Health Insurance for Whom?
The ‘Spill-up’ Effects of Children’s Health Insurance on Mothers

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A rich literature documents the benefits of social safety net programs for children. This paper focuses on an unexplored margin: how children’s programs impact parents’ well-being. We explore changes in children’s public health insurance and its effects on parents’ economic and behavioral outcomes. Using a simulated instrument for Medicaid eligibility expansions in the 1980s and 1990s, we isolate variation in children’s Medicaid eligibility due to changes in government policies. We find that increases in children’s Medicaid eligibility increases the likelihood a mother is married, decreases her labor market participation, and reduces her smoking and alcohol consumption. Our findings suggest improved maternal well-being as measured by the Center for Epidemiological Studies-Depression score, a proxy for mental health. These results uncover a new link that provides an important mechanism, parental well-being, for interpreting the literature’s findings on the long-term, short-term, and intergenerational effects of Medicaid coverage.

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Author order randomized using Ray and Robson ⓡ (2018) technique, the result of which was alphabetic order.

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1. Introduction

In this paper we focus on a relatively unexplored margin of the social safety net: how children's access to social safety net programs impacts their parents' well-being. Specifically, we explore how public health insurance expansions for children affect maternal labor and marriage market outcomes, health behaviors, and mental health. While there is a great deal of research about intergenerational spillovers of receiving social safety net benefits from parents to children, there is much less research about spillovers that go in the opposite direction (reverse intergenerational effects). Documenting this relationship of "spill-up" effects uncovers a new mechanism of how these programs affect children in the short- and long-run. In addition, this analysis helps re-interpret the literature on intergenerational effects and contributes to our understanding of the returns to public programs.

How does public health insurance for children affect parental outcomes? We hypothesize that having an uninsured child and/or out-of-pocket spending on private insurance can be a large financial burden and source of stress for parents, particularly low-income parents. Public insurance can help protect parents from worry about covering the cost of expected and unexpected medical costs, their children's health, and the financial cost of private insurance. The reduction in stress and lowered financial burden could impact labor market decisions, marriage market outcomes, and stress-related health behaviors. This hypothesis is based on the large literature on how public health insurance affects health and human capital,[1] as well as strong evidence that health insurance reduces one's own financial and mental health distress (Gross and Notowidigdo 2011; Finkelstein 2012).[2]

[1] See for example (Goodman-Bacon 2018; Cohodes et al. 2016; Wherry et al. 2018; Wherry and Meyer 2016; Miller and Wherry 2019; Finkelstein 2012; Currie and Gruber 1996a; 1996b).

[2] Financial disagreements are a predictor of divorce (Britt and Huston 2012; Dew, Britt, and Huston 2012).

To determine if children's access to public insurance affects parents, we exploit variation in eligibility criteria for Medicaid and State Children's Health Insurance Program (SCHIP) over time (1980s-2000s) and across states for different age groups.[3] Essentially, children who live in states that have more generous eligibility rules and allow older children to be on public insurance are more likely 1) to be insured by Medicaid as they age, and 2) to have spent a larger fraction of their childhood covered by public insurance. To focus on variation due to these policy changes rather than changes due to demographic changes within a state, we use a simulated instrument that assigns the Medicaid eligibility of a fixed population using the Medicaid eligibility rules for each state in each year (Currie and Gruber 1996a; Currie and Gruber 1996b). Using this simulated instrument, we study the effect of Medicaid expansions on mothers' outcomes measured from 1979-2010.[4]

We use data from the National Longitudinal Survey of Youth 1979 (NLSY 79) to measure decision-making and well-being by focusing on family dynamics including marital status, divorce, and family size, labor force participation and alcohol consumption.[5] We use the longitudinal aspect of the data by including individual fixed-effects to account for individual unobserved confounders. This model specification allows us to use within-mother changes in their children's eligibility to identify the effects of Medicaid expansions on parental outcomes.

The main identifying assumption of the simulated instrument is that changes in public insurance eligibility are not related to parental decision-making and well-being except through increased access to and use of public insurance by their children. However, there may be additional

[3] For the remainder of the paper, we will use "Medicaid" to encompass public insurance provided to children by both programs.
[4] We note that previous studies have documented a strong first stage association between simulated and actual Medicaid eligibility (Cohodes et al. 2016).
[5] Financial distress is a leading contributor to divorce, and access to public insurance greatly improves recipient's financial situations (Gross and Notowidigdo, 2011).

steps on the causal pathway, such as children's use of public insurance reducing financial stress. Many studies have investigated the validity of public insurance expansions as instruments for insurance coverage dating back to the seminal Currie and Gruber works (1996a; 1996b), and we also provide empirical support for this assumption in our data.

One of the reasons why the effect of children's public insurance eligibility on parents has been relatively unexplored in the literature is due to data requirements. One needs a dataset that links children to parents and has information about *all* children. These data also must contain detailed outcome information on parents, preferably with repeated measures, which is rare. We use the NLSY79 Child and Young Adult dataset, which tracks all children born to *women* from the main NLSY79 sample, thus we cannot link fathers to their children. For this reason our analysis focuses on mothers. In supplementary analysis, we use the Current Population Survey (CPS) to provide suggestive evidence for fathers.

Our results show that a 10 percentage point increase in children's simulated Medicaid eligibility increases a mother's likelihood of being married by 2.7%. We decompose this effect and find that the marriage effect is mostly (84%) driven by women staying married (less divorce).

We find that a 10 percentage point higher children's simulated Medicaid eligibility decreases the likelihood of mothers being in the labor force by 4.8%. The increase in mothers exiting the labor force comes from both the employed and the unemployed category, though there are important differences by race and socio-economic status. A plausible reason for women to exit the labor force (and enter into formal marriages) is to spend more time on home production, including childcare.

To understand how these changes impact women's overall well-being, we explore effects on mental health. We find a substantial and robust improvement in maternal mental health in the form of a decrease in Center for Epidemiological Studies Depression score (CES-D). A 10 percentage point increase in children's simulated Medicaid eligibility is associated with a 13% decrease in maternal CES-D.

This paper makes contributions to three strands of literature. First, this paper contributes to our understanding of intergenerational spillovers. Several articles focus on spillovers of parental insurance coverage on children's health insurance and annual wellness visits (Sacarny, Baicker, and Finkelstein 2020; Hamersma, Kim, and Timpe 2019; Venkataramani, Pollack, and Roberts 2017). However, there is a little research focusing on children's health insurance spillovers on adults (De Neve and Kawachi 2017).

Our findings help illustrate another mechanism for how children's health insurance affects their own outcomes: through parental responses to children's insurance. Children having Medicaid may increase mothers' likelihood of staying at home to spend more time with their children as well as reduce maternal stress.[6] These changes can improve children's long-term human and health capital.

