater than the change in probability given that the family does receive AFDC. Just looking at the change in probabilities can be misleading, however, since the proportion receiving AFDC that were also receiving Medicaid was already 0.975 in 1988, leaving little room for an increase. In addition, the proportion of children living in a dual-headed family that received Medicaid increased by only 6.3 percentage points, while the proportions conditional on having a single female family head or a single male family head increased by 8.5 and 13.6 percentage points, respectively.

This analysis suggests that changes in the rules may have played a role in the increased enrollment rates. However, this simple analysis does not provide any information on the relative effects of legislative changes, changes in population characteristics, and changes in the takeup rate. There are two primary ways this question may be addressed. One method is to impute eligibility to

¹⁰Note that eligibility thresholds for AFDC are much lower than the poverty level. Eligibility thresholds ranged from a low of 16.6 percent of the poverty level (Alabama) to a high of 76.7 percent of the poverty level (Alaska) in 1993 (National Governors' Association, 1993, Table 5).

children based on the law and their observed characteristics and then to compute reciprocity and eligibility rates. An alternative method is to decompose the change in enrollment into its component parts using a linear probability model.

B. Determining the Sources of the Enrollment Increase Using Eligibility Imputation

1. Imputing Eligibility

Since both the rules and the population characteristics changed between 1988 and 1993, when examining differences in eligibility over the period there are two questions to consider: what would the eligibility level have been if the rules changed but the characteristics of the population did not, and what would the eligibility level have been if only the population characteristics had changed? In order to examine the change in eligibility I estimate what the eligibility rate would have been under these two alternative hypotheses and compare it to the actual eligibility rate. The most difficult aspect of this method is the imputation of eligibility. The imputation must be done separately by state as well as by year, since there is a great deal of interstate variation. The imputation procedure included the following children as "eligible":

1. Children in families receiving AFDC were automatically assigned eligibility.
2. If a mandatory federal requirement was in place for that year, eligibility was assigned to all children who met that requirement.
3. The remaining children were then assigned eligibility according to the optional programs of their state of residence.

Details of the calculations are reported in the second part of Appendix A. The estimated fraction of eligible children, along with the fraction who actually are reported as covered by Medicaid, are graphed in Figure 2. As would be expected if takeup of the program is less than full, the estimated eligibility rate is less than the enrollment rate, although both fractions rose throughout the period.

2. Checking the Eligibility Imputation

Given the limited data in the March CPS and inevitable measurement errors in reported income and family structure, it is clear that the eligibility imputation method is subject to error.

Since these eligibility imputations are used throughout the rest of the paper, it is important to check the accuracy of the eligibility estimates. To check the estimates, I tabulate simulated eligibility against reported receipt of Medicaid by year. The main results of this cross-tabulation are reported in Table 3. The first column of the table contains the fraction of individuals who are deemed ineligible but nevertheless are recorded as covered by Medicaid. This fraction is relatively low (3 to 5 percent), but shows a rising trend over the 1988-1993 period. It is probable that these individuals either receive Medicaid due to a person-specific characteristic that I am unable to pick up in the data (for example, because they have a disability or because they are "medically needy") or they do not receive Medicaid at all (measurement error). The values in this column are small, however, so the extent of the undercount of eligible individuals appears minimized.

As shown in column 2 of Table 3, the fraction of individuals who are deemed eligible but who are not enrolled in the program is larger: between 24 and 32 percent. This disparity could originate from two sources. One is errors in reported Medicaid coverage¹¹ or in the measures used to determine eligibility that cause individuals to be counted as eligible when they should not be. The other possibility is that some eligible individuals are not taking up their Medicaid coverage. To assess the likely importance of these two phenomena, it is useful to examine the change in the fraction of eligible nonparticipants over time. Since the measurement error should be relatively constant over time, then if measurement error is the source of the difference, the noncoverage rate of children deemed eligible should be constant as well. This rate rises, however, from 23.6 percent of all

¹¹This possibility is of course always present. If the CPS does have a problem with undercounting Medicaid recipients in spite of evidence to the contrary presented above, then the undercount could be the source of the disparity. This is unlikely to be the primary cause, however, since the fraction increases with time, but there is no reason to believe that an undercount would be worsening as well. In addition, the group of Medicaid recipients that are not deemed eligible remains a relatively constant fraction of the entire population throughout the period (2.74 percent in 1988, 3.14 percent in 1991, and 3.91 percent in 1993.) It is unlikely that the undercount could be such that recipients that I deem eligible are undercounted while recipients that I do not deem eligible are not.

children deemed eligible in 1988 to 31.9 percent in 1991, falling slightly in 1992 and 1993. One possible reason for this increase is that states are not engaging in the necessary outreach efforts to enroll these newly-eligible children. This is plausible, since as eligibility thresholds increase to include more children whose families are not receiving AFDC, states do not have the opportunity to enroll children as their parents apply for aid.

The difficulty involved in enrolling children who are not on AFDC can be seen even in the pre-expansion (1988) data. At the time of the 1988 CPS, the primary source of Medicaid eligibility was through AFDC. Aside from AFDC, the principal way for a child to be eligible for Medicaid was for the child to be a member of a family that met income but not family structure criteria for AFDC and to be either under 5 years old or residing in a state that participated in the Ribicoff program.¹² Very few of the children eligible in this way were actually enrolled in the program, however. Figure 3 shows the enrollment rates by source of eligibility. It is clear from the figure that while basically all AFDC recipients appear to have been enrolled in Medicaid, only approximately a quarter of those eligible under the other rules were recorded as enrolled. This disparity between AFDC recipients and AFDC non-recipients persisted through 1993, although reciprocity rates did rise, in general, with children eligible through the mandatory federal expansions participating at a higher rate.

State variation in the percent of children eligible for but not receiving Medicaid provides further evidence that imputation errors are not the primary cause of the disparity between the population eligible for Medicaid and the population receiving it. If the apparent failure of eligible individuals to receive Medicaid is actually a result of errors in imputation, then it is unlikely that the states would follow similar patterns, since they have very different welfare programs. Figure 4 shows

¹²"Ribicoff program" refers to an optional eligibility category begun earlier in the 1980s. States may elect this program, which allows children up to an age determined by the state (often age 18) to be eligible for Medicaid if their families meet AFDC income requirements, regardless of family structure.

the percent of children who were eligible for Medicaid but who were not receiving it in three of the largest states: New York, California, and Texas. Except for Texas in 1988, the pattern of change from year to year is remarkably similar from state to state.¹³ The data show that all three states have trends that are similar to the national average. Aside from the spike for Texas between 1988 and 1989, the major difference between the states is the size of the fractions. The fraction of eligible individuals failing to receive Medicaid is consistently below the national average in New York, while in Texas and California the fraction is above the average (with California closer to the national average than Texas). Although it would be unwise to push the implications of these differences in levels too far, note that New York's welfare program is usually considered more generous than Texas' or California's. Therefore, the higher enrollment of eligibles in New York is likely to reflect a better outreach program rather than errors in imputation.

3. *Effects of Expanding Eligibility*

Imputation of eligibility can be used to address the question of the relative importance of the changes in rules, population, and takeup to the change in Medicaid enrollment. In addition to the estimated eligibility rate obtained above, I simulate the eligibility rate under two counterfactuals: if the rules had not changed, and if the characteristics of the population had not changed. To simulate the eligibility rate of children under the first counterfactual, I apply the 1988 rules to children from the 1989-1993 data. Similarly, to simulate the eligibility rate under the second counterfactual, I calculate eligibility for children from the 1988 CPS using the rules of 1989-1993. These simulated eligibility rates, the estimated takeup rates, and the fraction of children receiving Medicaid in each year are presented in Table 4. In addition, the simulated eligibility rates are plotted against the eligibility rates estimated using the actual laws and population characteristics in Figure 5.

¹³Texas was the first of the three states to expand its Medicaid eligibility above AFDC levels, and this appears to be reflected in the data.

It is clear from the graph that both sets of changes played a role in the eligibility increase, since in the later years the actual eligibility rate is higher than either of the simulated eligibility rates. The effect of the recession is also evident, since the actual eligibility rate moves above the simulated constant-population eligibility rate between 1990 and 1991. In addition, the constant-rules eligibility rate declines from 1988 to 1990 but increases thereafter, indicating an increase in the fraction of children who are poor.

Using these simulations, I can decompose the increase in the eligibility rate into the portion due to the legislation and the portion due to the changing population characteristics. Let the estimated eligibility rate at time t be $P(elig)_t$. This estimated eligibility rate is the estimated probability a child is eligible at time t given the rules in effect at time t . Using this notation, the change in eligibility between 1988 and 1993 can be written

$$(1) \quad \Delta P(elig)_{93-88} = [P(elig_{93}|rules_{93}) - P(elig_{93}|rules_{88})] \\ + [P(elig_{93}|rules_{88}) - P(elig_{88}|rules_{88})]$$

The first term corresponds to the change in eligibility due to changes in the rules, while the second term gives the change in eligibility due to changes in the characteristics of the potentially eligible population. Using the eligibility rates given in Table 4, 78.4 percent of the increase in the fraction of children under 15 eligible for Medicaid was due to the changes in the rules. This decomposition may also be written as

$$(2) \quad \Delta P(elig)_{93-88} = [P(elig_{93}|popn_{93}) - P(elig_{93}|popn_{88})] \\ + [P(elig_{93}|popn_{88}) - P(elig_{88}|popn_{88})]$$

where $P(elig_t | popn_t)$ is the probability a child is eligible at time t given his or her characteristics at time t . Written this way, the second term gives the fraction of the change in eligibility that can be attributed to the rules: 76.5 percent.

Comparing the fraction eligible for Medicaid and the fraction enrolled, (the second and sixth columns of Table 4), it is clear that while eligibility rates generally increased over the period, the fraction of children actually enrolled in the program did not increase commensurately. The difference between the fraction of the population enrolled in the program and the fraction eligible may be explained by changes in the takeup rate, which is defined as the probability a child receives Medicaid given that he or she is eligible. The estimated takeup rate declined (although non-monotonically) from 76.42 percent enrollment of the eligible population in 1988 to 68.72 percent enrollment in 1993. Using the estimated takeup rates and the estimated change in eligibility, the change in the probability of receiving Medicaid can be decomposed into the portion due to the change in eligibility and the portion due to the change in the takeup rate. Denote the Medicaid enrollment rate in period t by $P(Med)_t$, and the takeup rate in period t by $P(Med|elig)_t$. Since

$$(3) \quad P(Med)_t = P(Med|elig)_t \cdot P(elig)_t,$$

the change in the Medicaid enrollment rate between 1993 and 1988 is

$$(4) \quad \begin{aligned} \Delta P(Med)_{93-88} &= P(Med)_{93} - P(Med)_{88} \\ &= P(Med|elig)_{88} \cdot [P(elig)_{93} - P(elig)_{88}] \\ &\quad + P(elig)_{93} \cdot [P(Med|elig)_{93} - P(Med|elig)_{88}] \end{aligned}$$

The first term is the portion due to the change in eligibility, while the second term yields the portion due to changes in the takeup rate. Again using the information presented in Table 4, I find that the change in the probability of receiving Medicaid as calculated above was 5.6 percentage points, which represented an increase of 7.7 percentage points due to changes in eligibility and a decrease of 2.1 percentage points due to changes in the takeup rate. Thus although the increase in eligibility outweighed the fall in the takeup rate, some children who could have been covered were not. As

illustrated in Figure 3, this fall in takeup appears to be due primarily to the inclusion of non-AFDC eligibility.

