### NBER WORKING PAPER SERIES

# MEDICAID EXPANSIONS AND FERTILITY IN THE UNITED STATES

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Working Paper 12907 http://www.nber.org/papers/w12907

NATIONAL BUREAU OF ECONOMIC RESEARCH 1050 Massachusetts Avenue Cambridge, MA 02138 February 2007

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Medicaid Expansions and Fertility in the United States Thomas DeLeire, Leonard M. Lopoo, and Kosali I. Simon NBER Working Paper No. 12907 February 2007 JEL No. I18,I28

### ABSTRACT

Beginning in the mid 1980s and extending through the early to mid 1990s, a substantial number of women and children gained eligibility for Medicaid through a series of income-based expansions. Using natality data from the National Center for Health Statistics, we estimate fertility responses to these eligibility expansions. We measure changes in state Medicaid eligibility policy by simulating the fraction of a standard population that would qualify for benefits. From 1985 to 1996, the fraction of women aged 15 to 44 who were eligible for Medicaid coverage for a pregnancy increased on average by 24 percentage points. However, contrary to findings in the extant literature, our results do not indicate that this expansion in coverage had a statistically discernible effect on fertility.

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### Introduction

The Medicaid program provides health insurance coverage to low-income women and their children, a group that constitutes roughly two-thirds of the Medicaid population (Gruber, 2003). Although this group is a relatively healthy population compared to other populations that Medicaid covers, the program pays first-dollar coverage for medical expenses associated with childbearing (prenatal, delivery, and postnatal) and childhood health services that could otherwise represent substantial costs for low-income families. The Medicaid program has been expanded several times over its history to increase the number of individuals who qualify for benefits. By 2004, Medicaid paid for about 37 percent of all deliveries in the United States (Kaiser Family Foundation, 2006) and covered about 25 percent of all children (State Health Facts, 2007). Most women eligible for Medicaid qualify only for pregnancy-related care; nevertheless, 10 percent of all women in the United States were covered by Medicaid in 2004 (Kaiser Family Foundation, 2006).

Our paper examines whether by covering much of the health care expense associated with childbearing, including services provided during a child's first five years, Medicaid expansions are associated with changes in fertility in the United States. Medicaid has the potential to reduce greatly the financial costs associated with childbirth and to a lesser extent to reduce the financial cost of being a parent. Average prenatal care/delivery and health care expenses in the first year of a child's life cost roughly \$12,000 (based on Lewit and Monheit's (1992) estimates and inflated to 2006 dollars) and since Medicaid generally provides first-dollar coverage and prohibits cost sharing for children and pregnant women (Congressional Research Service, 2006) most if not all of the expenses would be covered by the Medicaid program. Moreover, Lino (2000) estimates that the direct economic cost of a low-income married couple's child during his or her first 18 years is approximately \$200,000 (in 2006 dollars). Thus, by some estimates, Medicaid covers roughly 6 percent of the direct financial economic costs of having a child by covering health care costs.<sup>1</sup>

An increasing number of families have become eligible to receive health insurance coverage through the Medicaid program because of federal and state policy changes. Medicaid was originally designed to provide health care for single-parent families eligible for welfare and for low-income blind, elderly, and disabled individuals. Initially, low-income single-parent families qualified for Medicaid in one of three ways: enrolling in the Aid to Families with Dependent Children (AFDC) program, having a child classified as Ribicoff child, or meeting the criteria of the medically needy (see Gruber (2003) for details). The program began a series of important changes around 1984 when families who did not qualify for AFDC but who had similar financial circumstances were made eligible. The Omnibus Budget Reconciliation Act (OBRA) of 1986 permitted states to increase eligibility for children and pregnant women with incomes up to 100 percent of the federal poverty limit (FPL). The OBRA of 1987 allowed states to expand eligibility further to 185 percent of the FPL, while the OBRA of 1989 mandated that states increase eligibility to 133 percent of the FPL for pregnant women and children age five or younger. Thus, by 1992, pregnant women and children

<sup>&</sup>lt;sup>1</sup> According to Espenshade (1977), the total cost of a child can be broken into two components: noneconomic costs and economic costs. The non-economic costs are exceedingly difficult to measure. They include, among other things, the fatigue caused by abnormal sleeping patterns and the concern caused by a sick child. The economic costs include both the direct financial costs as well as the opportunity costs. The estimates from Lino (2000) do not include the opportunity costs or the costs of prenatal care and delivery. Foster (2002) argues that the opportunity cost of a child is roughly the same as the direct financial economic cost.

age five or under with incomes below 133 percent of the poverty line qualified for the program, and in some states, such as California, Michigan, and Texas, the eligibility threshold was substantially higher (Gruber, 2003). In total, from 1987 to 1992, both the number of children age 18 or younger and the number of women between the ages of 15 and 44 who were eligible for Medicaid more than doubled (Cutler and Gruber, 1996).

The extant empirical research, as discussed below, has examined the effects of changes in the cost of children on "net fertility" – the likelihood a women has a birth. A change in net fertility could result either from changes in the timing of childbearing or changes in the total demand for children or "total fertility." Given the high costs of having children and the relatively large benefit gained when one becomes eligible for Medicaid, one might expect women to time their childbearing when the cost of having a child is relatively low even if the total number of children desired is held constant. At the same time, these expansions may have also induced some women to have additional children; either of these responses represents a change in her total fertility.

Most economic models of fertility focus on total fertility rather than net fertility. In these models, the response of total fertility to declines in the cost of children is typically indeterminate. Because Medicaid expansions will lower the "price" of a child, one might expect people to have more children (Becker, 1960; 1991). At the same time, the income effect may lead families to decide to have fewer children and devote more resources to those they do have (Becker and Lewis, 1973).

The objective of this paper is to measure the net fertility response to expansions in the Medicaid program that occurred between 1985 to 1996, which could result from either a change in the total demand for children or from a change in the timing of childbirth. Using natality data from the National Center for Health Statistics (NCHS) and a measure of the generosity of state Medicaid programs created from eligibility rules and the March Current Population Survey (CPS), we estimate the relationship between the number of births for both white and African American women aged 15 through 44 and the Medicaid expansions. We find no evidence that expansions in the eligibly of women for public health programs that cover the costs related to childbirth had an effect on net fertility in the United States, a result that differs from that found in previous research.

### **Literature Review**

Most empirical investigations of changes in the cost of a child have focused on short-term fertility responses. Leibowitz (1990) used data from the Rand Health Insurance Experiments in which the treatment group was given free health insurance for a period of either three or five years and the control group was provided health insurance with a co-payment and a maximum out-of-pocket expenditure. Leibowitz shows that women who received free health care services were 29 percent more likely to have a birth during the period of the study than women in the control group. Other researchers focusing on the effects of tax policy found that cost savings through the tax system can alter fertility choices (Baughman and Dickert-Conlin, 2003; Dickert-Conlin and Chandra, 1999; Whittington, Alm, and Peters, 1990). Perhaps most closely related to this paper, the literature on welfare policies and their influence on births yields conflicting results (Moffitt, 2003). Some researchers find positive effects of welfare on fertility (e.g., Lundberg and Plotnick, 1995; Kaestner, Korenman, and O'Neill, 2003; Lopoo and

DeLeire, 2006), while others find no relationship (e.g., An, Haveman, and Wolfe, 1993; Duncan and Hoffman, 1990; Hao and Cherlin, 2004; Hoffman and Foster, 2000; Hoynes, 1997; Mayer, 1997).