The relatively few papers that do focus on spillovers from children to parents mainly focus on adult children's educational attainment on elderly parents' health and mortality (Ma 2019; De Neve and Fink 2018). Koch (2015) is a notable exception and the closest paper to ours, which investigates the spillover effects of children's Medicaid eligibility on parental health insurance coverage. Using a regression discontinuity design focusing on the income eligibility cutoffs for Medicaid, the author finds that more generous child coverage crowds out private insurance coverage for adults and leads to worse self-reported health for mothers. This finding suggests that a main reason parents seek private health insurance for themselves is to gain coverage for their

[6] An additional strain of literature focuses on the effects of adult mental health on children's well-being and participation in public programs (Kahn, Brandt, and Whitaker 2004; Noonan, Corman, and Reichman 2016).

children.[7] We however find no evidence that increased access to public health insurance for children affects mother's health insurance status.

We also contribute to the broader literatures on the effects of Medicaid and on the determinants of mental health. In our particular case, mental health improvements for mothers do not come from improvements in physical health of the parent but the "peace of mind" from reduced financial risk due to children having health insurance or the improvements in health of and treatment availability for their children.[8] Much of the existing research on Medicaid spillovers focuses on mothers' access to public insurance. One such study finds that maternal access to public insurance improves child health, even if the mother has access to Medicaid at very early ages (East et al. 2017). Maternal access to Medicaid increases risky health behavior of mothers and is associated with worse health outcomes for babies (Guldi and Hamersma 2021; Dave, Kaestner, and Wehby 2019), but also improves mother's mental health measured by reductions in CES-D scores (Guldi and Hamersma 2021).

Finally, we contribute to the literature focusing on the effects of Medicaid on maternal labor supply. Results from this literature vary depending on context and target of the expansions. The introduction of Medicaid reportedly had no effect on labor supply (Strumpf 2011). The decoupling of cash welfare and Medicaid in the early 1980s had ambiguous impacts on married women's labor supply, and analysis of this period are sensitive to model specification (Yelowitz

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[7] Hamersma and Ye (2021) find a similar result of private insurance crowdout for parents.

[8] Generally, Medicaid is found to increase access to and use of health care (Finkelstein 2012; Baicker et al. 2013; Currie and Gruber 1996a) including for mental health (McMorrow et al. 2016; Frank, Goldman, and Hogan 2003); improve health of young children (Goodman-Bacon 2018; Baicker et al. 2013; Currie, Decker, and Lin 2008)); reduce mortality for near elderly adults (Miller, Johnson, and Wherry 2019); and reduce financial burden including bankruptcy (Gross and Notowidigdo 2011), although the harm from losing coverage may be larger than the benefit of gaining coverage (Argys et al. 2020). For mental health, Medicaid reduces out-of-pocket expense for mental health visits and pharmaceuticals (Ghosh, Simon, and Sommers 2019; Golberstein and Gonzales 2015), decreases psychological distress among low-income parents, reduces perceived unmet needs, and increases number of days with good mental health (Finkelstein 2012; McMorrow et al. 2016; Wen, Druss, and Cummings 2015; Hampton and Lenhart 2021).

1995; Montgomery and Navin 2000; Ham and Shore-Sheppard 2005). Dave et al. (2015) find expansions targeting pregnant women decreased labor supply of this group, especially for unmarried women. The novelty of our paper is based on the unexplored margin of *children's* Medicaid on mother's labor outcomes.

The remainder of the paper continues with the following sections. Section 2 discusses Medicaid expansions and simulated instruments. Section 3 presents our data. In section 4 we present our methods and identification strategy. We discuss our results in Section 5. We conclude in Section 6.

2. Medicaid Background

Medicaid is the largest provider of public insurance to children and non-elderly adults. The program covers nearly 20 percent of Americans and cost $557 billion in 2017 (Rudowitz, Hinton, and Antonisse 2018). Medicaid has grown rapidly given the program's fairly modest voluntary introduction in 1965. Between 1966 and 1970 nearly all states implemented a Medicaid program for their citizens. However, the generosity of these programs varied greatly, with Medicaid originally tied to cash welfare eligibility.[9] At the time, Medicaid also covered the medically needy[10] as well as children who were not categorically welfare-eligible[11] but whose family income would have qualified them.[12]

Beginning with the Deficit Reduction Act of 1984, the federal government started expanding Medicaid by increasing eligibility for pregnant women. Additional state and federal

[9] At the time cash welfare was provided through Aid to Families with Dependent Children (AFDC), the precursor to the current Temporary Assistance for Needy Families (TANF) program.
[10] https://www.kff.org/other/state-indicator/medicaid-eligibility-through-the-medically-needy-pathway/
[11] Two-parent households were not eligible for cash welfare at the time.
[12] See (Gruber 2000) for a more detailed description of Medicaid policies and history.

policies decoupled Medicaid from cash welfare and expanded eligibility. By the late 1980s states varied considerably in eligibility based on income and children's age. States could choose to provide Medicaid coverage to pregnant women and infants earning up to 185% of the federal poverty level (FPL).

Several federal expansions occurred in the early 1990s. First, the federal government extended coverage to all pregnant women and children up to age six in families below 133% of the FPL. Second, federal policy allowed all children born after September 30, 1983 and living below 100% of the FPL to enroll in Medicaid. Future expansions ensured that children meeting these eligibility requirements receive Medicaid coverage through age 19. Finally, in 1997, Congress created the State Children's Health Insurance Program (SCHIP) which provided insurance to children whose parents earned too much to meet traditional Medicaid cutoffs. SCHIP eligibility thresholds vary by state and over time, and SCHIP provides matching funds for states to cover children under the age of 19 whose parents earned under 200% of the FPL.[13]

Data

Our main sample data comes from the National Longitudinal Study of Youth 1979 (NLSY 79) from 1979 to 2010. We only use samples up to 2010 given the major reforms from the Affordable Care Act starting in 2010 that could affect mothers. NLSY 79 is a nationally representative study of youth aged 14 to 22 in 1979. Participants were surveyed annually from 1979 to 1994 and biennially thereafter. We use a restricted version of the data which provides the state of residence of each individual at each survey.[14] We link these data to the NLSY 79 Children

[13] States are free to expand coverage to children whose parents earn above 200% of the FPL and many have done so.
[14] We also use NLSY data provided by IPUMS USA (Ruggles et al. 2020)

and Young Adults survey, which follows all biological children born to women of the NLSY 79 cohort. Our research design requires information on all children for each mother, which few datasets have. The ability to link children and their mothers' responses is a major strength of the NLSY, despite a relatively small sample size of women. Additionally, we use detailed information on educational attainment, race/ethnicity, CES-D score, marital status, labor market outcomes, and risky health behaviors. The CES-D score is a seven-item measure of how often over the past week the respondent experienced depressive symptoms. Values vary from 0 (rarely or none) to 3 (most or all of the time). CES-D scores therefore range from 0 to 21. We include NLSY-provided sample weights in our analyses.