C. Decomposition of the Change in Enrollment Using a Linear Probability Model

The analysis of the causes of the Medicaid enrollment increase in the preceding section involved a "structural" approach: the effects of changes in the program rules and the population were studied by estimating both the actual level of eligibility and the level of eligibility if either the population or the rules had not changed. Although this method allows a comparison of various counterfactuals, it is limited by the accuracy of the eligibility imputation procedure. An alternative "reduced form" approach is to estimate the change in the probability of receiving Medicaid using a linear probability model. The benefit of this approach is that no imputation of eligibility is required. In exchange, however, the model forces the effect of the characteristics to be linear, and the counterfactual is less clear.

Consider an indicator variable Y_{it} , which equals 1 if child i in year t is on Medicaid and 0 otherwise, and let X_{it} be a vector of variables which determine the child's eligibility for Medicaid, including variables for age, state of residence, family structure, and family income as a fraction of the poverty level. Then

$$(5) \quad Y_{it} = X_{it}'\beta_t + \varepsilon_{it}$$

where ε_{it} represents a stochastic error term and β represents the effect of program rules in year t which translate observable characteristics into eligibility. In the aggregate,

$$(6) \quad \bar{Y}_{88} = \bar{X}_{88}' \hat{\beta}_{88} ,$$

where bars indicate mean values and hats indicate predicted values. Similarly for 1993,

$$(7) \quad \bar{Y}_{93} = \bar{X}_{93}' \hat{\beta}_{93} .$$

Thus the difference in the proportion of the population receiving Medicaid in 1988 and 1993 is

$$(8) \quad \bar{Y}_{93} - \bar{Y}_{88} = \hat{\beta}'_{88} (\bar{X}_{93} - \bar{X}_{88}) + \bar{X}'_{93} (\hat{\beta}_{93} - \hat{\beta}_{88}) \quad .$$

In this equation, the first term gives the effect on enrollment of the change in mean characteristics, which can be ascribed to the recession and other exogenous shifts in the income distribution. The second term is the structural change in the Medicaid program evaluated at the mean characteristics for 1993. This term gives the effect on enrollment of changes in the eligibility rules and the takeup rate. The results of these calculations are presented in Table 5.

The decompositions show that 68.8 percent of the increase in the enrollment of children in the Medicaid program that occurred between 1988 and 1993 was due to structural changes in the program. To compare this result to the results derived from the eligibility simulations, note that the second term in equation (8) gives the combined effect on enrollment of changes in the takeup rate and changes in the rules. Using the simulated eligibility data in Table 4, this combined effect is just $((0.2291 - 0.1619) - (0.1977 - 0.1760)) / (0.2291 - 0.1619)$, or 67.7 percent, which is very close to the result obtained using the linear probability model. Thus two alternative decompositions, one based on the assignment of eligibility, another based on a reduced form approach, lead to similar conclusions: approximately 68 percent of the increase in enrollment could be attributed to the changes in the rules and takeup rate. This figure translates into a 4.2 percentage point increase in the Medicaid coverage rate directly attributable to the expansions.

V. The Effects of the Expansions on Total Coverage Rates

The analysis thus far has concentrated on whether changes in coverage legislation led to an increase in Medicaid coverage, without asking whether the laws have had any effect on total health insurance coverage levels. The intent of the laws was to increase the fraction of the population with health insurance coverage by providing health insurance to children not poor enough to qualify for AFDC but too poor to have coverage from another source. If children who had other coverage prior

to the expansions became eligible, however, it is possible that the expansions may not have increased the rate of coverage if some children merely switched their source of coverage from private to public.

A cursory examination of Figure 6A, which shows the fraction of children with Medicaid, private coverage, and any health insurance coverage, suggests the possibility that such an offset effect may have occurred. Although private insurance coverage appears to have been declining slightly and Medicaid coverage appears to have been increasing slightly prior to the expansions, the rate of change of both forms of coverage accelerated between 1990 and 1993. This pattern is also found in Figure 6B, which shows the health insurance coverage rates for women ages 15 to 45, who as potentially pregnant women would also be affected by the Medicaid expansions. The conclusion that the Medicaid expansions had a negative effect on private coverage is not immediately obvious, however, particularly when the health insurance coverage patterns for single men ages 15 to 45 are examined (see Figure 6C). For all three groups the fraction with private insurance appears to have fallen between 1990 and 1993. The rate of total health insurance coverage stayed relatively constant for children, however, (although not for women or men) which may indicate that the expansions of Medicaid forestalled a decrease in the coverage rate for children.

A. Theoretical Framework

To provide a framework for an analysis of the effect of changing Medicaid coverage, I begin by laying out a simple theoretical model in which individuals can obtain health insurance coverage from a variety of alternative sources. Consider an economy in which firms attract workers of a given level of productivity by offering them a compensation package (w, α) , where w is the monetary wage and α is the fraction of the cost of health insurance to be paid by the firm. Firms either pay some fraction of the cost or none ($\alpha \geq 0$). If the firm provides insurance (that is, if $\alpha > 0$), then the firm is

in the covered sector, while firms providing no insurance make up the uncovered sector.¹⁴ Let θ_i represent the value of health insurance to worker i (or her family). This value depends on a variety of person-specific factors (e.g. the worker's degree of risk aversion), and has a distribution $F(\theta)$ in the population. The cost to the firm of insurance is π per worker, which is assumed to be constant for all firms. A firm will provide insurance to attract workers if the cost of insurance is less than the value of that insurance to the marginal worker. If a firm provides insurance, then the firm pays each worker the wage she would otherwise receive less the firm's share of the insurance cost:

$$(9) \quad w_0 - \alpha \pi.$$

The worker pays the balance of the cost of the insurance, $(1-\alpha) \pi$. The value of a compensation package (w, α) to the worker is then

$$(10) \quad w_0 - \alpha \pi - (1 - \alpha) \pi + \theta = w_0 - \pi + \theta.$$

In the uncovered sector, the firm pays the worker w_0 , which is also the value to the worker. Workers sort themselves into the covered or the uncovered sectors depending on their valuation of the insurance.¹⁵ Note that since the firm takes the cost of providing insurance out of the worker's wage, firms are indifferent between providing insurance and not providing insurance. The insurance rate in the economy is thus $1 - F_\theta(\pi)$ (see panel A of Figure 7).

Now suppose the government expands Medicaid to cover workers (and children of workers).

Let θ_m be the value of Medicaid coverage to the worker, where

¹⁴Note that in most data sets, including the CPS, a worker is considered to be covered by private insurance if the firm pays some part of the cost. Thus the distinction of covered and uncovered sectors accords with standard practice.

¹⁵If $\max(w_0 - \alpha \pi + \theta, w_0)$ is below the worker's reservation valuation, she does not work but may instead enroll in AFDC and receive health insurance coverage through Medicaid.

$$(11) \quad \theta_m = k\theta, \quad k < 1 \quad .^{16}$$

The value of Medicaid is assumed to be less than the value of private insurance since some doctors do not take Medicaid as payment,¹⁷ and those who do may provide lower quality care to their Medicaid patients. After the expansion, firms in the uncovered sector pay w_0 and workers receive net utility

$$(12) \quad w_0 + \theta_m = w_0 + k\theta,$$

while in the covered sector firms pay the same wage as before the expansion and workers receive the same utility. The relative size of the covered and uncovered sectors has changed, however. Before the expansion, a worker was indifferent between working in the covered and uncovered sectors if $\theta = \theta^* = \pi$. After the expansion, the marginal worker has valuation

$$(13) \quad \theta^* = \frac{\pi}{1-k}.$$

Since k is strictly less than one, the size of the uncovered sector increases relative to the size of the covered sector (see Figure 7), and thus the fraction of workers covered by private insurance falls.

The degree of "crowding out" is determined by the value of Medicaid insurance relative to the value of private insurance. If k is very close to one (that is, if Medicaid is valued almost as highly as private insurance) then the amount of crowding out will be large. If k is close to zero, however, then very little crowding out will be observed. Following an expansion of the Medicaid program to include working women (and the children of working women), this simple model implies that fewer

¹⁶The assumption of a linear relationship between θ and θ_m is not necessary, but is made for simplicity. More generally, the relationship could be characterized as $\theta_m = g(\theta)$, with $g(\theta)$ an increasing concave function.

¹⁷For evidence on the accessibility of care to patients with Medicaid coverage, see for example Yudkowski, Cartland, and Flint (1990), or Medicaid Access Study Group (1994).

women and children will be covered by private health insurance and more will be covered by Medicaid, with a net positive effect on total coverage.

The model has implications for the average wage observed in the population as well. Prior to the expansion, the average wage in the covered sector was $w_0 - \bar{\alpha}\pi$ and the average wage in the uncovered sector was w_0 , where $\bar{\alpha}$ denotes the average share of insurance premiums paid by firms that offer coverage. Thus before the expansions the average wage overall was

$$(14) \quad (1 - F_\theta(\pi))(w_0 - \bar{\alpha}\pi) + F_\theta(\pi)(w_0).$$

Following the expansion, wages remain the same, but the fraction of workers in each group changes, so the average wage observed in the population is

$$(15) \quad \left[1 - F_\theta \left(\frac{\pi}{1-k} \right) \right] (w_0 - \bar{\alpha}\pi) + F_\theta \left(\frac{\pi}{1-k} \right) w_0,$$

which is higher than the average wage prior to the expansion. Although I do not examine the effect of the expansion on wages in this paper, I plan to pursue such an examination in future work.