There is a large literature that has examined the impact of the expansions in Medicaid eligibility on health insurance coverage. Cutler and Gruber (1996) use the March CPS and a simulated Medicaid eligibility measure as an instrument for imputed eligibility to determine the effect of being eligible for Medicaid on the insurance status of children between 1987 and 1992. They estimate that a 10 percentage-point increase in Medicaid eligibility increased Medicaid coverage by 2.4 percentage points and reduced private coverage by 0.7 percentage points among individuals, and that the crowdout of private coverage by public coverage is on the order of 50% of the increase in total Medicaid enrollment among families. This paper has spurred a large literature that uses a variety of methods and data sets (e.g., Dubay and Kenney 1997, Thorpe and Florence 1998, Yazici and Kaestner, 2000, and Card and Shore Sheppard, 2004). Estimates are sensitive to choices made (particularly to how those children with both Medicaid and private coverage are treated) and fall on both sides of the Cutler and Gruber estimates. New research investigating the effect of SCHIP expansions also estimates large amounts of crowdout and relatively low rates of take-up (Lo Sasso and Buchmueller, 2004).

Even though the take-up rate among newly eligible children has been estimated to be rather low, we would expect nearly all pregnant women who are eligible for Medicaid (and not otherwise insured) to enroll in Medicaid at least to cover childbirth expenses. Nearly all births occur in hospitals and hospitals have the ability and incentive to enroll eligible women in the program so as to be reimbursed for expenses. Despite this, Medicaid expansions likely will have a causal impact on fertility only to the extent that women know prior to conception that they will be covered by Medicaid; the percentage of women who end up having their child's delivery expenses paid by Medicaid is likely an over-estimate of the number of women who are aware, prior to pregnancy, that Medicaid will cover the costs of delivery.

In summary, the prior literature shows that the Medicaid expansions were successful in extending coverage to low-income families and that fertility is responsive to financial incentives in the form of cash or in-kind transfers, in general. Thus, it is plausible that Medicaid expansions would affect fertility decisions.

More recent work on the effect of health insurance on fertility has used variation in state mandates to cover infertility treatment in commercially sold employer sponsored insurance. These papers (Hamilton and McManus, 2004; Schmidt, 2005; Bitler, 2006; Bitler and Schmidt 2006; and Bundorf, Henne and Baker 2007) find that extending insurance coverage for infertility treatment raises the use of infertility treatments, and increases fertility (at least among some women). On the other side of fertility technology, Mellor (1998), Kearney and Levine (2006), and Lindrooth and McCullough (2006) find that the public provision of contraceptive services leads to a reduction in childbearing.

To the best of our knowledge, there have been only two studies investigating the relationship between Medicaid expansions and fertility. Joyce, Kaestner, and Kwan (1998) used natality data from 15 states on birth rates among unmarried women aged 19 to 27 with 12 or fewer years of education to determine whether birth rates (and birth counts) changed following the expansions during the mid 1980s to early 1990s. They

used dummy variables for state/years with expansions<sup>2</sup> and found that the expansions were associated with a 5 percent increase in birth rates for white women and no change in birth rates for African American women.

Bitler and Zavodny (2004) used natality data from 1982 to 1996 to estimate the relationship between two measures of Medicaid –the state's eligibility threshold and a calculated index of generosity – and births. They find that expanding eligibility to 133% of poverty is associated with a 4 percent increase in births among unmarried women and 7-9 percent increase in births among women who did not complete high school..

Our work builds on Joyce et al. (1998) and Bitler and Zavodny (2004) in several ways. First, like Bitler and Zavodny (2004), we use data from all 50 states and the District of Columbia from the mid 1980s to the mid 1990s. Again, Joyce et al.'s data were restricted to 15 states between 1986 and 1992.<sup>3</sup>

Second, again like Bitler and Zavodny, our analytical sample is composed of all women ages 15 to 44, including those who are married and who have relatively high levels of education. In contrast, Joyce et al.'s study restricts their sample to unmarried women between the ages of 19 and 27 who have 12 or fewer years of education. Thus, in addition to providing our own estimates, we are able to determine whether Joyce et al's findings are robust to these sample changes.

Third, unlike the previous published study, we use a measure of Medicaid eligibility expansions (following the work of Currie and Gruber (1996) and Cutler and

<sup>&</sup>lt;sup>2</sup> One dummy variable records whether the state expanded eligibility to 100% of the poverty level by OBRA 1986, while the second dummy variable records whether the state expanded eligibility under the 1987 and 1989 OBRAs from 100% of poverty to 185% of poverty.

<sup>3</sup> Given the small number of states for which they had data, Joyce et al. called for more research into this question. "Our findings should be viewed as preliminary, and replication is needed at the national level. ...data on births are available nationally at the individual level, and we hope future research will continue our line of inquiry" (p. 113, Joyce et al., 1998).

Gruber (1996)) based on each state's income eligibility thresholds rather than using these thresholds directly. Our measure of Medicaid expansions represents an improvement because it captures more of the variation in Medicaid eligibility at the state by year level, rather than identifying the average changes due to expansions through a before-and-after approach. As explained in greater detail below, this measure should not be prone to bias caused by endogenous decisions made by individuals who want to qualify for benefits. This measure of Medicaid expansion only varies due to legislative changes thereby circumventing the bias caused by omitted factors and endogeneous decisions (Gruber 2003).

Fourth, our empirical model estimating the impact of Medicaid expansions is based on Currie and Gruber (2001) who adapt the simulated eligibility measures developed in earlier papers for use with natality data, and allows us not only to remove unobserved factors that are constant within states and within years as in Joyce et al. (1998) and Bitler and Zavodny (2004), but also to remove additional sources of unobserved heterogeneity by controlling for fixed effects and time trends within groups defined by race, education, age, and marital status.

# **Data and Methods**

#### Data

We use a variety of data sources for our analysis. For birth counts, we use the NCHS natality data series from 1985 to 1997. Data in the NCHS natality series are compiled from birth certificates through the Vital Statistics Cooperative Program, which guarantees some uniformity in the information collected. Each state submits data

9

electronically to the NCHS, and the resulting annual file contains a record for nearly all births that occur within the United States. The NCHS natality series also reports all information available on the U.S. Standard Certificate of Live Birth, including mother's age, race/ethnicity, state of residence, education level, and marital status. We restrict our analysis to births to white and African American women in the United States between the ages of 15 and 44, ages which are typically considered a woman's fertile period in the research literature.