Summary statistics for our analytic sample are in Table 1. Our main sample consists of approximately 4,700 women, who had at least one child and were interviewed multiple times in the NLSY 79. Not all participants were interviewed in every year. For the time-varying outcomes, 70 percent of the sample was married,[15] and 19 percent were divorced, with the median respondent included in 13 waves of the data. The average woman in our sample was employed in 63% and out of the labor force in 31% of survey periods. She completed 13 years of education, had an average income of $23,000, and a family income of just above $82,000. She reported drinking alcohol in the past 30 days 57% of the time. Between 22 and 29 percent of the sample reported smoking in each of the four surveys in which they were asked.

[15] These are mutually exclusive measures of marital status. We use married as a dominating state, so that if a woman was divorced and then remarried, she will be included as married for all survey periods in which she responds married even though she is also divorced.

Construction of Simulated Instrument

Our simulated instrument is constructed using data from March Current Population Survey (CPS). We use the full national CPS sample of children aged 0 to 17 from 1980 to 2010. Following Cohodes et al. (2016), Gross and Notowidigdo (2011), and Gruber and Simon (2008), we calculate annual state-level Medicaid eligibility for each age-by-birth cohort based on household income, accounting for household size, sex and unemployment status of the household head.

The simulated eligibility for Medicaid is the proportion of a fixed nationally representative sample of children who qualify for Medicaid given their household income and other characteristics listed above in a given state and year. By applying each state's eligibility rules to a fixed sample, our simulated instrument exploits only variation in Medicaid state laws and not changes in demographic characteristics over time and across states.[16] This addresses biases that may arise due to economic recessions or demographic trends across states affecting both Medicaid eligibility and coverage.

The simulated eligibility is the fraction of the fixed sample that would be eligible for Medicaid if the policies in state *s* when a child is age *a* in a given in year *t* were applied ($\overline{elig}_{sat}$). We link the simulated eligibility with the children in the NLSY 79 Children and Young Adults survey based on the state of residence, the year of the survey, and the birth year of the child.

We construct two separate mother-level instruments, one for our time-varying analyses on outcomes with several repeated measures over time and a second instrument for our cross-sectional analyses on outcomes with one or few observations per mother. To derive the time-varying,

[16] All household income measures are Consumer Price Index (CPI) corrected to account for changes in purchasing power. Groves (2020) argues the fixed year CPI correction contains a bias due to its assumption that low wage worker incomes rise by exactly the CPI and argues this is potentially an invalid assumption during the 1970s and possibly the early 1980s when inflation was very high. However, his analyses show results were not sensitive to this potential source of bias.

mother-level instrument, we aggregate the simulated eligibility of all of a woman's children in a given year to the mother-year level. This means that for a given mother, we average the simulated eligibility ($\overline{elig}_{sat}$) across all of her children in each year. A mother may have a different instrument value in each year due to changes in the age of her children and/or state-level policies. For our main time-variant sample, we construct the average simulated eligibility of a woman's children as:

$$Eligibility_{mt} = \frac{1}{J}\left(\sum_{j=1}^{J} \overline{elig}_{sat}^{j}\right) \tag{1}$$

where $j \in J$ indexes the mother's jth child and $\overline{elig}_{sat}$ refers to that child's eligibility in interview year t when the child is age a given their current state of residence s. We average the children's eligibility by summing eligibility of all children and dividing by J, her total number of children. Once children turn 18 and are no longer minors, we no longer consider their Medicaid eligibility, so we are only averaging across children below age 18. In other words, J is the number of children under 18 in year t.[17] This provides us with a dataset at the mother-year level, with each mother m in year t having an $Eligibility_{mt}$.

We also construct a measure of aggregate simulated eligibility, which can be thought of as the average eligibility of a woman's children over their life up to the time an outcome is measured. We use this measure in cross-sectional analyses:

$$AggregateEligibility_{mt} = \frac{1}{\sum_{j=1}^{J} A_j}\left(\sum_{j=1}^{J}\left(\sum_{a=1}^{A_j} \overline{elig}_{sat}\right)\right) \tag{2}$$

[17] As a robustness check, we calculate simulated eligibility including children over age 18 as having an eligibility of 0. This does not materially affect our instrument or our results (available upon request).

We separately calculate total eligibility for each child j up to the time when a mother received the CES-D instrument or other cross-sectional outcome by summing $\overline{elig}_{sat}$ for the child at every age. We then divide by A_j, the total number of years we have observed the jth child at year t. For example, consider a woman living in Florida interviewed in 1992, with children born in 1988 and 1990. For the older child we calculate the simulated eligibility of our CPS sample applying Florida's eligibility rules for children aged 0 in 1988, children aged 1 in 1989, children aged 2 in 1990, and children aged 3 in 1991. For the younger child, we apply Florida's eligibility rules for children aged 0 in 1990 and aged 1 in 1991. We then divide by the total number of years both children are in the sample (6 years).

Appendix Figure 1 provides visual evidence of the variation in eligibility which we exploit in our analyses. This figure shows simulated eligibility of our entire sample and by state, which provides additional information of when children's Medicaid eligibility increased. In the figure, one can see fairly large increases in child eligibility in the late 1980s and again in the late 1990s with the expansion of coverage through SCHIP.[18]

3. Methods and Identification Strategy

First, we perform time-varying analyses for mothers focusing on marital status, family size, labor force outcomes, and health behaviors. For these analyses, we estimate reduced form regressions of the form:

$$Outcome_{mt} = a + \beta_1 Eligibility_{mt} + X'_{mt}\beta_2 + \alpha_s \times \delta_c + \lambda_{mt} \times Y_t + \gamma_m + \varepsilon_{mt} \qquad (3)$$

[18] See Section 2 for more information on these expansions.

Where outcomes are listed above and *m* indexes the individual mother at time *t*. *Eligibility* is the simulated instrument defined in equation (1), and *X* is a time-varying control for age at interview.

We also include state-by-year-of-birth $(\alpha_s \times \delta_c)$, number of children-by-year of interview $(\lambda_{mt} \times Y_t)$, and individual fixed effects (γ_m). These fixed effects remove a large amount of variation related, for instance, to trends in outcomes over time (year of interview FE), fixed characteristics of the state of residence (state FE), and fixed characteristics of the mother herself (individual FE). They allow us to capture the causal effect of increases in Medicaid eligibility on maternal outcomes, within women, controlling for number of children. Our model assumes that our simulated instrument is not capturing variation in other state-level policies that may affect measured outcomes. As a robustness check, we include time-varying measures at the state level for earned income tax credit generosity. We cluster our standard errors at the state level to allow for serial correlation.