B. Examination of the Effect of Crowding Out

From the theoretical framework presented above, it is evident that there is potential for increases in Medicaid eligibility to have an adverse effect on private coverage. To examine whether this actually occurred, I utilize the fact that the Medicaid expansions had different effects on different states. Prior to any federally mandated expansion, the threshold for eligibility varied widely among states due to the large variation in state AFDC eligibility levels. By 1993, all states had raised their eligibility levels in response to the congressional mandate. Some states were forced to raise their eligibility standards by more than others to comply with the federal guidelines. For example, to meet the federal minimum of 133 percent of the poverty threshold for children under 6 years of age, Alabama had to increase its eligibility level 775 percent, while Utah only had to raise its eligibility

level 49 percent. This variation provides a simple test of the effect of the legislation. If the legislation had an effect on medical coverage, one would expect to see more of an effect in states that had a larger increase in their eligibility standards than in states where the increase was relatively small.

At the state level, coverage rates are a function of the fraction of children in the state who are eligible. The change in coverage rates for group g (which could be children, for example, or women of childbearing age) in state s that occurs between 1988 and 1993 is then a function of the change in fraction eligible. This can be written

$$(16) \quad \Delta Coverage_{g,s} = \alpha_g + \beta_g (\Delta Eligible)_{g,s} + \varepsilon_{g,s} ,$$

where β_g represents the group-specific effect of the change in eligibility. Since the change in eligibility incorporates not only the changes in the laws but the changes in the population characteristics, I instrument for the change in eligibility with a measure of the fraction affected by the legislation. To measure this fraction affected by the change in eligibility, I use the difference between the fraction of the group eligible in 1988 and the fraction of that group that would be eligible under the expanded rules. This constant-population measure of the fraction affected is free of the endogeneity bias that would be present if a measure which included the effects of both changes in the rules and changes in the population characteristics were used. Another advantage of this formulation is that the change in coverage need not be restricted to be the change in Medicaid coverage only. If expansions in the Medicaid program crowded out private coverage, then the above regression with the change in private coverage on the left hand side should yield a negative estimate of β_g .

An issue of concern is the possibility that there are omitted state effects which are correlated with the changes in the rules. If states which were strongly affected by the imposition of the federal standards were also the states that experienced adverse economic shocks, for example, then the estimate of β_g would not solely reflect the impact of the laws. That is, if

$$(17) \quad \varepsilon_{g,s} = \eta_s + \varepsilon_{g,s}^* ,$$

where

$$(18) \quad \eta_s = \gamma(\Delta \text{Eligible}) + \nu_s ,$$

then

$$(19) \quad \Delta \text{Coverage}_{g,s} = \alpha_g + (\beta_g + \gamma)(\Delta \text{Eligible})_{g,s} + (\varepsilon_{g,s}^* + \eta_s) .$$

To deal with this problem, I estimate equation (19) for single men ages 15 to 45 using the simulated eligibility and "fraction affected" under the rules for women ages 15 to 45. Since they are unaffected by the expansions, the estimate of the coefficient on eligibility should yield an estimate of γ .¹⁸

Subtracting this estimate from the results for the women and the children would then give the estimate of the effect of the laws controlling for state-specific shocks. In addition, I control for the effects of macroeconomic shocks by estimating a modified version of equation (19) including the change in the employment/population ratio in the state and controls for census division.

A summary of the measures of the fraction of children in each state eligible, the fraction receiving Medicaid, the fraction with private insurance, and the fraction with any insurance is presented in Table 6. From this table, it is clear that there was a great deal of variation in the effects of the eligibility expansions. Prior to the expansions, the fraction eligible for Medicaid ranged from a low of 7 percent in North Dakota to a high of 31.6 percent in Mississippi. After the expansions, most states had a far higher percentage of children eligible for Medicaid, with some of the states having double the previous fraction of children eligible. The fraction of children receiving Medicaid also increased in most states, although as noted previously, by less than the full amount of the increase in eligibility. It is also clear from the table that the fraction of children with private

¹⁸Single men are used specifically since they are not eligible for Medicaid unless they are disabled. In addition, it is unlikely that single men will erroneously report that they are covered by Medicaid, unlike men with families, whose children or wives may have coverage.

insurance (and the fraction with any coverage) changed over this time period. This information is displayed graphically for the United States as a whole in Figure 6A for children, and in Figures 6B and 6C for women and men ages 15 to 45.

The relationship between the fraction eligible and the fraction covered by state is displayed in Figure 8 for all three groups. Although there appears to be some correlations between eligibility and coverage, particularly for children, for the most part the states seem randomly scattered. The estimates of equation (19) for children, women, and single men are presented in Table 7A. As would be expected given the results from the first section of this paper, the estimate of the effect of the laws on Medicaid coverage for children (given in the first two columns of the top panel) is positive and significant. After controlling for the effects of macroeconomic shocks, the estimate is 0.45, which indicates that on average, a state with an increase in the fraction eligible of 8.9 percentage points (the mean increase) experienced a 4.0 percentage-point increase in its Medicaid coverage rate. This estimated increase is quite similar to the estimate of a 4.2 percentage-point increase in Medicaid due to the rules which was obtained in the first part of the paper.

The estimate of the effect of the expansions on private coverage for children is also positive, which is surprising, since the presence of crowding out would yield a negative coefficient. Controlling for macroeconomic shocks reduces the size of the coefficient, and it is no longer significantly different from zero. This result is evidence against crowding out having occurred. Although the estimate does not rule out the possibility of a small negative effect of Medicaid on private coverage, it is unlikely that the effect is sizably negative. This conclusion is evident from an examination of Figure 8 as well--there is no clear negative slope to the scatter of points in the plot of the change in private coverage against the change in eligibility. The effect on the rate of any coverage, however, is estimated to be positive and significant.

The coefficients from the Medicaid equation and the private equation do not add up to the coefficient from the any coverage equation because there are people with more than one type of coverage.¹⁹ In order to be certain that the people with more than one type of coverage are not causing any perverse effects, I reestimated equation (19) dividing the population into four mutually exclusive groups: children with Medicaid only, private coverage only, other government coverage only, and two or more forms of coverage. The estimated coefficients for Medicaid only and private only are presented in Table 7B. The estimates are smaller in magnitude, although the coefficients from the Medicaid equation are still statistically significant. In addition to examining the effect of reported multiple coverage sources, I checked whether these results were being driven by a few outlying states. An examination of Figure 8 does not reveal many obvious outliers aside from Vermont, which has been eliminated from the figure to allow the other states to be seen more clearly. Estimating the regressions with and without Vermont does not affect the results significantly. In addition, I estimated the regressions both with and without weights for population size (the results with the weights are reported in Tables 7A-C) and again the results are not significantly different from one another. Finally, I tried using median regression rather than mean regression, and aside from a decrease in the estimated significance, there was little difference.

For women, the effect of the expansions on both Medicaid and private coverage appears to be small and insignificant (see the second panel of Table 7A). Dividing the population into mutually exclusive groups yields similarly small, insignificant estimates of the effect of the expansions on both Medicaid and private coverage (the results are presented in the second panel of Table 7B). Since the expansions actually applied only to women who were pregnant, the insignificant results may be due in

¹⁹Children with other coverage from the government (such as CHAMPUS) are not counted as having either Medicaid or private coverage, but are included in the estimation of the effect of the expansions on the fraction with any coverage. Estimating equation (19) with the fraction of children with other government coverage yields an estimated coefficient of -0.030 with a standard error of (0.036).

part to the fact that I am examining all women of childbearing age rather than just pregnant women. To check my results for women further, I estimate equation (19) separately for married and unmarried women ages 15 to 45. Since the Medicaid expansions for women only applied to women who were pregnant, one might expect the effect of the expansions to be stronger for married women, who are more likely to be pregnant than unmarried women. The estimates, which are presented in Table 7C, seem to indicate that the effect of the expansions was stronger for married women, since the coefficient in the Medicaid regression is positive and significant. Again, however, I find no evidence of crowding out.

Before drawing any conclusions about the effect of the expansions, it is useful to examine the results for single men, the control group. For this group, I find a positive effect on Medicaid and a negative effect on private insurance and any coverage. Subtracting these coefficients from the coefficients from the regressions for children and women would decrease the magnitude of the estimated effect on Medicaid coverage slightly and increase the estimated effect on private and any coverage. None of the coefficients for the men are statistically significant, however, so it seems unwise to rely heavily on the coefficients.

While standard theoretical models such as the one presented above suggest that an increase in Medicaid availability would tend to reduce the provision of private health insurance, there are several reasons why this effect may be quite small. Private coverage and coverage by the Medicaid program are not perfect substitutes: since Medicaid usually pays doctors far less than they ordinarily charge, many doctors do not accept Medicaid, and those who do accept it have an incentive to provide lower quality care to their Medicaid patients. In the framework laid out above, this finding indicates that the value of k is very close to zero. Thus parents may be reluctant to drop private coverage for lower-quality public coverage. Alternatively, parents of children who are eligible but already covered by private insurance may be unaware that their children are eligible, particularly since they may have

little incentive to explore public coverage options. Finally, since private coverage is often a benefit of employment, particularly for higher-paying jobs, parents in families who are poor enough to qualify for Medicaid may be less likely to have jobs that provide health insurance to the children in the family.

C. Comparisons with Cutler and Gruber

In a recent paper Cutler and Gruber (1995) use March CPS health insurance coverage data to estimate the effect of Medicaid expansions on private health insurance coverage of children and women. Unlike the results presented in Tables 7A-7C, their estimates suggest that the Medicaid expansions had a significant negative effect on private coverage. They find that for each 10 percentage point increase in eligibility there is a 0.74 percentage point decline in private coverage for children and a 0.45 percentage point decline for women (Cutler and Gruber, 1995, pp. 14-15). At this writing the reasons for the differences between my findings and those of Cutler and Gruber are unclear. In Appendix B, I outline their procedure and evaluate some simple hypotheses about the sources of the difference: none of these directly explain the discrepancy.

One important difference between Cutler and Gruber's procedure and my procedure is the use of aggregated versus micro-level data. Cutler and Gruber use micro-level data on health insurance coverage and eligibility and instrument eligibility with a state-level average rate based on the eligibility of a fixed (national) sample of individuals. Since their instrument is the same for all individuals in a given state and year, however, their estimates of crowd-out are identified by cross-state correlations of private insurance coverage, Medicaid coverage, and eligibility (see Appendix B).²⁰ Moreover, the direct use of grouped data circumvents a problem that arises in micro-level estimations that include group-level covariates (Moulton, 1986). As I show in Appendix B, the

²⁰For children, the value of the instrument is calculated for state-year-age cells rather than state-year cells. Hence the instrument is the same for all children in a given state, year, and age group.

standard errors from the IV procedure employed by Cutler and Gruber are understated. Some preliminary simulations suggest that Cutler and Gruber's standard errors are understated by 30-50 percent. Since their estimated crowd-out effects are only marginally significantly different from zero (with t-ratios close to 2), an allowance for the understatement leads to the conclusion that their findings are consistent with those reported here.