Table 1 shows annual birth counts for mothers in the United States who were between the ages of 15 and 44 for each year from 1985 to 1997. Births counts during this period ranged between 3.7 and 4.1 million per year. Births counts were rising during the mid to late 1980s reaching a peak in 1990 before falling every year from 1990 to 1997.

Table 1 also reveals several important issues to consider with the NCHS data. Throughout the period, but especially from 1985 through 1989, the natality files lack information on the educational attainment for a large number of mothers. During these years, data on race and marital status are also missing in a small number of cases. For our initial analyses, we use only those cases with complete information on education, race, and marital status. This duplicates the work of previous researchers who also only used complete cases in their analyses.<sup>4</sup> We also run robustness checks restricting our sample to births beginning in 1989 to help determine the impact the missing cases may have on our results.

<sup>&</sup>lt;sup>4</sup> Bitler and Zavodny (2000) restrict their sample to women whose age, race, marital status, and number of previous live births were reported on the birth certificate. Joyce et al. (1998) did not use data from some states (Nebraska and New York) that omitted information on marital status and education. Based on the information we report in Table 1, we lose a considerable number of births if we restrict our sample to the women who reported education on the birth certificate.

For our analysis, we group women into 44 unique demographic cells in each state and each year (identical groups as those used by Currie and Gruber, 2001).<sup>5</sup> For each race, we count the number of births to teens aged 15 to 18. For women aged 19 and older we create three age categories: 19 to 24, 25 to 34, and 35 to 44 and separate them further by four categories of mothers' education: high school drop-out, high school graduate, some college, and at least a college education. Finally, for mothers with at least a high school education, we also classify mothers by their marital status. This procedure yields 22 cells for white mothers and 22 cells for African American mothers.

Our Medicaid expansion measure (simulated eligibility) varies by year, state, and cell from 1985-1996. To create this variable, we combine three years of the March CPS (1996, 1997, and 1998) to obtain adequately sized nationally representative samples (of at least 300 women) in each of the 44 age/education/marital status demographic cells.<sup>6</sup> We calculate the fraction of the women in each demographic cell who would be eligible for Medicaid in each state and in each year from 1985 to 1996 (adjusting incomes for inflation). For example, we take the nationally representative sample of White women aged 19-24 who are high school dropouts and calculate the fraction that would be eligible for Medicaid if they lived in Alaska in 1985, in Alaska in 1986 (with inflation adjustments), and similarly if they lived in each state in each year. The use of a national sample for each cell is to account for the fact that a given income threshold change may have different ramifications depending on the income distribution and family structure of

<sup>&</sup>lt;sup>5</sup> Currie and Gruber (2001) include an additional race category "other" thereby generating 66 cells. We chose not to use "other" since in our data there is heterogeneity in the composition of this category across states.

<sup>&</sup>lt;sup>6</sup> Note that even with three years of CPS data, there are seven cells for African American women that fail to reach a sample size of 300 women of childbearing age per cell. These cells have an average of 165 women each.

that demographic group. This procedure yields 107,712 observations [44 (cells)\*51(states)\*12(years)\*4(quarters)] on Medicaid eligibility by demographic group, year, and state.

For specification checks, we recreate this simulated eligibility measure in two different ways. First, we repeat our original exercise using a base sample that changes over time (taking the CPS of year t-1, t, and t+1 to calculate simulated eligibility for year t, and so on with a moving three year window to ensure adequate sample size). We refer to this variable as the "Moving National Simulated Medicaid Measure." Second, we repeat our original exercise using a region-specific sample instead of running a national sample through each state. That is, if one considers the fact that the national sample is wealthier than the actual population of Alabama and poorer than the actual population in Alaska, we want to take into account the fact that a 10 point change in the FPL rule for Alabama may be a more substantial change in Alabama than for the nation as a whole. By taking a representative sample at the region level (for example, the South Census region for Alabama), we make the simulation sample more similar to the actual socioeconomic composition of the state than is the national sample. We increased the number of CPS years from which the base sample is drawn (to 8 from 3) to ensure adequate sample size. This measure, called "Region-Based Simulated Medicaid Measure," is otherwise the same.

Our simulated measure of eligibility can be interpreted as an exogenous index of the expansiveness of Medicaid eligibility. This measure represents an improvement in the measurement of the Medicaid expansions used in the fertility literature, but follows a standard method used in other papers in the Medicaid literature. Increases in eligibility thresholds only matter to the extent actually eligibility increases. For example, an increase in the thresholds from 100% of the poverty line to 120% might induce a smaller increase in eligibility than an increase from 120% to 140% because of the distribution of family income.

The measure is also an improvement over using actual eligibility (which, we could not use in this paper in any case as the natality data do not contain information on income). Actual Medicaid eligibility is likely to be endogenous as eligibility is partially determined by unobserved individual and family characteristics that may be correlated with the demand for children, and because women may reduce their hours of work (and their earnings) when they choose to have children. By contrast, the measure of Medicaid expansions we use is exogenous, and varies by state and by year only to the extent that policy changes.

Figure 1 illustrates our measure of the proportion of the population of women aged 15 to 44 who were eligible for Medicaid each year from 1985 to 1996. The graph shows the rapid expansion of the program. In 1985, just over 11 percent of all women were eligible for Medicaid. By 1996, over 35 percent of all women were eligible.

# Methods

Ideally, to determine if Medicaid has an influence on fertility, we would take a population of low-income women and randomly assign them to a treatment group that would be eligible for Medicaid, including prenatal care and health care for the child, and to a control group that would not be eligible to receive these benefits (similar to the RAND experiment in Leibowitz (1990)). We could then compare the fertility patterns of

the treatment and control groups to determine the effect of Medicaid expansions on fertility.

Unfortunately, other than that from the RAND experiment, this type of experimental data is not available. To estimate the relationship between Medicaid expansions and birth counts, therefore, we estimate the following equation:

(1) 
$$\ln(\operatorname{birth})_{\operatorname{stqc}} = \beta_0 + \beta_1 \operatorname{Med}_{\operatorname{st}(q-3)c} + \beta_2 \operatorname{UR}_{\operatorname{st}(q-3)} + \operatorname{Wel}_{\operatorname{st}(q-3)}'\beta_3 + \beta_4 \operatorname{A}_{\operatorname{st}(q-3)} + \beta_5 \operatorname{Pop}_{\operatorname{st}} + \beta_6 s_s + \beta_7 t_t + \beta_8 q_q + \beta_9 c_c + \beta_{10} c_c * s_s + \varepsilon_{\operatorname{stqc}},$$

where the outcome is the natural logarithm of the birth count in state *s* in year *t* in quarter q in cell *c*; Med is the simulated Medicaid eligibility measure; UR is the state unemployment rate; **Wel** is vector of welfare measures, including the maximum AFDC/TANF benefit available for a family of three, an indicator equal to one if the state had a family cap provision, an indicator for a time limit waiver, and an indicator equal to one starting in the year TANF was implemented and every year thereafter; A is an indicator equal to one in the years state *s* restricted state Medicaid funding for abortions; and Pop is the state population of women aged 15-44. The unemployment rate, welfare variables, and Medicaid measures are lagged three quarters to allow for gestation.<sup>7</sup> Following the previous studies on this topic, we also include state fixed effects to control for unobserved measures that are common to all mothers within a given year, and quarter fixed effects to remove the unmeasured factors that contribute to seasonal fluctuations in births. In addition to the state, year, and quarter indicators, we also include fixed effects

<sup>&</sup>lt;sup>7</sup> Because we lagged several variables by three quarters, have birth data from 1985 to 1997, and have simulated Medicaid eligibility from 1985-1996, our actual time series runs from the last quarter of 1985 through the first three quarters of 1997.

to capture unobservable fertility differences at the cell and the cell by state levels. These additions allow us to control for unobserved but constant factors that vary across demographic cells within states that also might be correlated with Medicaid eligibility.