As a follow-up analysis, we focus on measures of maternal well-being, primarily the CES-D score. This measure was only captured at most at four points in time, in the 1992 and 1994 interviews and when a mother reached age 40 and 50. It thus does not provide enough variation to include maternal fixed effects as in equation (3). Instead, we estimate:

$$Outcome_{mt} = a + \beta_1 AggregateEligibility_{mt} + X'_{mt}\beta_2 + \alpha_s \times \delta_c + \lambda_{mt} \times Y_t + \varepsilon_{mt} \qquad (4)$$

This is a similar model to equation (3), except we omit γ_m, include additional covariates, and use the simulated instrument $AggregateEligibility_{mT}$ defined in equation (2):

4. Results

In this section, we present three main pieces of empirical evidence. First, we present time-varying effects of children's Medicaid eligibility on maternal outcomes for family dynamics, labor force participation, and health behaviors. Next, we show effects of children's Medicaid eligibility on mothers' mental health. Third, we provide support for the identifying assumptions of our analysis. The point estimates in the tables are for a 0-to-1 or 100 percentage point increase in simulated eligibility. When interpreting these results, we will primarily discuss 10 percentage points (ppt) changes in eligibility, dividing our main results by 10.

In Table 2, we use equation (3) to estimate the effect of childhood Medicaid expansions on family dynamics and maternal labor market outcomes using an individual fixed effects model. We find increasing simulated eligibility for a mother's children by 10 ppt is associated with a 1.87 ppt increase in the likelihood of a mother being married at the time of interview. This is equivalent to a 2.7% increase, and this result is statistically significant at the 0.1% level. Next, we decompose this effect into changes in mothers never being married versus mothers getting divorced. We find the effect on being married is primarily driven by reductions in divorce (84%).

In terms of labor force effects, a 10 ppt increase in Medicaid eligibility for one's children increases the likelihood of being out of the labor force by 1.5 ppt, a 4.8% decrease. We decompose this effect to determine the source of mothers exiting the labor force; were employed mothers leaving jobs or were they unemployed and ceased their job search? The point estimate on employed is larger suggesting mothers leaving jobs are driving the effects on mothers being out of the labor force. However, the effect on employed is not statistically significant at conventional levels, and the smaller estimate on unemployed is significant at the 5% level. Additionally, the percent change is larger for unemployed, suggesting nearly an 8% decrease.

For maternal CES-D scores, we present results in Table 3. The point estimates show the effect of increasing Medicaid eligibility by 100 ppt on CES-D score. The outcome variable CES-D score is a score based on respondents' response to 7 statements relating to depressive symptoms over the past week. For example, one of the statements is "I had trouble keeping my mind on what I was doing" and mothers report a number between 0-3 corresponding to the frequency with which they felt this where 0 is "Rarely or none of the time" and 3 is "Most of the time". Therefore, the maximum score is 21.

We estimate this specification at four separate time periods or ages: in 1992, when mothers are between 27 and 34 years old; in 1994, when mothers are between age 29 and 36; in the first survey in which a women participates after she turns 40; and in the first survey in which a women participates after she turns 50. These are the only survey years in which respondents were given the CES-D instrument. Our estimates use a substantially smaller sample size, and we do not have enough variation over time to estimate these analyses using an individual fixed effects estimator. Instead, we estimate equation (4), focusing on cross-sectional variation in aggregate eligibility.

Column (1) provides estimates of CES-D scores measured in 1992. A 10 ppt increase in aggregate eligibility from equation 2 is associated with a -0.58 point decrease in one's CES-D score. This is a 12.5% reduction in CES-D score. It suggests that if we increased aggregate eligibility for one's children from 0 to 100%, maternal depressive symptoms in two of the seven CES-D items would decrease from "always" to "rarely."[19] Effects are of a comparable size and statistical significance for the 1994 sample and for mothers interviewed after age 40 and age 50. The results consistently point to a decrease in CES-D scores of between 12 and 15% from a 10 ppt increase in eligibility. This effect is economically meaningful and statistically significant at the 0.1

[19] This is just for illustrative purposes as this is an out of sample prediction given the mean value of CES-D is 4.6 and this example suggests a decrease of 5.8.

percent or 0.001 level in all analyses; our findings indicate that increased child eligibility for public insurance improves maternal mental health.

In Table 4, we explore additional outcomes focusing on health insurance and socioeconomic indicators as well as health behaviors. In Panel A of Table 4, we find no evidence of a relationship between simulated eligibility and health insurance take-up, nor educational attainment of mothers.[20] Given that our eligibility measure is that of the child, this lack of a relationship between the simulated instrument and maternal health insurance is a good check to rule out an alternative mechanism: mother's insurance. Medicaid eligibility has a negative, but statistically insignificant effect on maternal income and household income. The effect size varies from 0.5% for household income to 0.7% for maternal income, but each estimate has large bounds.

We also investigate the effect of Medicaid expansions on specific health behaviors of the mother, including drinking and smoking in Panel B of Table 4. We use a time varying measure of alcohol, though we note that drinking variables are not captured as often as the other sociodemographic variables, thus these analyses have smaller sample sizes. However, a 10 ppt increase in Medicaid eligibility for children reduces alcohol consumption of mothers by 3.5 ppt, a 6.1% decrease. Smoking is asked only periodically and does not allow for an individual fixed effect analysis. However, we find strong evidence in all four periods in which cigarette smoking data is available that simulated eligibility is associated with substantial reductions in the likelihood of smoking.

[20] NLSY asks about any health insurance. Questions about Medicaid or types of insurance are poorly reported.

<u>Heterogeneity by Race/Ethnicity and Baseline SES</u>

Previous work has suggested that Black and Hispanic children are more likely to be eligible for Medicaid. We analyze our effects separately by race and ethnicity in Table 5 (time-varying outcomes) and Table 6 (cross-sectional outcome CES-D) to test whether effects differ by these groups. Because of smaller sample sizes, the estimates for Black and Hispanic women are noisier, thus we focus on two large groups: 1) Black and Hispanic mothers combined in Panel A, and 2) all non-Black non-Hispanic mothers in Panel B, a group which mostly consists of White mothers. See Appendix Table B1 for estimates broken out separately for Black mothers and Hispanic mothers.

Across all main time-varying outcomes and both panels in Table 5, the estimated effects of public insurance for children are in the same direction for Black and Hispanic mothers as well as non-Black non-Hispanic mothers. However, there are some notable differences in the magnitudes of these effects. The coefficient sizes on being married for both groups are similar to the overall effect from Table 2, but the effect size as a percent of the group-specific mean is nearly twice as large for Black and Hispanic mothers compared to White mothers and mothers of other race (3.5% vs. 1.9% per 10 ppt increase in simulated eligibility). This is driven by fewer women reporting never being married for Black and Hispanic mothers and by reductions in divorce for non-Black non-Hispanic mothers. The effects on labor market outcomes are generally larger for Black and Hispanic mothers, including the fact that Black and Hispanic mothers have a 2.4 ppt increase (7.4%) in being out of the labor force for a 10 ppt increase in simulated eligibility, which is nearly twice as large as the 1.3 ppt increase (4.2%) for non-Black non-Hispanic mothers.