VI. Summary and Conclusion

In this paper I have used tabulations of the CPS to discern whether the changes in Medicaid eligibility that occurred as a result of federal legislation from 1986 to 1990 have had an effect on enrollments. Examining the fraction of children enrolled in Medicaid, I find that enrollments did increase in the period 1988-1993, although not uniformly across all affected groups of children. Comparing the population deemed eligible for Medicaid with the population actually receiving Medicaid, I find that the proportion that was eligible for Medicaid but was not receiving it increased from 1988 to 1991 and essentially remained constant from 1991 to 1993. Using various methods to decompose the enrollment increase into its components, all of which produced comparable results, I find that approximately 68 percent of the increase in eligibility can be ascribed to the changes in the rules. The balance of the enrollment increase is due to an increase in the fraction of children in poverty, while the takeup rate declined over the period.

Results from a state-level analysis of changes in the fraction of children participating in the program confirm that the legislation had a causal effect in increasing the enrollment of children. Again using state-level analysis, I find no evidence that the increase in eligibility has caused families to drop private coverage for their eligible children in favor of Medicaid coverage. Rather, health insurance coverage for eligible children seems to have increased above what they would have had in the absence of the expansions. For women, who would potentially be covered if they were pregnant,

I find that the only significant effect of the expansions was a positive effect on enrollment in the program for married women.

It is important to note that although the new eligibility rules appear to have had an effect, a significant fraction of eligible children are not enrolled in the program. Moreover, it is clear that there is some variation in enrollment rates between states (I find that New York had a lower percentage of eligible children who were not enrolled than Texas, for example.) This variation is important to consider as Congress prepares to drop some entitlement programs in favor of block grants, thereby increasing state autonomy. Much of the Medicaid legislation studied in this paper gave states a great deal of independence, and it is noteworthy that the percent of children eligible but not enrolled increased until 1992, when the OBRA 1990 change making coverage for all children under age 9 in families with incomes below the poverty threshold mandatory rather than optional took effect. If Medicaid becomes a block-grant program, the standardization in programs that took place as a result of the expansions studied in this paper may be reversed. As states would be given a fixed amount of money to spend, they may respond by contracting their programs. If public insurance really does crowd out private insurance, in spite of the evidence to the contrary found in this paper, then as a consequence of this contraction, private coverage should be observed to rise. Thus the legislation currently pending in Congress will provide another test of the crowding-out hypothesis.

If increasing indigent children's access to health care continues to be a national policy goal, decreasing the complexity of the program might be an important step to take.²¹ In addition, since a significant fraction of the eligible population is not receiving Medicaid, a priority of Medicaid administrators and lawmakers should be to increase the enrollment of the eligible population.

²¹It has been found that 60 percent of all people who are denied Medicaid eligibility are not rejected because of excess income or resources, but because of procedural noncompliance (Wiener and Engel, 1991). It is unclear whether a block-grant approach would have an effect on program complexity.

Progress in that direction has already been made, as states have implemented programs that allow enrollment and utilization to be accomplished more easily. These programs have included presumptive eligibility (allowing pregnant women and children to receive medical care while their application is pending), outreach programs, and services such as transportation to health care providers. A future area of research would be to examine whether these programs have any effect on enrollment separate from the effects investigated in this paper. It is also important to look at participation and provision of care by doctors and other health-care providers--even if enrollments have increased, it would not matter if doctors are not participating. Since doctors are not obligated to participate in the program,²² it is possible that children in some areas of the country may not be receiving care. In addition, the quality of care provided under the program may be different from that provided to individuals with private insurance--an issue which I am currently exploring.

²²Note that payments are made to providers, who if they choose to participate must accept Medicaid as payment in full. In addition, reimbursement rates from Medicaid are usually far lower than what doctors charge their regular patients.

Appendix A: Data Appendix

Using the CPS to Examine Health Insurance Coverage

The primary data sources for this paper are the 1988-1993 CPS March supplements. The CPS offers the advantages of health insurance coverage information which is from a large sample of the population and which has been collected over a sustained period of time. There are several potential problems with using the CPS, however. One problem is that previous research has found evidence of an undercount of health insurance coverage in the CPS. Another issue that has been identified is whether respondents answer the CPS health insurance questions as instructed (that is, they provide information about their coverage over the previous year) or whether respondents report their coverage as of a point in time. In order to examine whether and how the CPS should be used for my study, I address these issues by comparing results from the March CPS with two alternative sources: the National Medicaid Expenditure Survey (NMES) of 1987¹ and the 1993 CPS April benefits supplement.

Since previous research has found evidence of an undercount of Medicaid reciprocity in the CPS, it is useful to compare results from the CPS with results from a data set that is not believed to have such an undercount. One such data set is the NMES, which I compare with the 1988 CPS.² Both the CPS and the NMES are probability samples, and both provide weights that enable the researcher to obtain a nationally representative sample. The chief differences between these two data sets are in their sample size and their focus. The CPS has a total sample size of over 160,000 individuals, of which approximately 41,000 are children (the exact sizes vary by year). The 1987 NMES by comparison has a total sample size of 38,446³, of which only 9225 are children with round 4 information. In terms of focus, the NMES was designed by the U.S. Department of Health and Human Services specifically for the purpose of analysis and evaluation of health care policy. The CPS, on the other hand, was designed for collection of information about unemployment and the

¹The NMES was sponsored by the U.S. Department of Health and Human Services, Agency for Health Care Policy and Research. The data were collected by Westat, Incorporated, of Rockville, MD and the National Opinion Research Center of the University of Chicago.

²I use Round 4 of the NMES because it was conducted in December 1987, which is closest to the CPS survey date of March 1988.

³Note that this sample size only includes the Household Survey component of the NMES, and does not include the Survey of American Indians and Alaska Natives component and the Institutional Population component.

labor market. Consequently, the non-central role of health care evaluation may contribute to a possible Medicaid undercount in the CPS.

The 1988 CPS is particularly useful for this comparison since the questionnaire and processing procedures were revised during that year, partially in an attempt to obtain more reliable information about health insurance coverage. In particular, questions about sources of coverage from outside the household were added, as well as direct questions about the coverage of children by Medicaid or private sources (see Levit, Olin, and Letsch (1992) for a summary of the changes). In addition, the processing system was updated to take account of these changes and others that had been made to the questionnaire since the system was introduced. Because of these changes, the Census Bureau processed the 1988 March data twice: using the old system, which did not take account of the new data, and using the new system. I compare both data files with the NMES.

One potential problem with the CPS which may lead to different estimates of Medicaid coverage than those obtained from the NMES is the fact that while each NMES round only surveys coverage since the previous round (usually a period of about three months), the CPS question asks about coverage in the previous year. Swartz (1986) notes that if one views the CPS estimate as being a year-round estimate (as it would be if the question were truly answered about the entire previous year),⁴ and compares it to year-round estimates from other surveys, then one will find that the Medicaid population has been undercounted. She argues convincingly, however, that if one views the CPS estimate of Medicaid coverage as being a point-in-time estimate (as it would be if the respondent answered the question on the basis of his or her current health insurance status), then the CPS estimates are quite close to estimates from other surveys. To support her claim, she compares year-round estimates from the 1977 National Medical Care Expenditure Survey (NMCES), the 1980 National Medical Care Utilization and Expenditure Survey (NMCUES), and the March 1980 CPS and finds that the estimate from the CPS is only 75-80 percent of the estimates from the NMCES and the NMCUES.⁵ When she compares the 1980 CPS estimate with the point-in-time estimates derived

⁴It is important to note that a question referring to coverage for an entire year may be problematic for respondents who had more than one type of health insurance coverage over the year or who were not covered by Medicaid or other government-funded health insurance over the entire year.

⁵She finds that the CPS estimate of the population covered by Medicaid is only 7.6 percent of the total population, while the estimates from the NMCES and the NMCUES are 9.2 percent and 10.2 percent, respectively (Swartz, 1986, table 4).

from the 1977 NMCES and the 1980 NMCUES, and the 1983 CPS estimate with the fourth quarter estimate from the Survey of Income and Program Participation (SIPP), however, she finds that the CPS estimate actually lies in the middle of the estimates from the other surveys.⁶

I obtain evidence about whether the March CPS is a point-in-time estimate by comparing the 1993 March supplement with the 1993 April supplement. The April supplement (Survey of Employee Benefits) was asked of a subsample of people from the regular CPS sample who were either employed or formerly employed. Responses were then matched by the Census Bureau to the 1993 March responses. Both the March and April questionnaires contained questions about whether the respondent had health insurance. The time period covered by the questions was different, however. The March question was about health insurance last year while the April question was about current health insurance coverage.⁷ If the response to the March question represented a year-round estimate of health insurance coverage and the response to the April question represented a point-in-time estimate of coverage, unless there was a trend towards greater coverage of the population, the estimate of the fraction covered from the March supplement should be larger than the estimate from the April supplement. When I compare these two estimates, however, I find that the fraction covered by health insurance is 0.7511 from the March supplement and 0.8208 from the April supplement. This result seems to provide further, although rough, evidence that the March question yields a point-in-time estimate rather than a year-round estimate of health insurance coverage.

Using the 1988 CPS estimate of the fraction of children covered by Medicaid as a point-in-time estimate, I compare it to the estimate derived from the NMES. This comparison is presented in Table A1 (for all children) and Table A2 (for children under 10 only). For the NMES, there are two potential Medicaid variables: the edited variable and the unedited variable. The unedited variable was checked for logical inconsistencies, which resulted in an increase in the percentage of the population

⁶Some of the NMCES estimates lie above the CPS estimate and others lie below it. All of the NMCUES estimates lie above the CPS estimate, while the SIPP estimate lies below that of the CPS.

⁷The wording of the March questions was: "During [previous year] was anyone in this household covered by Medicare? ... Medicaid? ... CHAMPUS, VA, or military health care?" and "Other than government sponsored policies, health insurance can be obtained privately or through a current or former employer or union. Was anyone in this household covered by health insurance of this type at any time during [previous year]?" The wording of the April questions for the employed subsample was: "Are you covered by this [employer-provided] health insurance plan?" and "Are you covered by any health insurance plan not provided by your current employer?" The unemployed subsample was asked: "Are you covered by a health insurance plan?"

of children covered by Medicaid. Both are presented in Tables A1 and A2.⁸ The rewritten 1988 CPS has both edited and unedited variables as well, although in the 1988 file processed under the old system only an edited variable is available in the data.⁹ Comparing the Medicaid estimates to the NMES estimate, I find that the estimates from both the original and the rewritten files are *higher* than the NMES estimate. The difference between the NMES and the old CPS is not statistically significant, although the estimate from the rewritten file is significantly higher (see Table A3).¹⁰ I also compared the estimates of Medicaid reciprocity by age, family type, and geographic division of residence. In most cases, both of the CPS estimates are higher than the NMES estimates, although the differences are not always statistically significant.¹¹

There are several possible answers to the question of why I found no evidence of under-reporting in the CPS estimates of Medicaid enrollment. One plausible explanation lies in the fact that I am looking only at children, while past estimates have not examined children separately. The Census Bureau takes additional steps to assign Medicaid coverage to children, particularly with the new questionnaire and processing system. This procedure does not occur with adult respondents (who are necessarily the majority), so a tabulation of the proportion of the entire sample covered by Medicaid might pick up the undercount of adults without distinguishing the more accurate count of the children. To check my results further, and perhaps to shed more light on the question of whether there is a differential undercount between adults and children, it might be beneficial to repeat these

⁸Table A2 is included in order to describe the population which is most affected by the changes in Medicaid rules.