Prior to describing results from this model (and in an attempt to duplicate results from prior research), we report findings from a model using state, year, and quarter indicators only, i.e., without the cell and cell-state indicators (Model 1). In Model 2, we add state-year linear time trends to the Model 1.<sup>8</sup> Models 3 through 5 represent our preferred specifications. In Model 3, we estimate the model described above, which identifies the Medicaid coefficient using variation within state cells over time (these models also include time and quarter fixed effects). In Model 4, we add cell fixed effects to Model 2; in Model 5, we add both cell fixed effects and cell by state fixed effects to Model 2. We compare the results from these more richly specified models to those reported in the literature.

# Results

Table 2 reports results by race for each of our five different specifications. Results from Model 1 in the top panel (which includes only the Medicaid eligibility measure, the statelevel unemployment rate, the welfare variables, Medicaid restrictions on abortion funding, state population, state, year, and quarter fixed effects), suggest a positive and statistically significant relationship between Medicaid eligibility and births for white women. Since the Medicaid eligibility measure is in percentage terms, the coefficient

 $<sup>^{8}</sup>$  Joyce at al (1998) also estimated models with state-year linear trends.

implies that a one percentage point increase in the population eligible for Medicaid is associated with a 0.9 percent increase in the number of births among white women.

In Model 2, we add linear time trends by state. The estimated relationship between Medicaid eligibility and births falls slightly: a one percentage point increase in eligibility is associated with a 0.8 percent increase in births. In Model 3, we add cell and cell by state fixed effects to the Model 1 specification. This addition is to account for differences in fertility along these demographic characteristics that are time invariant but differ by state. For example, the fertility rate of 25- to 34-year-old, unmarried, white women with less than a high school education may be different in Massachusetts than it is in Louisiana. After accounting for these differences, the coefficient on Medicaid eligibility declines slightly (to 0.006) and becomes less precisely measured, leading to a statistically insignificant result.<sup>9</sup> In Model 4, we add cell fixed effects to the Model 2 specification, and the coefficient falls to about zero. In Model 5, we add state by year linear trends to the Model 4 specification. Again, the coefficient is very close to zero.

We find a similar pattern for African American women, reported in the second panel. Models 1 and 2 show large and statistically significant coefficients for Medicaid eligibility: a one percentage point increase in Medicaid eligibility is associated with a 2.5 percent increase in births. In Model 3, however, the coefficient declines substantially (to 0.007) and is no longer statistically significant. As with white women, the coefficient for Medicaid is even smaller but remains positive in Models 4 and 5.

While we measure the changes in the number of births for all women by race in Table 2, one might expect to see larger effects in the relationship among lower

<sup>&</sup>lt;sup>9</sup> It is noteworthy that the addition of the cell fixed effects (and the cell by state fixed effects) explains a considerable amount of the variation in birth counts. The R-squared statistic increases from 0.396 to 0.869 with the inclusion of these cell fixed effects.

socioeconomic status women. In Tables 3 through 5, we show results using the same models for three sub-samples: (1) unmarried women with a high school education or less (excluding teens), (2) all unmarried women, and (3) women who are teenagers or who have less than a high school education. For all three sub-samples, we separately examine white and African American women.

In Table 3, we analyze the relationship for unmarried women with a high school education or less, excluding women 18 and younger. Results from Models 1 and 2 show very large, positive, and statistically significant coefficients for Medicaid eligibility. Once we include cell fixed effects in the models, however, the magnitude of the coefficients drops appreciably. The coefficient in Model 3, suggests a marginal effect of 1.1 percent, while Model 4 and 5 suggest the effect is closer to zero. None of the estimates in Models 3 though 5 is statistically significant, however. The patterns for the sign, magnitude, and statistical significance for the Medicaid coefficient among unmarried, African American women with a high school education or less is similar to that for white women.

In Table 4, we model the relationship between Medicaid eligibility and births among unmarried women. Adding more educated unmarried women does not change the substantive conclusions we reach based on Table 4. We see positive relationships for both racial groups in Models 1 and 2, but once we control for cell fixed effects, the coefficients are small and statistically insignificant.

In Table 5, we report the estimated relationship between Medicaid eligibility and births for women under age 19 and older women who have less than a high school education. Among white women, Models 1 and 2 suggest no relationship between births and Medicaid expansions. In the remaining models, however, we do find a positive and statistically significant relationship. Model 3 implies that a one percent increase in Medicaid eligibility among teenagers and women with less than a high school education is associated with a 1.4 percent increase in births. Models 4 and 5 both suggest a slightly smaller, but statistically significant, effect of around 0.8 percent.

By contrast, we find no relationship between Medicaid eligibility and births for African American teenagers and African American women with less than a high school education. The pattern of the coefficient estimates is similar, however. The coefficient estimates from Model 1 and 2 are trivial in size. We see a larger, but statistically insignificant estimate in Model 3. The coefficient estimates for Models 4 and 5 are similar in size to that found among white teens and high school dropouts, but the standard errors are much larger suggesting no statistically discernable relationship.

Collectively, these results suggest that results using state, year, and quarter fixed effects as well as results from models that include state-year linear time trends are quite different from those found when one also uses cell by state fixed effects. In the specifications with cell by state fixed effects and state-level time trends, we find no relationship between birth counts and Medicaid expansions except among white teens and women with less than a high school education.

#### **Robustness Tests**

In this section, we estimate a series of additional models to determine if the results reported in the previous section are robust to different data choices.

First, several demographic cells had no births in a given state in a given year. Since we take the natural log of births, the outcomes in these cells are undefined. Rather than dropping these cases, we assigned these cells a value of 1 implying a logged value of 0. To determine if this choice influenced our results, we reran all of the models dropping the cells with 0 births. The results (available upon request) are nearly identical to those reported above.

Second, we ran the models reported in Tables 2 through 5 using slightly different measures of simulated Medicaid eligibility. The first, called "Region-Based Simulated Medicaid Measure," uses a CPS sample representative at the region level, rather than national level, and the second, called "Moving National Simulated Medicaid Measure," uses a national sample that changes over time. Results from these models, reported in Appendix Table 1, are nearly identical to those reported in the text.