In Table 6, we perform similar subsample analyses by race and ethnicity focusing on CES-D as our dependent variable. Results are quite similar across both groups, indicating that public insurance eligibility for children improve mental health for mothers across these racial/ethnic groups. The effects in 1994 are somewhat nosier and less consistent between the subsamples, but still show evidence across subsamples of a strong relationship between simulated eligibility and fewer depressive symptoms. See Appendix Table B2 for estimates broken out separately for Black mothers and Hispanic mothers.

Table 7 contains subsample analyses by socioeconomic status in childhood. Low SES means the mother's childhood household reported being in poverty at least once before 1985. Those with lower SES are more likely to be eligible for Medicaid. Results differ slightly in terms of statistical significance, but overall are qualitatively similar for marital outcomes. However, the magnitude of the overall effect for marriage is substantially larger for the low SES sample. For mothers who qualify as low SES growing up, a 10 ppt increase in simulated Medicaid eligibility for children increases the likelihood they are married by 3.7% compared to 2.1% for high SES moms. For labor force outcomes, simulated eligibility is associated with substantially less employment among high SES women, while it is associated with much lower rates of unemployment among low SES women.

In Table 8, we report CES-D results by mothers' childhood SES. This table has several interesting results. First, the low SES sample has a substantially higher mean of depressive symptoms as measured by the CES-D. A 10 ppt increase in simulated Medicaid eligibility for one's child is associated with substantial reductions in CES-D score for both high and low SES women. The effect size is approximately 13 percent for each group in 1992. However, we find stronger effects of simulated eligibility on CES-D scores among low SES women for the later time periods, with the low SES women effect size being between 33 and 67% larger than that of the high SES group. This suggests that our results for low SES reflect the higher likelihood of this group of women receiving Medicaid coverage for their children, a test of the mechanism of our effect.

Robustness to Model Covariates

As a robustness check, Appendix Figure 2 incrementally adds covariates to our model to show that results on time-varying outcomes from Table 2 are not materially affected by the specification we us. The first point estimate, labeled 1, includes only individual FE and age. Each estimate builds on the previous iteration so that we add: (2) year of interview FE; (3) state of residence FE; (4) number of children FE; (5) year of birth FE; (6) state by year of birth FE; and (7) number of children by year of interview FE. Specification 7 is our main estimate from Table 2 and neither our point estimate nor the confidence intervals vary greatly depending on the specification. Appendix Figure 3 provides a similar analysis for our cross-sectional outcomes in Table 3. The main difference is that these analyses do not include individual FE and only estimate the first 6 specifications described above, with specification 6 reflecting our main analysis from Table 3. The main takeaway is that our estimates are quite stable regardless of the covariates included in this specification.

Testing Identifying Assumptions

We perform several additional analyses to test the identifying assumptions of our models presented above. First, we may be concerned that our simulated instrument is correlated with other changes such as state-level programs that affect our main outcomes through a non-health insurance mechanism. To provide empirical evidence for the validity of our instrument, we construct a placebo sample of women without children who are matched on baseline characteristics to mothers in our sample.[21] If the only way our main instrument is affecting outcomes is through children's Medicaid, then we can test our instrument on a sample of women without children.

We use propensity score matching to create a sample of women who are similar to our main sample. These women (non-mothers) receive the simulated instrument of the mothers they are matched with, although they would in reality receive a simulated instrument of zero because they are childless. We then estimate models using equation (3) or equation (4) on this matched sample. The results of this analysis are presented in Table 9. Overall, we show that our simulated instrument in this childless women sample is not associated with any of our dependent variables from Tables 2 and 3; the point estimates are smaller and not statistically significant. This increases our confidence that our instrument is only working through children's Medicaid rather than capturing other types of changes that are correlated with our sample of mothers.

Additional Robustness Checks

We estimate several additional models to test the robustness of our estimates. First, we include additional time varying covariates that may affect Medicaid eligibility and/or marriage and labor market outcomes. For this we include state level earned income tax credit following Bastian and Michelmore (2018).[22] We present results in Appendix Table A1 which largely confirm our main results.

An alternative explanation for our results is that maternal health is improved at the time of birth and all benefits that we find from that point on are actually a reflection of that improved

[21] We match mothers on baseline characteristics including childhood poverty, number of siblings, educational attainment of parents, armed forces qualification test in 1981, family size in 1980, and highest grade in 1980 using propensity score matching.
[22] We cannot run this analysis for CES-D using equation (4) because we only have cross-sectional variation in EITC in the year in which CES-D questions are asked.

health, rather than children's eligibility expansions (Guldi and Hamersma 2021). This could be the case if expansions of maternal health or health insurance coverage are highly collinear with child expansions. We argue this is not the case for several reasons. First, we do not find evidence that maternal health insurance and Medicaid expansions for children are correlated in Table 4.

Second, our analyses use two separate, but related, instruments for childhood expansions, one that exploits aggregate eligibility similar to Cohodes et al. (2016), and another that exploits contemporaneous eligibility. In both instruments, we account for eligibility for all children in the household. We find consistent evidence of these measures relating to maternal family decisions and mental health. Additionally, we use a longer period of variation than Guldi and Hamersma (2021), who use variation across one year of birth data.

To test whether maternal Medicaid eligibility rather than children's eligibility is driving our results, we drop children's eligibility when children are age 0, or times in which maternal eligibility likely mirrored children's eligibility. Results of these analyses, presented in Appendix Table A2 and A3, do not materially affect our main results.

Appendix Table A4 and A5 present results separately by number of children a mother has and provides qualitatively similar results, with some evidence of a larger reduction in CES-D score from children's Medicaid eligibility in Appendix Table A5. To test whether Medicaid expansions affected the NLSY sample differently by time period, we split our sample by before 1990 and 1990 onwards in Appendix Table A6. These results show substantially stronger results in the earlier sample. This is logical given that our sample ages over time such that all later estimates will be for mothers who are older and who likely have more resources and are thus less likely to have children using Medicaid. Our estimates suggest that our results are nearly twice as large for the earlier sample period for marriage, divorce, and labor market participation.[23]

Lastly, we use randomized inference to test if our results might be driven by random noise. Using 300 iterations, we randomly assign each child a placebo state of residence, a year of interview, and a year of birth. Randomized inference p-values are based on how many placebo point estimates are larger in magnitude than the main point estimate. To address the clustering nature of treatment assignment, each child born in the same year is assigned the same placebo birth year; each child living in the same state is assigned the same placebo state of residence; and each interview year is assigned the same placebo interview year. This is more conservative than only assigning each birth year-by-state of residence-by-interview year the same placebo combination.

Appendix Table A7 and A8 present results for these analysis. The top two rows are the main results from Table 2 and 3. The third row shows the original p-value from clustering standard errors, and the forth row shows randomized inference p-values. Since we are using 300 iterations, we can only say that p-values are less than 0.003 when no placebo estimates are larger in magnitude than the main point estimate. All statistically significant results are still significant when using randomized inference, consistent with our findings not being driven by random noise.