⁹To obtain the edited variable, the Census Bureau assigned Medicaid coverage to children under 21 years of age in families where either the householder or the spouse reported being covered by Medicaid. In addition, in the rewrite file, children in the household were assigned coverage based on the new question about coverage of children in the household.

¹⁰The test for statistical significance is accomplished using a t-test of the difference in means.

¹¹The significant differences in the family type variables can almost certainly be attributed to discrepancies in the variable definitions across the data sets. In the NMES, for instance, family type is only defined by the presence or absence of the child's parents. Although the working definition for "mother" and "father" is not clearly explained in the documentation, it appears that a child living with a mother and a stepfather would be coded as being in a female-headed family. This would explain why the proportion of children in female-headed families enrolled in Medicaid according to the NMES is significantly lower than the proportion according to the CPS. The fact that the proportion in all three family types is lower for the NMES than for the CPS can be explained by the fact that children living with neither of their original parents are not included in any of the three groups.

tabulations with adults from the CPS and NMES. Based on my results, however, it seems reasonable to use the CPS to measure Medicaid enrollment for children. In addition, although the CPS estimates are larger than the NMES estimates, the differences are usually quite small. This result, together with the results of the comparison between the 1993 March and April CPS estimates of coverage, has led me to adopt the assumption that the March CPS Medicaid coverage responses refer to coverage as of a point in time rather than for the full year.

Eligibility Imputation

For 1988, children were imputed to be eligible if their family received AFDC, if their age and poverty level fell below the threshold set by their state, or if they met their state's Ribicoff program criteria (not all states had Ribicoff programs in all years). For 1989, children were assigned eligibility as above, and in addition were assigned eligibility if they were less than 6 years old and their family income was below the AFDC threshold for their state of residence. In addition to the criteria noted above, children were assigned eligibility for 1990 if they were less than 7 years old and their family income was below the AFDC level, or if their family income was below 75 percent of the poverty level and they were less than 1 year old. Under the 1991 rules, children were assigned eligibility as above, and were also assigned eligibility if they were less than 6 years old and their family income was less than 133 percent of the poverty level. Children were assigned eligibility under the 1992 rules if, in addition to the criteria above, they were less than 9 years old and their family income was less than 100 percent of the poverty level. Finally, under the 1993 rules children were assigned eligibility if they were less than 10 years old and their family income was less than 100 percent of the poverty level, in addition to the criteria listed above. Note that I do not attempt to impute eligibility or model participation in the AFDC program. The only instance in which not modeling AFDC would be a problem is if a child was eligible for AFDC but was not receiving funds from the program. That child would not appear to be Medicaid-eligible under my imputation procedure until the expansions took place. This might cause an artificial increase in the group of children who are eligible for Medicaid but who are not receiving it. In order to discover whether this was a problem, I assigned all children whose family income was less than 125 percent of the AFDC threshold and whose family was single-headed to the eligible group. Doing this rough AFDC imputation did not change the results substantively.

Data on optional Medicaid coverage by state used in this imputation were obtained from Hill (1990, Table 1), National Governors' Association (1991, 1993), Congressional Research Service

(1988, 1993), Health Care Financing Administration (1991), and American Academy of Pediatrics (1989, 1990, 1991, 1992, 1993). Data on AFDC thresholds were obtained from the National Governors' Association (1993, Table 5). There was no consistent trend across states in AFDC levels over this time period. The fraction of children eligible in each year under this procedure is given in the first column of Table 4.

Appendix B: Comparison of Results to Those of Cutler and Gruber (1995)

Using pooled data from the 1988-1993 March CPS, Cutler and Gruber estimate the following equation:

$$COV_i = \beta_1 ELIG_i + X_i\beta + \sum \alpha_s state_i + \sum \alpha_t time_i + \varepsilon_i$$

where COV_i is an indicator for insurance coverage for individual i , X is a vector of characteristics of the individual and the family, $state_i$ and $time_i$ are state and year dummy variables, and $ELIG_i$ is an estimate of the individual's eligibility for Medicaid. Because of potential measurement error and omitted variable bias, they instrument for eligibility using state and year legislative characteristics. To construct their instrument, they select a national random sample for each year and calculate the eligibility of that sample under the rules in each state.¹² The fraction eligible in each state is then used as the instrument. My approach, as outlined previously, is very similar. Rather than using the micro-level data, however, I aggregate the data and examine the differences in state averages over time. Another difference is that instead of using the simulated eligibility of a randomly selected national sample as the instrument, I simulate the eligibility of the 1988 population under both the 1988 rules and the 1993 rules, and use the change in eligibility as the instrument. This instrument incorporates differences in the income distribution across the states which are ignored by using the eligibility rate for a national sample.

To discover whether the difference in instruments was the source of the disparity in results, I selected a national random sample and used the fraction of the sample eligible in each state as the instrument in my regression. In the first stage this instrument performs less well for children, although for women and men it seems to perform similarly to the instrument I use. One possible reason for this difference is the fact that eligibility for women (and hence men) is much more uniform across states than eligibility for children, who have different thresholds for eligibility based on age both within and across states. Thus differences in the income distribution across states are likely to play a larger role in the state variation in eligibility for children. The results from the second stage are reported in Table B1. The results for men and women are quite similar to the results reported in Table 7A, although the measured "crowding out" for men is statistically significant and somewhat larger in magnitude. None of the estimates for children are significant. It is interesting to note that

¹²Since eligibility for children depends on the age of the child, for children they calculate eligibility by state-year-age cell.

the coefficient on private insurance is negative when their instrument is used, although the standard errors are quite large. I address the issue of the magnitude of standard errors below.

The micro-level data might seem to be preferable to state-level averages, since ordinarily the large number of observations allows more precise estimates of the parameters of interest. In this case, however, that preference is less clear since the instrument varies only across groups. This grouped instrument, combined with the possibility of intragroup error correlation, may yield standard errors which are underestimated for the coefficient of interest. Correlation of the errors may occur since the CPS data are drawn from a population with a grouped structure (both geographic and temporal). In the regression framework above, the group effects are partially controlled by the inclusion of state and time dummy variables. However, it is not possible to eliminate the grouping entirely since a state-time interaction effect still exists. This group effect is likely to be very small, but using an instrument which does not vary within groups exacerbates the problem.

Moulton (1986) examines the effects of ignoring intragroup error correlation on OLS estimates and finds that the bias in the standard errors may be substantial. To obtain an estimate of the size of the effect in the IV case, consider the simple model

$$(B1) \quad Y_{ist}^1 = Y_{ist}^2 \alpha + X_{ist} \beta + \gamma_s + \delta_t + \varepsilon_{ist} ,$$

$$\varepsilon_{ist} = \phi_{st} + v_{ist}$$

$$i = 1, 2, \dots, N; s = 1, 2, \dots, N_s; t = 1, 2, \dots, N_t$$

where Y^1 and Y^2 are endogenous variables, γ_s and δ_t are state and time effects, and X_{ist} is a vector of exogenous variables. The errors are composed of a group-specific component ϕ_{st} and an individual-specific component v_{ist} , are assumed to be uncorrelated across groups, and are homoskedastic with variance $\sigma_\phi^2 + \sigma_v^2$. Z_{st} is an $N \times 1$ instrument vector (note that the value of the instrument does not vary within state-year cell).

To simplify the notation, write the matrix of all right-hand-side variables (including Y^2) as X and the vector of coefficients as β . In addition, let $g = (s, t)$, $g = (1, \dots, m)$ index groups, so that each state-year cell is a separate group (there are thus $m = N_s N_t$ different groups). The instrumental variables estimator is

$$(B2) \quad \hat{\beta} = (X' P_Z X)^{-1} X' P_Z y, \text{ where } P_Z = Z(Z' Z)^{-1} Z' .$$

The asymptotic distribution of this estimator can be shown to be $N(0, V)$, where

$$(B3) \quad V = [M_{xz} M_{zz}^{-1} M'_{xz}]^{-1} (M_{xz} M_{zz}^{-1} \Delta M_{zz}^{-1} M'_{xz}) [M_{xz} M_{zz}^{-1} M'_{xz}]^{-1}, \text{ with}$$

$$M_{xz} \equiv \text{plim} \frac{1}{N} (X'Z),$$

$$M_{zz}^{-1} \equiv \text{plim} \frac{1}{N} (Z'Z), \text{ and}$$

$$\Delta = E(Z' \varepsilon \varepsilon' Z).$$

Under the assumptions made above, if Z is a single instrument vector then Δ can be written

$$(B4) \quad E[Z' \varepsilon \varepsilon' Z] \\ = Z_1^2 \left(\sum_i E(\varepsilon_{i1}^2) + \sum_{i \neq j} E(\varepsilon_{i1} \varepsilon_{j1}) \right) + \dots + Z_m^2 \left(\sum_i E(\varepsilon_{im}^2) + \sum_{i \neq j} E(\varepsilon_{im} \varepsilon_{jm}) \right) \\ = \frac{1}{N} \sum_{g=1}^m Z_g^2 (N_g (\sigma_\phi^2 + \sigma_v^2) + N_g (N_g - 1) \sigma_\phi^2).$$

Under the alternative assumption that there is no group-specific component of the error, $\sigma_\phi^2 = 0$, so

(B4) reduces to

$$(B5) \quad \frac{1}{N} \sum_{g=1}^m Z_g^2 N_g \sigma_v^2.$$

It is clear that (B4) is larger than (B5), since (B4) includes a set of terms that reflect the off-diagonal elements of the residual covariance matrix. An examination of the ratio of (B4) to (B5) thus provides an estimate of the magnitude of the potential understatement, since (B4) is the correct expression if intragroup error correlation exists while (B5) is the expression reported by a standard regression package.