Third, we also have concerns about missing data on education and race. Table 6 shows the mean number of births (based on data with complete information from the NCHS) and the mean percentage of women eligible for Medicaid (from quarter q-3) by sub-sample from 1985 to 1997. For teens and high school dropouts, the difference in the mean number of births from 1985 to 1997 is 840 per state. If one considers the difference between 1989 and 1997, the change is only 31 births. Table 1 demonstrates that the unusually low rates from 1985 to 1988 are due to missing data. Given the potential influence of missing data in the early years of our time series, we reran all of the models using data from 1989 to 1997 and report the results in Tables 7 through 10.<sup>10</sup> Since the

<sup>&</sup>lt;sup>10</sup> Importantly, we still see considerable expansion of the Medicaid program during this time. For instance, the percentage of teens and high school dropout who were eligible increased 18.1 percentage points during this time, and the percentage of unmarried women who were eligible increased 18.2 percentage points.

majority of the Medicaid expansions occurred prior to 1992, we also report results using data from 1989 to 1992.

Table 7 reports the results for all women aged 15 to 44. Our findings for white women aged 15 to 44 from 1989 to 1992 and 1989 to 1997 are very similar to those reported in Table 2. For Models 1 and 2, we find a marginal effect of roughly 0.8 to 1.0 percent. In Models 3 through 5, we find no statistically significant coefficients with estimates that are much smaller in magnitude. For African American women, the coefficient for Medicaid expansions are similar in magnitude to that found in Table 2. Unlike the estimates for Models 3 through 5 in Table 2, however, the coefficients are negative in Table 7. They are also insignificant in nearly all instances.

In Tables 8 and 9, both using unmarried women, we report results that are nearly identical to the results using the full sample: they are large, positive and statistically significant in Models 1 and 2 and much smaller and insignificant in Models 3 through 5. In Table 10, we report the results for the sub-sample of teenagers and women with less than a high school education (the only sub-sample for which we found a statistically significant association in the main analysis using data from 1985 through 1997). In this sub-sample and with this restricted number of years of data, none of the coefficients in Models 3 through 5 are statistically significant for either white or African Americans.

One potential explanation for our results is that the Medicaid variable is picking up both the positive effect due to the reduction in the cost of a child as well as a negative effect due to the family planning services for which eligible families qualify. Together, these two countervailing influences net one another out. To determine the importance of this potential explanation, we report results for first births in Table 11. Low-income women without children would not qualify for Medicaid; therefore, they do not have the family planning services available to them. Thus, we should only observe the positive influence of Medicaid, assuming it exists, on first births.

In Table 11, we report results for first births only. While the coefficients are a bit different in magnitude, the pattern found in the results is the same as we found using all births. As such, we conclude that the negative influence of family planning services is not suppressing the positive influence of Medicaid expansions.

Finally, it is worth trying to understand why our results are different from Joyce et al. (1998). In addition to the slightly different samples chosen, we might see differences due to the shorter time series they used or the smaller sample of states. In Table 12, we report results using unmarried, white women with a high school education or less, the sample quite similar to the group that generated their strongest finding.

Row 1 reports results from the five models using all unmarried women with a high school education or less. Results from Model 1 and Model 2 suggest a marginal effect of 1.3 percent.<sup>11</sup> However, once we include cell by state fixed effects, the coefficient estimates flip sign and are statistically significant. Because the results from 1986 to 1992 might be particularly influenced by missing cases, we re-estimated the models using all 13 years of data (1985-1997) in row 2. Interestingly, the results using the 15 states over the entire period are similar, but less positive in all instances. For comparison purposes, we report results using all 51 states but from 1986 to 1992 in the

<sup>&</sup>lt;sup>11</sup> It is informative to compare our estimate to that found in Joyce et al. (1998). Joyce and colleagues find that the birth change is associated with the first phase of the expansion of Medicaid, which they date in Table 2, p. 111. Using our simulated Medicaid eligibility measure, we calculated the mean difference in proportion eligible from 1986 to the date reported in their Table 2. Our crude approximation suggestions that eligibility increased by 3.6 percent on average. Given the mean change in the birth rate of 5 percent found in Joyce et al. (1998), a one percentage point increase in eligibility is associated with a 1.4 percent increase in the birth rate suggesting that our estimate (1.3) is quite close to theirs.

third row. Results from these models suggest that these 15 states are not generalizable to the results for the entire nation. Once we include the other 36 states, we find large and statistically significant results for all models. Finally, in the last row, we report results using all 51 states over the 12 year period. Results from this model are consistent with the findings from earlier models suggesting that one would want to include the entire time series rather than just the late 1980s, a period when the number of birth were rising naturally (and even more precipitously given the missing data issues). Here too, our results suggest that the findings based on the 15 states are probably not generalizable to the entire nation.

#### Conclusion

Beginning in the mid 1980s and continuing through the mid 1990s, the criteria for Medicaid eligibility changed, increasing the proportion of the population eligible for the program. Given the high costs of pregnancy, childbirth and childhood related health care, Medicaid receipt constitutes a considerable reduction in the cost of a child. As such, using natality data from the NCHS and a measure of Medicaid eligibility expansions, we asked if fertility changed in response to these Medicaid expansions. In addition to capitalizing on variation within states over time as in previous work, we construct an empirical test at the demographic-cell level, following Currie and Gruber (2001). Contrary to the previous literature on the topic, we find no statistically significant relationship between Medicaid expansions and fertility in the United States during this period. This result persists using sub-samples of potentially low-income women and a variety of robustness checks. Our results do not suggest that expansions in Medicaid designed to increase health insurance coverage among low-income families induce women to have more children. If there is any fertility effect at all, it is probably much smaller than suggested by Joyce et al. (1998). However, more research is needed to determine whether Medicaid expansions might lead to other changes in family structure.

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Annual Cour	Annual Counts for Domestic Births to Women Aged 15 to 44							
Year	Total Births	Missing	Missing	Missing	Total Cases			
		Education	Race	Marital	with			
				Status	Complete			
					Information			
1985	3,749,179	886,810	627	2,110	2,859,632			
1986	3,745,120	899,145	679	2,132	2,843,164			
1987	3,797,708	912,339	498	2,110	2,882,761			
1988	3,897,495	1,093,417	571	3,309	2,800,198			
1989	4,027,873	358,772	0	0	3,669,101			
1990	4,144,917	289,825	0	0	3,855,092			
1991	4,097,184	132,470	0	0	3,964,714			
1992	4,050,786	63,894	0	0	3,986,892			
1993	3,985,357	59,860	0	0	3,925,497			
1994	3,937,359	56,657	0	0	3,880,702			
1995	3,884,620	58,921	0	0	3,825,699			
1996	3,877,301	55,095	0	0	3,822,206			
1997	3,867,296	55,869	0	0	3,811,427			
~	10.017	11 0	37 . 11 . D . C		* *			

Table 1.Annual Counts for Domestic Births to Women Aged 15 to 44

Source: National Center for Health Statistics Natality Data Series, Various Years

/ V	Model 1	Model 2	Model 3	Model 4	Model 5
White					
	0.009**	0.008**	0.006	0.000	0.001
	(0.002)	(0.002)	(0.005)	(0.004)	(0.003)
$R^2$	0.355	0.396	0.869	0.884	0.911
Ν			53,856		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					
African					
Åmerican					
	0.025**	0.025**	0.007	0.001	0.002
	(0.002)	(0.002)	(0.006)	(0.003)	(0.003)
$R^2$	0.648	0.679	0.881	0.887	0.914
Ν			53,856		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					

Table 2.Coefficient Estimates for Medicaid Eligibility from WLS Model of Log BirthCounts, by Race, 1985-1997

Table 3.