5. Discussion and Conclusion

Our results indicate that increases in children's Medicaid eligibility lead to mothers being more likely to remain married, less likely to work outside the home, and less likely to consume alcohol or smoke. We also find evidence of an improvement in maternal mental health, as captured by CES-D scores.

[23] All CES-D questions are asked post 1990 so we cannot perform this analysis separately pre- and post-1990.

Taken together, these results suggest an improvement in overall maternal well-being. However, higher rates of marriage and lower labor force participation for women may not be universally welfare-improving. For instance, if Medicaid eligibility increases the likelihood of a woman remaining in an unhappy marriage and/or reduces her labor force participation and thus her professional capital and outside options, these women could be worse off. If on the other hand, the effects on labor and marriage reflect reduced financial constraints and better intra-household division of labor, then many women would be better off.

To unpack this more, we consider our how our effects may impact maternal welfare. Our marriage results are consistent with that of Yelowitz (1998) who finds that 1980s and 1990s child expansions increased marriage.[24] Marital disruption can have negative outcomes for children and adults including decreasing health insurance coverage of both mothers and child (Peters, Simon, and Taber 2014) and increasing financial strain (Finkelstein 2012; Gross and Notowidigdo 2011).[25] While the direction of causality is unclear as child health problems increase financial strain and increase the likelihood of the dissolution of a relationship (Reichman, Corman, and Noonan 2004), the positive benefits of increasing Medicaid eligibility are clear.

The relatively large effects we find on labor market outcomes suggest that lack of public insurance for children leads to maternal job-lock. That mothers are participating in the labor force to provide health insurance for their children and when Medicaid eligibility for children is increased, they are able to leave the market without negative consequences for their children's access to health care.[26] Additionally and consistent with our findings, maternal labor supply

[24] More recent Medicaid expansions provide contradictory evidence on marriage effects. Slusky and Ginther provide evidence of fewer medical divorces among those aged 50-64 with a college degree to protect the assets of the healthy spouse (Slusky and Ginther 2017), while Hampton and Lenhart (2019) find evidence of lower marriage rates following the most recent Medicaid expansions.
[25] Others argue Medicaid expansions actually decreased savings (Gruber and Yelowitz 1999).
[26] A large literature on job lock and Medicaid exists, but generally focuses on adult expansions. See e.g. (Hamersma and Kim 2009; Garthwaite, Gross, and Notowidigdo 2014; Argys et al. 2020)

responds to children's health (Corman, Noonan, and Reichman 2005; Gould 2004; Eriksen et al. 2021).

Recent work suggests large benefits of Medicaid expansion on children's future health and human capital outcomes (see e.g. Cohodes et al. 2016; East et al. 2017; Miller and Wherry 2019). Improvements in maternal well-being and higher rates of parents remaining married may provide a potential mechanism for improved children's outcomes. Related to our finding strong improvements in maternal mental health associated with children's Medicaid expansions at several different ages, Guldi and Hamersma (2021) find improvements in maternal mental health caused by Medicaid expansions for pregnant women; this effect persists through age 3 of the child.[27] Additionally, Reichman et al. (2015) provide evidence that higher rates of post-partum depression are associated with reduced likelihood of a couple remaining together after a birth, as well as worse maternal mental health and infant health post birth (Slomian et al. 2019). These effects suggest the strong interconnectedness of children's health insurance and maternal marriage market decisions, labor market decisions, and depressive symptoms.

Using a longitudinal panel of mothers followed for nearly 30 years, we find evidence that Medicaid eligibility increases the probability of a mother marrying, remaining married, and decreases the labor force participation of these women. We provide strong evidence of a positive effect of this increased eligibility on maternal health behaviors in terms of reduced drinking and smoking, and improvements in maternal mental health as measured by CES-D. Our results point to an additional positive spillover of children's Medicaid eligibility: improvements in maternal health. They also provide evidence of a potential mechanism through which long-term benefits of

[27] While this study uses a different source of variation, that of maternal Medicaid expansions, the results complement those of our own, using child Medicaid expansions, in finding improved maternal mental health from Medicaid expansions. However, these need not be mutually exclusive and the effects may in fact build on each other.

Medicaid coverage in childhood works. Future research should investigate whether these effects persist into old age.

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Table 1: Summary statistics

Panel A: Main Time-Varying Instrument and Outcomes	Mean	SD	N
Simulated Elig. - Time Varying	0.310	0.155	54,655
Married	0.698	0.459	54,650
Divorced	0.191	0.393	54,650
Never Married	0.103	0.304	54,650
Out of Labor Force	0.314	0.464	43,548
Employed	0.628	0.483	43,548
Unemployed	0.058	0.235	43,548

Panel B: Main Cross-Sectional Instruments and Outcomes	Mean	SD	N
Simulated Elig. - Year 1992	0.246	0.097	3,186
Simulated Elig. - Year 1994	0.262	0.107	3,339
Simulated Elig .- Age 40	0.307	0.134	3,515
Simulated Elig. - Age 50	0.318	0.133	3,163
CESD - Year 1992	4.630	4.273	3,186
CESD94 - Year 1994	4.398	4.478	3,339
CESD40 - Age 40	3.618	4.325	3,522
CESD50 - Age 50	4.485	4.720	3,218

Panel C: Baseline Characteristics	Mean	SD	N
Childhood Poverty Freq. Before 1985	1.431	1.812	4,695
Number of Siblings in 1979	4.040	2.687	4,689
Mother's Highest Grade in 1979	10.621	3.143	4,427
Father's Highest Grade in 1979	10.625	3.948	3,982
Armed Forces Qualification Test in 1981	37.898	27.259	4,539
Family Size in 1980	4.253	2.235	4,595
Highest Grade in 1980	11.066	1.919	4,595

Panel D: Secondary Time-Varying and Cross-Sectional Outcomes	Mean	SD	N
Health Insurance - Time Varying	0.866	0.341	33,121
Highest Grade - Time Varying	12.95	2.33	54,574
Income - Time Varying (2020 $)	23,374.5	30,957.2	52,744
Family Income - Time Varying (2020 $)	82,371.3	111,785.2	45,777
HH Poverty - Time Varying	0.168	0.374	45,944
Any Alcohol - Time Varying	0.572	0.495	21,682
Smoking - Year 1992	0.288	0.453	3,215
Smoking - Year 1994	0.290	0.454	3,345
Smoking - Year 1998	0.280	0.449	3,376
Smoking - Year 2008	0.225	0.417	3,215

Table 2: Regression on Main Time-Varying Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.187***	-0.158***	-0.0501*	0.152*	-0.104	-0.0468*
	(0.0406)	(0.0382)	(0.0229)	(0.0583)	(0.0581)	(0.0219)
N	54,523	54,523	54,523	43,307	43,307	43,307
Dep. Var. Mean	0.698	0.191	0.103	0.314	0.628	0.058