This ratio can be written

$$(B6) \quad 1 + N \left[\frac{\frac{1}{N} \sum_{g=1}^m Z_g^2 f_g^2 \left(\frac{k}{1-k} \right)}{\frac{1}{N} \sum_{g=1}^m Z_g^2 f_g} \right],$$

where k is the ratio of the group-specific variance to the total variance: $k = \frac{\sigma_\phi^2}{\sigma_\phi^2 + \sigma_v^2}$, and f_g is the

fraction of the sample in group g : $N_g = f_g N$. The greater the magnitude of (B6), the more the standard errors have been understated. There are several issues to note in determining the magnitude of this expression. As would be expected, the larger the between-group variance relative to the within-group variance, the greater the degree of understatement. Somewhat surprising is the role played by the sample size. Rather than decreasing as the sample size increases, (B6) increases with N , so that the larger the sample, the greater the degree of error misstatement. Intuitively, this occurs because adding more observations to the sample adds less new information than expected because only some of the variation is between groups. Indeed, if there is no within-group variation ($\sigma_v^2 = 0$), then one observation per group is all that is needed, and any additional observations will add no new information.

To estimate the magnitude of the potential understatement of the standard errors in the specification used by Cutler and Gruber, I performed a simple "back-of-the-envelope" calculation using micro-level data from 1988 and 1993 (the years I use in my specification, and the endpoints of the years used by Cutler and Gruber¹³). For simplicity, I do these calculations for the sample of women, since the grouping in the instruments for children is across age as well as state and time. In the expression above, Z_g is the value of the instrument for group g (the simulated eligibility under the rules in state s at time t for the national random sample) and f_g is the fraction of the sample in that group. Calculations of the square root of (B6) for various values of $\frac{k}{1-k}$ are presented in Table B2.

Note that the standard errors will be understated even when the group variance is very small relative to the total variance.

To determine an approximate value of $\frac{k}{1-k}$ for the specification used by Cutler and Gruber,

I run two regressions for each coverage variable using the micro-level data for women for 1988 and 1993. The first regression is as close to their specification as possible, and includes a full set of state

¹³It is possible that the difference between the results may be due in part to the difference in the number of years used. However, Cutler and Gruber state that when they restrict their regressions to the first and last years of their sample, the results are very similar to the results reported in the paper.

and year dummies as well as the other exogenous variables. The second regression includes exogenous variables and the full state-by-year interaction. The mean squared error from the first regression yields an estimate of $\sigma_\phi^2 + \sigma_v^2$, while the mean squared error from the second regression yields an estimate of σ_v^2 , since the group variance has been absorbed into the regression. The results are reported in Table B3. Although the within-group component of the variance is quite small, the combination of the grouped instruments and the large sample size yield an adjustment to the standard errors that affects the conclusions that can be drawn. When the group effect is accounted for, the crowding-out effect is no longer significantly different from zero.

It is not possible to extrapolate the effects of such a correction on the estimated standard errors of the crowd-out coefficients for children from the results presented here. The regressions for children incorporate more variability in the instrument since the groups involve differences across age as well as state and year. This would tend to reduce the magnitude of the correction. The sample size is larger, however, which would tend to increase the magnitude of the correction. At present I am examining how large this correction may be for children.

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Figure 1
Federal Legislation Related to Medicaid Coverage
of Pregnant Women, Infants, and Children
1986-1990

Sources: Chang and Holahan (1990), Green Book (1986-1991)

Notes:

1. OBRA=Omnibus Budget Reconciliation Act, MCCA=Medicare Catastrophic Coverage Act, FSA=Family Support Act
2. The provision of MCCA that would have raised the eligibility threshold to 100% of the Federal poverty level was superseded by OBRA 1989.

Figure 2: Fraction of Children Eligible and Fraction Enrolled in Medicaid

Figure 3: Fraction Receiving Medicaid by Most Likely Source of Eligibility

Figure 4: Comparison of Fraction Eligible but not Enrolled: NY, TX, CA

Figure 5: Actual and Simulated Eligibility Levels

Figure 6A: Health Insurance Coverage
Children, 1985-1993

Figure 6B: Health Insurance Coverage
Young Women, 1985-1993

Figure 6C: Health Insurance Coverage
Young Single Men, 1985-1993

Figure 7

Figure 8

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Table 1: Sample Fractions, Children Under 15

Variable	1988 CPS	1989 CPS	1990 CPS	1991 CPS	1992 CPS	1993 CPS
Medicaid recipient	0.162	0.163	0.167	0.196	0.212	0.229
Age <=2	0.210	0.211	0.211	0.213	0.211	0.210
Age 3-5	0.206	0.205	0.205	0.203	0.204	0.205
Age 6-8	0.205	0.204	0.202	0.200	0.198	0.197
Age 9-11	0.193	0.196	0.198	0.199	0.199	0.198
Age 11-14	0.185	0.185	0.184	0.185	0.188	0.190
Northeast	0.182	0.190	0.191	0.191	0.189	0.183
Midwest	0.252	0.248	0.241	0.243	0.243	0.246
South	0.348	0.345	0.339	0.341	0.338	0.343
West	0.218	0.215	0.228	0.225	0.230	0.228
Two parent family	0.743	0.746	0.739	0.730	0.720	0.718
Female head	0.227	0.224	0.228	0.238	0.245	0.244
Male head	0.030	0.030	0.033	0.033	0.035	0.037
Pct. of pov. level:						
< 50 %	0.114	0.112	0.105	0.114	0.121	0.128
50 %-74 %	0.063	0.057	0.058	0.064	0.068	0.065
75 %-99 %	0.054	0.050	0.060	0.059	0.056	0.056
100 %-124 %	0.053	0.055	0.054	0.054	0.056	0.056
125 %-149 %	0.053	0.054	0.053	0.053	0.055	0.054
150 %-174 %	0.051	0.053	0.052	0.061	0.056	0.052
175 %-199 %	0.053	0.055	0.054	0.050	0.057	0.055
> =200 %	0.559	0.563	0.564	0.545	0.532	0.536
Children in family receiving AFDC	0.122	0.119	0.118	0.132	0.142	0.143
Sample size	35751	33095	36712	37157	36245	36433

Note: The data are from the Current Population Survey March supplements 1988-1993. The fractions are weighted by the CPS March supplement weight. The fraction of children who are Medicaid recipients is tabulated from the edited Medicaid variable.

Table 2
Analysis of Change in Medicaid Reciprocity

		Fractions of Children Receiving Medicaid (standard errors)						
		1988 CPS	1989 CPS	1990 CPS	1991 CPS	1992 CPS	1993 CPS	Change 88 to 93
Overall		0.162 (0.002)	0.163 (0.002)	0.167 (0.002)	0.196 (0.002)	0.216 (0.002)	0.229 (0.002)	0.067 (0.003)
By age:								
Infants		0.207 (0.008)	0.224 (0.009)	0.235 (0.008)	0.287 (0.009)	0.310 (0.009)	0.332 (0.010)	0.125 (0.013)
1		0.196 (0.008)	0.196 (0.008)	0.232 (0.008)	0.272 (0.009)	0.305 (0.009)	0.327 (0.010)	0.131 (0.013)
2		0.166 (0.007)	0.190 (0.008)	0.213 (0.008)	0.241 (0.009)	0.276 (0.009)	0.305 (0.009)	0.139 (0.011)
3		0.178 (0.007)	0.168 (0.008)	0.188 (0.008)	0.213 (0.008)	0.243 (0.009)	0.269 (0.009)	0.091 (0.011)
4		0.176 (0.007)	0.186 (0.008)	0.169 (0.007)	0.218 (0.008)	0.240 (0.009)	0.270 (0.009)	0.094 (0.011)
5		0.181 (0.007)	0.189 (0.008)	0.180 (0.007)	0.205 (0.008)	0.226 (0.008)	0.243 (0.009)	0.062 (0.011)
6		0.176 (0.007)	0.170 (0.008)	0.167 (0.008)	0.204 (0.008)	0.215 (0.008)	0.225 (0.008)	0.049 (0.011)
7		0.169 (0.007)	0.161 (0.008)	0.157 (0.007)	0.188 (0.008)	0.213 (0.008)	0.208 (0.008)	0.039 (0.011)
8		0.171 (0.008)	0.155 (0.008)	0.149 (0.007)	0.170 (0.007)	0.199 (0.008)	0.211 (0.008)	0.040 (0.011)
9		0.141 (0.007)	0.149 (0.008)	0.131 (0.007)	0.158 (0.007)	0.195 (0.008)	0.198 (0.008)	0.057 (0.011)
10		0.137 (0.007)	0.149 (0.008)	0.149 (0.007)	0.161 (0.007)	0.166 (0.008)	0.166 (0.008)	0.029 (0.011)
11		0.126 (0.007)	0.131 (0.007)	0.145 (0.007)	0.155 (0.007)	0.162 (0.007)	0.168 (0.008)	0.042 (0.011)
12		0.137 (0.007)	0.121 (0.007)	0.123 (0.007)	0.165 (0.008)	0.151 (0.007)	0.177 (0.008)	0.040 (0.011)
13		0.124 (0.007)	0.127 (0.008)	0.119 (0.007)	0.139 (0.007)	0.163 (0.008)	0.153 (0.007)	0.029 (0.010)
14		0.125 (0.007)	0.110 (0.007)	0.124 (0.007)	0.132 (0.007)	0.142 (0.007)	0.154 (0.008)	0.029 (0.011)

See notes following continuation of table.