White $0.054^{**}$ $0.054^{**}$ $0.011$ $0.004$ $0$ R <sup>2</sup> $0.585$ $0.636$ $0.839$ $0.871$ $0$ N         14,688         14,688         14,688         14,688         14,688           State FE         Yes         Yes         Yes         Yes         Yes         Yes           Year FE         Yes         Yes         Yes         No         Yes         Yes         Yes           State Year         No         Yes         No         Yes	Race, 1985-15					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		Model 1	Model 2	Model 3	Model 4	Model 5
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	White					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		0.054**	0.054**	0.011	0.004	0.004
N14,688State FEYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYesCell FENoNoYesYesYesCell*StateNoNoYesNoYesFENoNoYesNoYesAfrican American $0.034^{**}$ $0.034^{**}$ $0.012$ $0.007$ 0(0.004)(0.003)(0.011)(0.004)(0R <sup>2</sup> 0.691 $0.725$ $0.883$ $0.902$ 0N14,68814,68814,68814,688State FEYesYesYesYesYesYear FEYesYesNoYesYesYesState*YearNoYesNoYesYesYesCell FENoNoYesYesYesYes		(0.005)	(0.004)	(0.008)	(0.004)	(0.004)
State FEYesYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYeslinear trendCell FENoNoYesYesCell*StateNoNoYesNoYesFENoNoYesNoYesAfrican American $(0.004)$ $(0.003)$ $(0.011)$ $(0.004)$ $(0.004)$ $(0.003)$ $(0.011)$ $(0.004)$ $(0$ $R^2$ $0.691$ $0.725$ $0.883$ $0.902$ $0$ N14,688YesYesYesYesState FEYesYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYesLinear trendCell FENoNoYesYes	$R^2$	0.585	0.636	0.839	0.871	0.894
Year FEYesYesYesYesYesYesState*YearNoYesNoYesYesYeslinear trendImage: Cell FENoNoYesYesYesCell*StateNoNoYesNoYesYesFEImage: Cell*StateNoNoYesYesYesAfrican AmericanImage: Cell*StateNoNoYesYesImage: Cell*StateNoNoYesNoYesImage: Cell*StateNoNoYesNoYesState FEYesYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesYesYesYesIinear trendImage: Cell FENoNoYesYesYes	Ν			14,688		
State*YearNoYesNoYesYeslinear trendNoNoNoYesYesYesCell FENoNoNoYesNoYesFENoNoYesNoYesYesAfrican American $0.034^{**}$ $0.034^{**}$ $0.012$ $0.007$ 0 $(0.004)$ $(0.003)$ $(0.011)$ $(0.004)$ $(0.004)$ R <sup>2</sup> $0.691$ $0.725$ $0.883$ $0.902$ 0N14,688YesYesYesYesState FEYesYesYesYesYesYesState*YearNoYesNoYesYesYeslinear trend Cell FENoNoYesYesYesYes	State FE	Yes	Yes	Yes	Yes	Yes
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Year FE	Yes	Yes	Yes	Yes	Yes
$\begin{array}{c ccccc} Cell FE & No & No & Yes & Yes & Yes \\ Cell*State & No & No & Yes & No \\ FE & & & & & & & & & & & \\ \hline African \\ American & & & & & & & & & & \\ & & & & & & & & $	State*Year	No	Yes	No	Yes	Yes
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	linear trend					
FE       African American       0.034**       0.034**       0.012       0.007       0 $(0.004)$ $(0.003)$ $(0.011)$ $(0.004)$ $(0)$ $R^2$ $0.691$ $0.725$ $0.883$ $0.902$ $0$ N       14,688       14,688       14,688       14,688       14,688         State FE       Yes       Yes <td>Cell FE</td> <td>No</td> <td>No</td> <td>Yes</td> <td>Yes</td> <td>Yes</td>	Cell FE	No	No	Yes	Yes	Yes
African American $0.034^{**}$ $0.034^{**}$ $0.012$ $0.007$ $0$ (0.004) $(0.004)$ $(0.003)$ $(0.011)$ $(0.004)$ $(0$ $R^2$ $0.691$ $0.725$ $0.883$ $0.902$ $0$ N14,68814,68814,688State FEYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYesInear trendCell FENoNoYesYes	Cell*State	No	No	Yes	No	Yes
American $0.034^{**}$ $0.034^{**}$ $0.012$ $0.007$ $0$ $(0.004)$ $(0.003)$ $(0.011)$ $(0.004)$ $(0$ $R^2$ $0.691$ $0.725$ $0.883$ $0.902$ $0$ N14,68814,68814,688State FEYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYesInear trendCell FENoNoYesYes	FE					
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	African					
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	American					
R20.6910.7250.8830.9020N14,68814,688State FEYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYeslinear trendCell FENoNoYesYes		0.034**	0.034**	0.012	0.007	0.006
N14,688State FEYesYesYesYear FEYesYesYesYesState*YearNoYesNoYeslinear trendCell FENoNoYesYes		(0.004)	(0.003)	(0.011)	(0.004)	(0.004)
State FEYesYesYesYesYear FEYesYesYesYesYesState*YearNoYesNoYesYeslinear trendCell FENoNoYesYes	$R^2$	0.691	0.725	0.883	0.902	0.919
Year FEYesYesYesYesState*YearNoYesNoYesYeslinear trendCell FENoNoYesYes	Ν			14,688		
State*YearNoYesNolinear trendCell FENoNoYesYes	State FE	Yes	Yes	Yes	Yes	Yes
linear trend Cell FE No No Yes Yes	Year FE	Yes	Yes	Yes	Yes	Yes
Cell FE No No Yes Yes	State*Year	No	Yes	No	Yes	Yes
	linear trend					
	Cell FE	No	No	Yes	Yes	Yes
Cell*State No No Yes No YE	Cell*State	No	No	Yes	No	Yes

Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts for Unmarried Women with a High School Education or Less (excluding teens), by Race, 1985-1997

Model 1 Model 2 Model 3 Model 4 Model 5 White 0.052\*\* 0.052\*\* 0.006 0.000 0.002 (0.002)(0.002)(0.007)(0.005)(0.005) $\mathbf{R}^2$ 0.556 0.593 0.876 0.889 0.915 Ν 31,824 State FE Yes Yes Yes Yes Yes Year FE Yes Yes Yes Yes Yes State\*Year Yes No Yes Yes No linear trend Cell FE No No Yes Yes Yes Cell\*State No Yes No Yes No FE African American 0.037\*\* 0.037\*\* 0.011 0.005 0.005 (0.004)(0.002)(0.002)(0.009)(0.004) $R^2$ 0.678 0.705 0.896 0.899 0.924 Ν 31,824 State FE Yes Yes Yes Yes Yes Year FE Yes Yes Yes Yes Yes State\*Year Yes No Yes No Yes linear trend Cell FE Yes Yes No No Yes Cell\*State No No Yes No Yes FE

Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts
for Unmarried Women, by Race, 1985-1997

Table 4.