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Table 3: Regression on Main Cross-Sectional Outcomes; CES-Depression Scale

	(1)	(2)	(3)	(4)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-5.810***	-4.721***	-5.532***	-5.597***
	(1.092)	(0.910)	(0.803)	(0.667)
N	3,186	3,339	3,522	3,219
Dep. Var. Mean	4.63	4.40	3.62	4.48

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE, Current number of children FE and Race FE. Regressions weighted by sample weight provided by NLSY.
Sample code:
```
reghdfe cesd_7item_40 Zany1_40 i.year AGEATINT [aw=SAMPWEIGHT] if firstyearabove40==1 & fips>0, vce(cluster fips) a(i.fips##i.yob i.numkid  i.SAMPLE_RACE_78SCRN)
```

Table 4: Regression on Secondary Outcomes

Panel A: Secondary Outcomes, Socio-Economic Status

	(1)	(2)	(3)	(4)	(5)
	Health Ins. - Time Varying	Highest Grade - Time Varying	Income - Time Varying	Family Income - Time Varying	HH Poverty - Time Varying
Simulated Elig.	0.0497	0.0113	-1734.9	4174.0	-0.0316
	(0.0336)	(0.0860)	(2446.0)	(11105.9)	(0.0277)
N	32,479	54,446	52,744	45,777	45,777
Dep. Var. Mean	0.87	12.95	23374.45	82371.33	0.17

Panel B: Secondary Outcomes, Health Behaviors

	(6)	(7)	(8)	(9)	(10)
	Any Alcohol - Time Varying	Smoking - Year 1992	Smoking - Year 1994	Smoking – Year 1998	Smoking - Year 2008
Simulated Elig.	-0.345*	-1.177***	-1.221***	-1.199***	-0.999***
	(0.132)	(0.153)	(0.179)	(0.106)	(0.0880)
N	21,381	3,215	3,345	3,376	3,215
Dep. Var. Mean	0.57	0.29	0.29	0.28	0.22

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model for time-varying outcomes includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Model for cross-sectional outcomes includes Age, Current state-by-year of birth FE, Current number of children FE and Race FE.

Regressions weighted by sample weight provided by NLSY. Income measured in real 2020 dollars.

Sample code:
```
reghdfe mom_insurance Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips) a(id $tvfe)
reghdfe current_smoker98 Zany1_1998 AGEATINT [aw=SAMPWEIGHT] if fips>0 & year==1998, vce(cluster fips) a($csfe)
```

Table 5: Main Results by Race/Ethnicity, Time-Varying Outcomes

Panel A: Black or Hispanic Women

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.152**	-0.0748	-0.0692*	0.239***	-0.197***	-0.0395
	(0.0638)	(0.0592)	(0.0494)	(0.0841)	(0.0651)	(0.0433)
N	26,910	26,910	26,910	21,482	21,482	21,482
Dep. Var. Mean	0.44	0.23	0.32	0.32	0.57	0.10

Panel B: Not Black and Not Hispanic Women

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.149**	-0.159**	-0.0200	0.129*	-0.0807	-0.0484
	(0.0474)	(0.0482)	(0.0260)	(0.0235)	(0.0607)	(0.0474)
N	27,577	27,577	27,577	21,797	21,797	21,797
Dep. Var. Mean	0.77	0.18	0.04	0.31	0.65	0.04

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.
Regressions weighted by sample weight provided by NLSY.
Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Table 6: Main Results by Race/Ethnicity, Cross-Sectional Outcomes; CES-Depression Scale

Panel A: Black or Hispanic Women

	(7)	(8)	(8)	(9)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-4.810***	-2.751**	-5.025***	-4.852***
	(1.004)	(0.899)	(0.812)	(1.072)
N	1,623	1,683	1,765	1,631
Dep. Var. Mean	5.23	4.92	4.05	4.60

Panel B: Not Black and Not Hispanic Women

	(7)	(8)	(8)	(9)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-5.948***	-5.945***	-5.478***	-5.346***
	(1.521)	(1.177)	(0.992)	(1.113)
N	1,507	1,595	1,700	1,518
Dep. Var. Mean	4.46	4.24	3.50	4.46

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE and current number of children FE.
Regressions weighted by sample weight provided by NLSY.
Sample code: `reghdfe cesd_7item_40 Zany1_40 i.year AGEATINT [aw=SAMPWEIGHT] if firstyearabove40==1 & fips>0, vce(cluster fips) a(i.fips##i.yob i.numkid  i.SAMPLE_RACE_78SCRN)`

Table 7: Main Results by Childhood SES, Time-Varying Outcomes

Panel A: High SES

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.173**	-0.172*	-0.0237	0.132**	-0.124*	-0.00858
	(0.0569)	(0.0644)	(0.0201)	(0.0442)	(0.0480)	(0.0253)
N	23,873	23,873	23,873	18,288	18,288	18,288
Dep. Var. Mean	0.81	0.15	0.04	0.27	0.69	0.04

Panel B: Low SES

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.208*	-0.150*	-0.0749	0.190	-0.0974	-0.0907*
	(0.0776)	(0.0706)	(0.0391)	(0.124)	(0.113)	(0.0384)
N	30,610	30,610	30,610	24,986	24,986	24,986
Dep. Var. Mean	0.56	0.25	0.18	0.36	0.55	0.09

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Table 8: Main Results by Childhood SES, Cross-Sectional Outcomes

Panel A: High SES				
	(7)	(8)	(8)	(9)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-5.097***	-2.612*	-3.552**	-2.846*
	(1.036)	(1.102)	(1.277)	(1.243)
N	1,402	1,478	1,598	1,445
Dep. Var. Mean	4.06	3.79	3.07	3.94

Panel B: Low SES				
	(7)	(8)	(8)	(9)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-6.809***	-5.418***	-6.649***	-6.055***
	(1.711)	(1.454)	(1.101)	(1.239)
N	1,699	1,767	1,843	1,697
Dep. Var. Mean	5.33	5.16	4.28	5.18

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE, Current number of children FE and Race FE. Regressions weighted by sample weight provided by NLSY.
Sample code:
```
reghdfe cesd_7item_40 Zany1_40 i.year AGEATINT [aw=SAMPWEIGHT] if firstyearabove40==1 & fips>0, vce(cluster fips) a(i.fips##i.yob i.numkid  i.SAMPLE_RACE_78SCRN)
```

Table 9: Placebo Tests, Matched Non-Mother Women Unaffected by Policy

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Married	Divorced	Never Married	OOLF	Employ	Unemp.	CESD 1992	CESD 1994
Simulated Elig.	0.0622	-0.006	-0.0416	-0.007	0.007	0.002	2.986	0.219
	(0.0371)	(0.0313)	(0.0242)	(0.0309)	(0.035)	(0.0258)	(1.980)	(2.083)
N	19,868	19,868	19,868	17,696	17,696	17,696	997	836