Table 2, continued
Analysis of Change in Medicaid Reciprocity

Fractions of Children Receiving Medicaid (Standard errors)							
	1988 CPS	1989 CPS	1990 CPS	1991 CPS	1992 CPS	1993 CPS	Change 88 to 93
By family structure:							
two parents	0.064 (0.001)	0.067 (0.002)	0.073 (0.002)	0.096 (0.002)	0.108 (0.002)	0.118 (0.002)	0.054 (0.002)
male head	0.177 (0.011)	0.184 (0.012)	0.219 (0.012)	0.202 (0.010)	0.236 (0.012)	0.290 (0.012)	0.113 (0.016)
female head	0.480 (0.006)	0.479 (0.006)	0.461 (0.006)	0.502 (0.005)	0.530 (0.005)	0.548 (0.005)	0.068 (0.009)
Reciprocity by % of the poverty level:							
<50%	0.633 (0.008)	0.667 (0.008)	0.640 (0.008)	0.691 (0.007)	0.742 (0.007)	0.731 (0.007)	0.098 (0.011)
50%-74%	0.566 (0.010)	0.580 (0.011)	0.604 (0.011)	0.662 (0.010)	0.692 (0.009)	0.682 (0.009)	0.116 (0.013)
75%-99%	0.385 (0.011)	0.338 (0.012)	0.424 (0.011)	0.436 (0.011)	0.471 (0.011)	0.517 (0.011)	0.132 (0.016)
100%-124%	0.198 (0.009)	0.216 (0.009)	0.218 (0.009)	0.284 (0.010)	0.304 (0.010)	0.340 (0.010)	0.142 (0.013)
125%-149%	0.010 (0.006)	0.128 (0.008)	0.142 (0.008)	0.168 (0.008)	0.200 (0.009)	0.232 (0.009)	0.222 (0.011)
150%-174%	0.078 (0.005)	0.103 (0.007)	0.086 (0.006)	0.108 (0.006)	0.125 (0.007)	0.142 (0.008)	0.064 (0.009)
175%-199%	0.065 (0.004)	0.055 (0.005)	0.069 (0.006)	0.069 (0.005)	0.070 (0.005)	0.123 (0.007)	0.058 (0.008)
>=200%	0.018 (0.001)	0.019 (0.001)	0.020 (0.001)	0.027 (0.001)	0.026 (0.001)	0.032 (0.001)	0.014 (0.001)
AFDC non-recipients	0.048 (0.001)	0.054 (0.001)	0.059 (0.001)	0.077 (0.001)	0.089 (0.002)	0.104 (0.002)	0.056 (0.002)
AFDC recipients	0.981 (0.002)	0.974 (0.002)	0.974 (0.002)	0.979 (0.002)	0.983 (0.002)	0.981 (0.002)	0.000 (0.003)

Notes: Computed from weighted tabulations of the CPS March supplements. The standard errors in the first five columns are computed as $[p(1-p)/n]^{1/2}$. The standard errors in the last column are computed as $(\sigma_{88}^2 + \sigma_{93}^2)^{1/2}$.

Table 3
Comparison of Imputed Eligibility and Actual Medicaid Coverage,
All Children Under 15 Years of Age

	Probability of Coverage for Children Presumed Ineligible	Probability of Noncoverage for Children Presumed Eligible
1988	3.33	23.58
1989	3.52	26.40
1990	3.69	28.85
1991	4.14	31.87
1992	4.39	31.07
1993	5.40	31.28

Notes: Fractions are expressed as percentages and are computed from weighted tabulations of the 1988-1993 CPS March supplements. Eligibility is determined by comparing individual characteristics with provisions in the law (see text).

Table 4
Fraction Eligible: Actual and Simulated

Year	Fraction eligible in year indicated	Fraction eligible (1988 population)	Fraction eligible (1988 rules)	Takeup rate: $P(\text{receive} \text{elig})$	Fraction receiving Medicaid	Fraction with any coverage
1988	0.1760	0.1760	0.1760	0.7642	0.1619	0.8726
1989	0.1827	0.1872	0.1718	0.7360	0.1631	0.8730
1990	0.1927	0.1973	0.1719	0.7115	0.1668	0.8707
1991	0.2412	0.2315	0.1869	0.6813	0.1956	0.8740
1992	0.2662	0.2471	0.1933	0.6893	0.2157	0.8788
1993	0.2766	0.2530	0.1977	0.6872	0.2291	0.8828

Notes: Computed from weighted tabulations of the 1988-1993 March CPS. The fraction eligible in each year was estimated by imputing eligibility to children from the CPS of that year based on their characteristics and the rules applicable in that year. The constant-population eligibility fraction was calculated by applying the rules for each year to children from the 1988 CPS. The constant-rules eligibility fraction was calculated by applying the 1988 rules to children from the 1988-1993 CPS. The takeover rate is the fraction of all children imputed to be eligible who report receiving Medicaid.

Table 5
Decomposition of Change in Mean Reciprocity Rates

	Children under 15
$\bar{Y}_{88}$	0.1619
$\bar{Y}_{93}$	0.2291
$\hat{\beta}'_{88}(\bar{X}_{93} - \bar{X}_{88})$	0.0211
$\bar{X}'_{93}(\hat{\beta}_{93} - \hat{\beta}_{88})$	0.0462

Notes: Computed from weighted linear probability model regressions of the probability of receiving Medicaid on children's characteristics. Data are from the 1988 and 1993 CPS March supplements. The first two rows are the mean reciprocity rates for the indicated years. The third row gives the effect of the change in mean population characteristics, i.e. the effect of the recession and other exogenous shifts. The fourth row gives the structural change in the Medicaid program evaluated using the mean population characteristics for 1993. It shows the effect on Medicaid reciprocity due to shifts in eligibility standards. For discussion, see text.

Table 6

State-Level Fractions: Children, 1988 and 1993

State	Fraction eligible for Medicaid (1988 pop'n.)		Fraction receiving Medicaid		Fraction with private insurance		Fraction with any insurance	
	1988 rules	1993 rules	1988	1993	1988	1993	1988	1993
Alabama	0.199	0.346	0.209	0.182	0.601	0.707	0.796	0.844
Alaska	0.201	0.255	0.186	0.191	0.759	0.733	0.860	0.908
Arizona	0.090	0.243	0.071	0.236	0.709	0.688	0.787	0.890
Arkansas	0.239	0.333	0.198	0.175	0.592	0.621	0.759	0.794
California	0.227	0.292	0.186	0.268	0.681	0.628	0.841	0.857
Colorado	0.119	0.257	0.118	0.177	0.745	0.762	0.876	0.902
Connecticut	0.106	0.142	0.088	0.218	0.886	0.772	0.955	0.946
Delaware	0.096	0.180	0.110	0.174	0.830	0.790	0.917	0.916
Florida	0.185	0.237	0.143	0.289	0.669	0.565	0.799	0.820
Georgia	0.145	0.236	0.169	0.233	0.729	0.606	0.870	0.814
Hawaii	0.088	0.213	0.082	0.234	0.7908	0.780	0.920	0.962
Idaho	0.072	0.228	0.066	0.139	0.790	0.770	0.832	0.858
Illinois	0.242	0.286	0.236	0.245	0.745	0.702	0.938	0.906
Indiana	0.085	0.192	0.083	0.204	0.813	0.742	0.865	0.919
Iowa	0.160	0.258	0.136	0.164	0.818	0.787	0.937	0.918
Kansas	0.054	0.152	0.042	0.149	0.867	0.809	0.907	0.919
Kentucky	0.124	0.255	0.141	0.238	0.682	0.671	0.830	0.869
Louisiana	0.211	0.351	0.241	0.275	0.580	0.590	0.803	0.845
Maine	0.212	0.256	0.197	0.242	0.800	0.720	0.957	0.906
Maryland	0.142	0.196	0.163	0.203	0.758	0.762	0.903	0.936
Massachusetts	0.184	0.210	0.188	0.189	0.817	0.746	0.953	0.900
Michigan	0.228	0.271	0.202	0.237	0.795	0.742	0.945	0.926
Minnesota	0.192	0.241	0.169	0.251	0.800	0.765	0.937	0.963

Table 6, continued

Mississippi	0.316	0.371	0.256	0.284	0.630	0.605	0.849	0.841
Missouri	0.149	0.204	0.138	0.228	0.803	0.674	0.927	0.878
Montana	0.126	0.275	0.166	0.279	0.657	0.744	0.807	0.964
Nebraska	0.104	0.196	0.099	0.167	0.804	0.779	0.895	0.922
Nevada	0.110	0.208	0.130	0.106	0.752	0.677	0.827	0.761
New Hampshire	0.018	0.081	0.025	0.175	0.888	0.774	0.892	0.895
New Jersey	0.166	0.192	0.130	0.148	0.838	0.772	0.947	0.901
New Mexico	0.114	0.302	0.088	0.283	0.667	0.601	0.747	0.838
New York	0.249	0.307	0.245	0.263	0.700	0.678	0.900	0.905
North Carolina	0.149	0.220	0.113	0.266	0.763	0.683	0.861	0.894
North Dakota	0.070	0.165	0.057	0.189	0.868	0.810	0.935	0.950
Ohio	0.196	0.258	0.190	0.218	0.761	0.728	0.915	0.907
Oklahoma	0.155	0.246	0.130	0.211	0.661	0.623	0.801	0.799
Oregon	0.170	0.242	0.170	0.214	0.741	0.757	0.886	0.917
Pennsylvania	0.132	0.198	0.122	0.179	0.829	0.790	0.922	0.935
Rhode Island	0.127	0.153	0.145	0.231	0.848	0.726	0.957	0.927
South Carolina	0.224	0.268	0.147	0.300	0.752	0.702	0.890	0.918
South Dakota	0.101	0.234	0.089	0.190	0.746	0.681	0.830	0.849
Tennessee	0.182	0.229	0.142	0.323	0.740	0.673	0.867	0.900
Texas	0.134	0.265	0.126	0.229	0.636	0.596	0.756	0.806
Utah	0.134	0.184	0.078	0.132	0.823	0.823	0.879	0.898
Vermont	0.129	0.496	0.101	0.237	0.850	0.810	0.907	0.964
Virginia	0.121	0.208	0.134	0.154	0.769	0.779	0.911	0.914
Washington	0.139	0.242	0.166	0.149	0.745	0.802	0.901	0.914
West Virginia	0.215	0.282	0.232	0.320	0.703	0.599	0.894	0.880
Wisconsin	0.149	0.211	0.152	0.176	0.836	0.802	0.955	0.927
Wyoming	0.092	0.166	0.090	0.156	0.808	0.778	0.897	0.892

Notes: Computed from weighted tabulations of the 1988-1993 CPS March Supplements. The difference between the first two columns is the fraction affected used in the regression analysis.

Table 7A
State-level Regressions: Non-Exclusive Insurance Groups

Estimated second stage regression equation: $\Delta Coverage_{g,s} = \alpha_g + \beta_g (\Delta eligible)_{g,s} + \varepsilon_{g,s}$

Children						
Change in fraction covered by:						
	Medicaid		Private ins.		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.487** (0.151)	0.452** (0.181)	0.380* (0.189)	0.246 (0.189)	0.634** (0.133)	0.522** (0.147)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes
Women ages 15-45						
Change in fraction covered by:						
	Medicaid		Private ins.		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.096 (0.068)	0.101 (0.081)	0.093 (0.087)	0.074 (0.089)	0.113 (0.084)	0.089 (0.090)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes
Single Men ages 15-45						
Change in fraction covered by:						
	Medicaid		Private ins.		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.058 (0.076)	0.057 (0.083)	-0.215 (0.131)	-0.173 (0.132)	0.008 (0.207)	-0.066 (0.143)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes

Notes: Changes are differences between 1988 and 1993 March CPS. The coefficients for Medicaid and private insurance do not add up to the coefficient for any coverage because of people with more than one type of coverage. Regressions are weighted by the size of the population under age 65 in each state. The sample size in all cases is 50. Standard errors are in parentheses. ** indicates significance at the 95% level, while * indicates significance at the 90% level. The first stage coefficients are 0.805 (0.119) for children, 0.923 (0.089) for women, and 0.885 (0.146) for men.