Table 5.

	Model 1	Model 2	Model 3	Model 4	Model 5
White					
	0.000	-0.001	0.014*	0.009**	0.008**
	(0.003)	(0.002)	(0.006)	(0.003)	(0.003)
$R^2$	0.544	0.613	0.812	0.866	0.879
Ν			9,792		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					
African					
American					
	0.001	-0.000	0.011	0.006	0.006
	(0.002)	(0.001)	(0.012)	(0.004)	(0.005)
$R^2$	0.654	0.694	0.877	0.900	0.916
Ν			9,792		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					

**Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts for Teens and High School Dropouts, by Race, 1985-1997** 

rercentage of ropulation Engible for Medicald and Birth Counts, by Subgroups							
Year	Teens and H	IS Dropouts	Unmarried v	vomen ≤HS	Unmarrie	d women	
			Education (ex	cluding teens)			
	Lagged	Births	Lagged	Births	Lagged	Births	
	Medicaid		Medicaid		Medicaid		
1985	26.9	585.3	28.2	408.9	17.7	278.8	
1986	27.0	578.6	28.3	411.6	17.7	281.2	
1987	28.5	580.8	29.7	423.0	18.7	289.5	
1988	35.1	541.2	35.8	398.3	23.1	274.4	
1989	45.6	1394.0	45.8	990.5	30.6	646.4	
1990	53.3	1567.0	53.3	1117.3	36.5	720.2	
1991	56.7	1644.7	56.9	1180.7	39.4	766.8	
1992	57.3	1631.7	57.5	1177.0	40.0	767.4	
1993	58.5	1591.8	58.7	1147.7	41.0	759.7	
1994	59.7	1548.5	59.9	1132.5	42.0	761.9	
1995	60.7	1496.8	60.9	1082.1	43.0	736.3	
1996	63.8	1468.9	64.0	1072.4	45.6	729.3	
1997	63.7	1424.9	64.0	1044.1	45.6	708.8	
1997-	36.8	839.6	35.8	635.2	27.9	430.0	
1985							
1997-	18.1	30.9	18.2	53.6	15.0	62.4	
1989							

 Table 6.

 Percentage of Population Eligible for Medicaid and Birth Counts, by Subgroups

*Notes*: Simulated Medicaid variable measured from quarter q-3.

Counts, by Ka		<u>92 anu 1969 to</u>		26.1.1.4	
	Model 1	Model 2	Model 3	Model 4	Model 5
White					
1989-1992	0.010**	0.010**	0.003	-0.004	-0.002
	(0.002)	(0.002)	(0.005)	(0.003)	(0.003)
$R^2$	0.318	0.328	0.956	0.928	0.967
Ν			17,952		
1989-1997	0.008**	0.008**	-0.000	-0.003	-0.001
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
$R^2$	0.327	0.339	0.959	0.931	0.971
Ν			39,270		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					
African					
American					
1989-1992	0.026**	0.026**	-0.002	-0.004	-0.003
1,0, 1,,2	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
$R^2$	0.651	0.660	0.955	0.928	0.961
N	01001	0.000	17,952	0.19 = 0	0.001
1989-1997	0.024**	0.024**	-0.002	-0.005*	-0.004
1707 1771	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$R^2$	0.665	0.672	0.959	0.937	0.966
N	0.000	0.072	39,270	0.907	0.900
11			59,270		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
Cen <sup>*</sup> State	110	110	100	110	103

Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts, by Race, 1989 to 1992 and 1989 to 1997

Table 7.

Table 8.

111100, 1909 00	Model 1	Model 2	Model 3	Model 4	Model 5
White	11104011	11104012	11104013	1110401	1110 401 0
1989-1992	0.049**	0.059**	0.001	-0.003	-0.003
1,0, 1,,=	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)
$R^2$	0.598	0.628	0.949	0.925	0.961
N	0.270	0.020	4,896	0.925	0.901
1989-1997	0.044**	0.047**	0.001	0.000	0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
$R^2$	0.606	0.627	0.954	0.933	0.969
N	0.000	0.027	10,710	0.955	0.909
1.			10,710		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					
African					
American					
1989-1992	0.028**	0.032**	-0.004	-0.004	-0.004
	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)
$R^2$	0.675	0.687	0.954	0.938	0.961
Ν			4,896		
1989-1997	0.026**	0.027**	0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
$R^2$	0.680	0.688	0.962	0.950	0.969
Ν			10,710		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					

Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts for Unmarried Women with a High School Education or Less (excluding teens), by Race, 1989 to 1992 and 1989 to 1997

for Unmarrie	d Women, by	Race, 1989 to 1	992 and 1989	to 1997	
	Model 1	Model 2	Model 3	Model 4	Model 5
White					
1989-1992	0.054**	0.057**	0.002	-0.004	-0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
$R^2$	0.573	0.588	0.959	0.930	0.968
Ν			10,608		
1989-1997	0.047**	0.047**	-0.001	-0.003	-0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
$R^2$	0.569	0.584	0.961	0.935	0.972
Ν			23,205		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					
African					
Åmerican					
1989-1992	0.038**	0.039**	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
$R^2$	0.679	0.688	0.962	0.936	0.966
Ν					
1989-1997	0.034**	0.034**	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
$R^2$	0.686	0.693	0.965	0.946	0.971
Ν			23,205		
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					

**Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts for Unmarried Women, by Race, 1989 to 1992 and 1989 to 1997** 

Table 9.

for Teens and High School Dropouts, by Race, 1989 to 1992 and 1989 to 1997							
	Model 1	Model 2	Model 3	Model 4	Model 5		
White							
1989-1992	-0.002	-0.003	0.002	-0.002	-0.002		
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)		
$R^2$	0.617	0.632	0.942	0.936	0.957		
Ν			3,264				
1989-1997	-0.005*	-0.006*	0.002	0.002	0.001		
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)		
$R^2$	0.633	0.650	0.953	0.949	0.970		
Ν			7,140				
State FE	Yes	Yes	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes	Yes		
State*Year	No	Yes	No	Yes	Yes		
linear trend							
Cell FE	No	No	Yes	Yes	Yes		
Cell*State	No	No	Yes	No	Yes		
FE							
African							
Åmerican							
1989-1992	-0.003	-0.003	-0.004	-0.006	-0.005		
	(0.002)	(0.001)	(0.005)	(0.004)	(0.004)		
$R^2$	0.652	0.660	0.954	0.939	0.962		
Ν			3,264				
1989-1997	-0.005**	-0.005**	-0.001	-0.003	-0.002		
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)		
$R^2$	0.652	0.661	0.963	0.951	0.971		
Ν			7,140				
State FE	Yes	Yes	Yes	Yes	Yes		
Year FE	Yes	Yes	Yes	Yes	Yes		
State*Year	No	Yes	No	Yes	Yes		
linear trend							
Cell FE	No	No	Yes	Yes	Yes		
Cell*State	No	No	Yes	No	Yes		
FE							

**Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts for Teens and High School Dropouts, by Race, 1989 to 1992 and 1989 to 1997** 

Table 10.

	Model 1	Model 2	Model 3	Model 4	Model 5
- White					
Unmarried	0.043**	0.043**	0.010	0.005	0.005
Women ≤	(0.005)	(0.004)	(0.008)	(0.003)	(0.003)
High School					
Unmarried	0.027**	0.026**	0.006	0.001	0.002
Women	(0.002)	(0.002)	(0.007)	(0.004)	(0.004)
Teens and	-0.029**	-0.031**	0.012	0.008**	0.007**
High School	(0.003)	(0.003)	(0.006)	(0.002)	(0.002)
Dropouts	(0.005)	(0.005)	(0.000)	(0.002)	(0.002)
-					
African					
American					
Unmarried	0.028**	0.028**	0.006	0.001	0.001
Women ≤	(0.003)	(0.003)	(0.008)	(0.004)	(0.004)
High School					
Unmarried	0.015**	0.015**	0.004	-0.000	0.000
Women	(0.002)	(0.002)	(0.007)	(0.003)	(0.003)
Teens and	-0.028**	-0.029**	0.006	0.000	0.001
High School	(0.003)	(0.002)	(0.009)	(0.005)	(0.001)
Dropouts	(0.003)	(0.002)	(0.00))	(0.003)	(0.005)
- <b>T</b>					
State FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State*Year	No	Yes	No	Yes	Yes
linear trend					
Cell FE	No	No	Yes	Yes	Yes
Cell*State	No	No	Yes	No	Yes
FE					

Table 11.Coefficient Estimates for Medicaid Eligibility from WLS Model of Log First BirthCounts, by Race

<sup>1</sup> mary fical ba	mpic				
	Model 1	Model 2	Model 3	Model 4	Model 5
1986-1992	0.013**	0.013**	-0.002**	-0.002*	-0.003**
15 states	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
1985-1997	0.006**	0.006**	-0.004**	-0.004**	-0.004*
15 states	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
1986-1992	0.019**	0.018**	0.016*	0.011**	0.012*
51 states	(0.003)	(0.002)	(0.008)	(0.003)	(0.005)
1985-1997	0.012**	0.010**	0.012	0.006	0.006
51 states	(0.003)	(0.002)	(0.007)	(0.004)	(0.004)

Table 12.Comparison of Coefficient Estimates using Joyce et al. (1998) Sample and CompleteAnalytical Sample

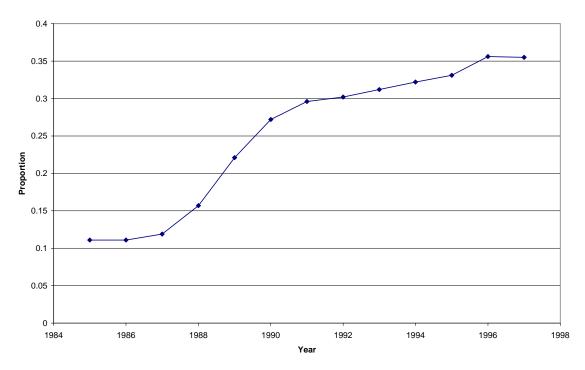


Figure 1: Proportion of Women 15-44 Eligible for Medicaid

Source: Authors' calculation using simulated Medicaid eligibility.

# Appendix Table 1. Coefficient Estimates for Medicaid Eligibility from WLS Model of Log Birth Counts using Alternative Simulated Medicaid Eligibility Measures, 1985-1996

	Model 1	Model 2	Model 3	Model 4	Model 5
Region-Based Simulated Medicaid					
Measure					
White, All Women 15-44	0.010**	0.010**	0.006	0.001	0.002
	(0.002)	(0.002)	(0.006)	(0.004)	(0.004)
White, Unmarried Women with a High	0.058**	0.059**	0.009	0.005	0.006
School Education or less (excluding teens)	(0.004)	(0.003)	(0.009)	(0.005)	(0.005)
White, Unmarried Women	0.058**	0.058**	0.005	0.001	0.003
	(0.003)	(0.002)	(0.008)	(0.005)	(0.006)
White, Teens and High School Drop-outs	0.013**	0.012**	0.014	0.011*	0.011*
	(0.002)	(0.001)	(0.008)	(0.004)	(0.005)
African American, All Women 15-44	0.025**	0.025**	0.006	0.004	0.002
	(0.001)	(0.001)	(0.008)	(0.003)	(0.003)
African American, Unmarried Women with	0.037**	0.038**	0.011	0.014**	0.010
a High School Education or less (excluding	(0.004)	(0.003)	(0.014)	(0.004)	(0.005)
teens)					
African American, Unmarried Women	0.037**	0.037**	0.009	0.008*	0.007
	(0.002)	(0.002)	(0.012)	(0.004)	(0.005)
African American, Teens and High School	-0.002	-0.003	0.012	0.010	0.008
Drop-outs	(0.003)	(0.002)	(0.015)	(0.005)	(0.005)
Moving National Simulated					
Medicaid Measure					
White, All Women 15-44	0.015**	0.014**	0.003	-0.002	-0.002
	(0.003)	(0.002)	(0.005)	(0.004)	(0.003)
White, Unmarried Women with a High	0.053**	0.053**	0.007	0.002	0.002
School Education or less (excluding teens)	(0.004)	(0.003)	(0.006)	(0.004)	(0.004)
White, Unmarried Women	0.056**	0.056**	0.002	-0.003	-0.002
	(0.003)	(0.002)	(0.006)	(0.004)	(0.004)
White, Teens and High School Drop-outs	0.011**	0.010**	0.012	0.007*	0.007*

	(0.002)	(0.002)	(0.006)	(0.003)	(0.003)
African American, All Women 15-44	0.025**	0.025**	0.002	-0.003	-0.003
	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
African American, Unmarried Women with	0.034**	0.033**	0.007	0.002	0.002
a High School Education or less (excluding	(0.003)	(0.002)	(0.007)	(0.003)	(0.003)
teens)					
African American, Unmarried Women	0.035**	0.035**	0.006	0.001	0.001
	(0.002)	(0.002)	(0.007)	(0.003)	(0.004)
African American, Teens and High School	-0.001	-0.002	0.008	0.002	0.003
Drop-outs	(0.002)	(0.001)	(0.009)	(0.004)	(0.004)