Table 7B
State-level Regressions: Exclusive Insurance Groups

Estimated second stage regression equation: $\Delta Coverage_{g,s} = \alpha_g + \beta_g (\Delta eligible)_{g,s} + \varepsilon_{g,s}$

Children						
Change in fraction covered by:						
	Medicaid only		Private ins. only		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.297** (0.129)	0.328* (0.151)	0.244 (0.207)	0.137 (0.214)	0.634** (0.133)	0.522** (0.147)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes
Women ages 15-45						
Change in fraction covered by:						
	Medicaid only		Private ins. only		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.065 (0.059)	0.065 (0.070)	0.082 (0.084)	0.062 (0.089)	0.113 (0.084)	0.089 (0.090)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes
Single Men ages 15-45						
Change in fraction covered by:						
	Medicaid only		Private ins. only		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.066 (0.071)	0.053 (0.080)	-0.238* (0.132)	-0.196 (0.136)	-0.106 (0.141)	-0.066 (0.143)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes

Notes: Changes are differences between the 1988 and 1993 March CPS. The coefficients for Medicaid and private insurance do not add up to the coefficient for any coverage because the categories "other government insurance only" and "two or more forms of insurance" are not included in the table. Regressions are weighted by the size of the population under age 65 in each state. The sample size in all cases is 50. Standard errors are in parentheses. ** indicates significance at the 95% level, while * indicates significance at the 90% level. The first stage coefficients are 0.805 (0.119) for children, 0.923 (0.089) for women, and 0.885 (0.146) for men.

Table 7C
State-Level Regressions: Women by Marital Status

Estimated second stage regression equation: $\Delta Coverage_{g,s} = \alpha_g + \beta_g (\Delta eligible)_{g,s} + \varepsilon_{g,s}$

Married Women ages 15-45
Change in fraction covered by:

	Medicaid only		Private ins. only		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.111** (0.036)	0.107** (0.044)	0.089 (0.107)	0.093 (0.112)	0.067 (0.107)	0.049 (0.111)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes

Unmarried Women ages 15-45
Change in fraction covered by:

	Medicaid only		Private ins. only		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	-0.033 (0.090)	-0.049 (0.108)	0.142 (0.108)	0.138 (0.129)	0.146 (0.089)	0.094 (0.106)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes

Notes: Changes are differences between the 1988 and 1993 March CPS. The coefficients for Medicaid and private insurance do not add up to the coefficient for any coverage because the categories "other government insurance only" and "two or more forms of insurance" are not included in the table. Slightly over half of the sample of women 15-45 are married. Regressions are weighted by the size of the population under age 65 in each state. The sample size in all cases is 50. Standard errors are in parentheses. ** indicates significance at the 95% level, while * indicates significance at the 90% level. The first stage coefficients are 0.788 (0.108) for married women and 0.747 (0.096) for unmarried women.

Table A1: Fraction Covered by Medicaid in the NMES and CPS, All Children

	NMES (1987, round 4)	1988 CPS (original ADF)	1988 CPS (rewrite file)
Fraction receiving Medicaid (unedited)	0.134	n.a.	0.139
Fraction receiving Medicaid (edited)	0.140	0.143	0.162
Sample Size	7798	35764	35751

See notes following Table A2.

Table A2: Fraction Covered by Medicaid in the NMES and CPS, Children Under 10

	NMES (1987, round 4)	1988 CPS (original ADF)	1988 CPS (rewrite file)
Fraction receiving Medicaid (unedited)	0.147	n.a.	0.152
Fraction receiving Medicaid (edited)	0.154	0.155	0.176
Sample Size	5370	24447	24449

Notes: The CPS fractions are weighted by the March supplement weight and the NMES fractions are weighted by the Round 4 weight. All children refers to children less than 15 years old. The March 1988 rewrite file data are the 1988 data processed using the procedures implemented in 1989, while the original 1988 Annual Demographic File (ADF) data are the same data processed using the procedures used prior to 1989. No unedited variable is available in the original 1988 ADF.

Table A3
Analysis of Measurement Error in Medicaid Reciprocity

	Means (Standard deviations)				
	NMES	1988 CPS (original ADF)	1988 CPS (rewrite)	t-statistic (NMES -ADF)	t-statistic (NMES- rewrite)
Medicaid recipient	0.140 (0.347)	0.143 (0.350)	0.162 (0.368)	-0.691	-5.017
Medicaid receipt given age:					
0	0.183 (0.387)	0.182 (0.386)	0.207 (0.405)	0.054	-1.275
1	0.147 (0.354)	0.169 (0.375)	0.196 (0.397)	-1.277	-2.816
2	0.174 (0.379)	0.150 (0.357)	0.166 (0.372)	1.362	0.451
3	0.172 (0.378)	0.155 (0.362)	0.178 (0.382)	0.935	-0.328
4	0.181 (0.385)	0.158 (0.365)	0.176 (0.381)	1.301	0.281
5	0.160 (0.367)	0.167 (0.373)	0.181 (0.385)	-0.406	-1.213
6	0.153 (0.360)	0.159 (0.365)	0.176 (0.381)	-0.349	-1.329
7	0.118 (0.323)	0.148 (0.355)	0.169 (0.374)	-1.935	-3.260
8	0.127 (0.334)	0.152 (0.359)	0.171 (0.376)	-1.519	-2.655
9	0.112 (0.316)	0.131 (0.338)	0.141 (0.349)	-1.205	-1.832
10	0.115 (0.319)	0.131 (0.337)	0.137 (0.344)	-1.012	-1.389
11	0.116 (0.321)	0.115 (0.319)	0.126 (0.332)	0.061	-0.607
12	0.125 (0.331)	0.120 (0.325)	0.137 (0.344)	0.303	-0.722
13	0.106 (0.308)	0.115 (0.319)	0.124 (0.330)	-0.581	-1.157
14	0.092 (0.289)	0.116 (0.320)	0.125 (0.331)	-1.607	-2.201

Table A3, continued
Analysis of Measurement Error in Medicaid Reciprocity

	Means (standard deviations)				
	NMES	1988 CPS (original ADF)	1988 CPS (rewrite file)	t-statistic (NMES- ADF)	t-statistic (NMES- rewrite)
Medicaid receipt given:					
Two parents	0.043 (0.203)	0.053 (0.223)	0.064 (0.245)	-3.205	-6.601
Male headed family	0.111 (0.316)	0.110 (0.313)	0.177 (0.382)	-0.036	-2.282
Female headed family	0.413 (0.493)	0.442 (0.497)	0.480 (0.500)	2.442	-5.635
Census division=1	0.107 (0.310)	0.133 (0.340)	0.144 (0.351)	-1.234	-1.750
Census division=2	0.157 (0.364)	0.167 (0.374)	0.183 (0.387)	-0.828	-2.138
Census division=3	0.148 (0.356)	0.167 (0.374)	0.188 (0.390)	-1.746	-3.639
Census division=4	0.137 (0.344)	0.118 (0.322)	0.124 (0.329)	1.139	0.777
Census division=5	0.127 (0.333)	0.119 (0.323)	0.150 (0.357)	0.833	-2.342
Census division=6	0.130 (0.336)	0.153 (0.360)	0.182 (0.386)	-1.354	-3.003
Census division=7	0.177 (0.382)	0.127 (0.333)	0.151 (0.358)	3.778	1.937
Census division=8	0.123 (0.329)	0.081 (0.273)	0.094 (0.292)	6.029	1.926
Census division=9	0.118 (0.323)	0.167 (0.373)	0.180 (0.384)	-4.236	-5.327

Notes: Computed from weighted tabulations of the NMES and CPS (original ADF and rewrite files). The census divisions correspond to the following geographic areas: New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. The value at which the t-statistic is significant at the 5% level for a two-tailed test is 1.96.

Table B1
State-level Regressions Using a National Random Sample Instrument

Estimated second stage regression equation: $\Delta Coverage_{g,s} = \alpha_g + \beta_g (\Delta eligible)_{g,s} + \varepsilon_{g,s}$

Children						
Change in fraction covered by:						
	Medicaid		Private ins.		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.913 (0.979)	0.352 (0.606)	-0.459 (1.207)	-0.334 (0.550)	0.394 (0.853)	0.016 (0.510)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes
Women ages 15-45						
Change in fraction covered by:						
	Medicaid		Private ins.		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.071 (0.069)	0.082 (0.082)	-0.007 (0.082)	0.041 (0.089)	-0.007 (0.081)	0.040 (0.089)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes
Single Men ages 15-45						
Change in fraction covered by:						
	Medicaid		Private ins.		Any coverage	
	(a)	(b)	(a)	(b)	(a)	(b)
Δ fraction eligible	0.114 (0.068)	0.099 (0.073)	-0.354** (0.115)	-0.226* (0.115)	-0.167 (0.126)	-0.111 (0.126)
Δ empl./pop'n?	no	yes	no	yes	no	yes
Census division?	no	yes	no	yes	no	yes

Notes: Changes are differences between 1988 and 1993 March CPS. The coefficients for Medicaid and private insurance do not add up to the coefficient for any coverage because of people with more than one type of coverage. Regressions are weighted by the size of the population under age 65 in each state. The sample size in all cases is 50. Standard errors are in parentheses. ** indicates significance at the 95% level, while * indicates significance at the 90% level. The first stage coefficients are 0.078 (0.111) for children, 1.023 (0.102) for women, and 1.306 (0.181) for men.

Table B2
Estimates of Error Misspecification

$\frac{k}{1-k} = \frac{\sigma_{\phi}^2}{\sigma_v^2}$	Ratio of standard errors: true/misspecified
0	1
0.00001	1.006984
0.0001	1.067787
0.0005	1.304164
0.001	1.549738
0.01	3.875162
0.1	11.88145

Notes: Computed from instruments obtained by calculating the eligibility according to the laws of each state for a random sample of women ages 15-45 in the 1988 and 1993 March CPS.

Table B3
Estimates of the Effect on the Standard Errors

Women	Medicaid	Private Insurance	Any Coverage
$\frac{k}{1-k}$	0.001397	0.000512	0.000895
Estimate of (B6)	1.7197	1.3105	1.5013
Coefficient from Cutler and Gruber Table 4	0.008	-0.045	0.046
Standard error	0.018	0.027	0.025
Approximate adjusted standard error	0.031	0.035	0.038

Notes: The first two rows are computed from 1988 and 1993 March CPS samples of women ages 15-45. The third and fourth rows are from Cutler and Gruber (1995), Table 4. The fifth row equals the fourth row multiplied by the second row.