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

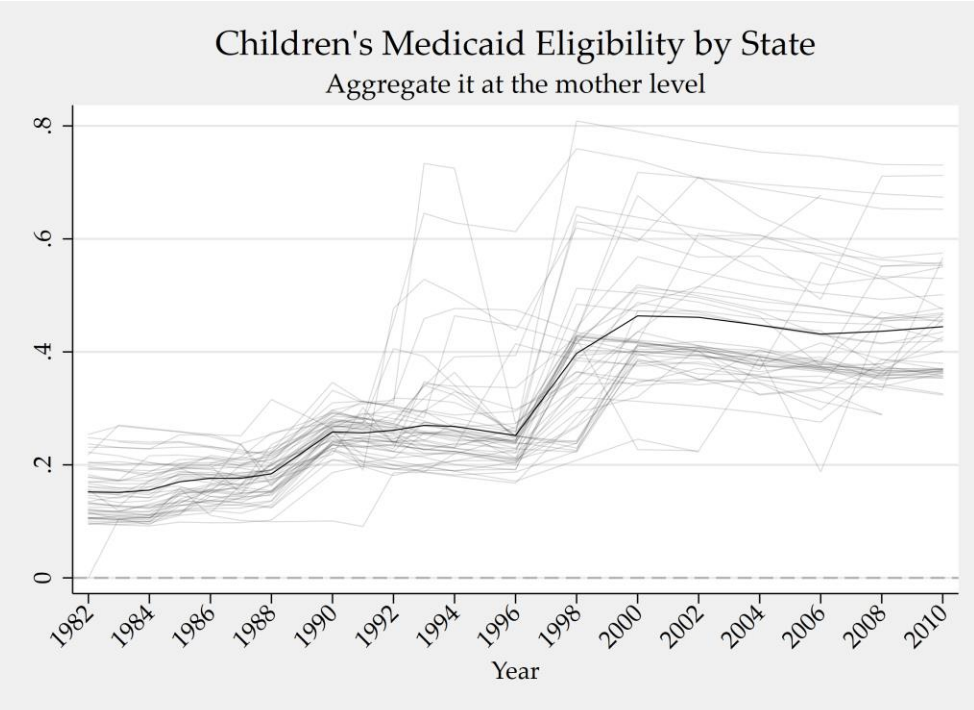
Regressions weighted by sample weight provided by NLSY.

Sample code: `reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips) a(id i.fips##i.yob i.numkid##i.year)`

No CESD at age 40 or 50 because not sufficient matched observations.

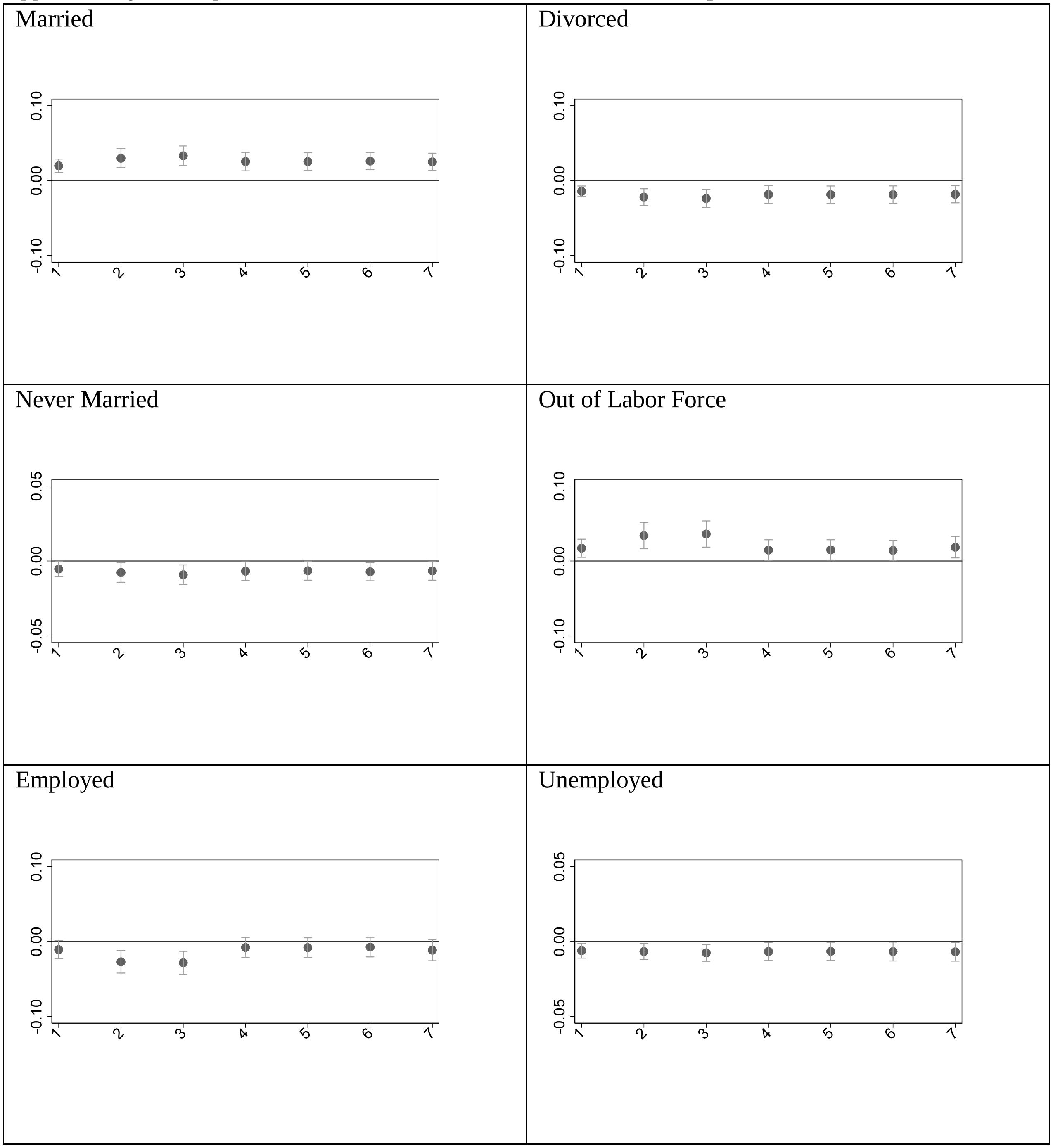
Sample constructed by matching women currently without children to mothers in the main sample based on baseline characteristics (childhood poverty freq. before 1985, number of siblings in 1979, mother's highest grade in 1979, father's highest grade in 1979, armed forces qualification test in 1981, family size in 1980, highest grade in 1980).

Appendix Figure 1. Variation in treatment variable over time, overall and by state



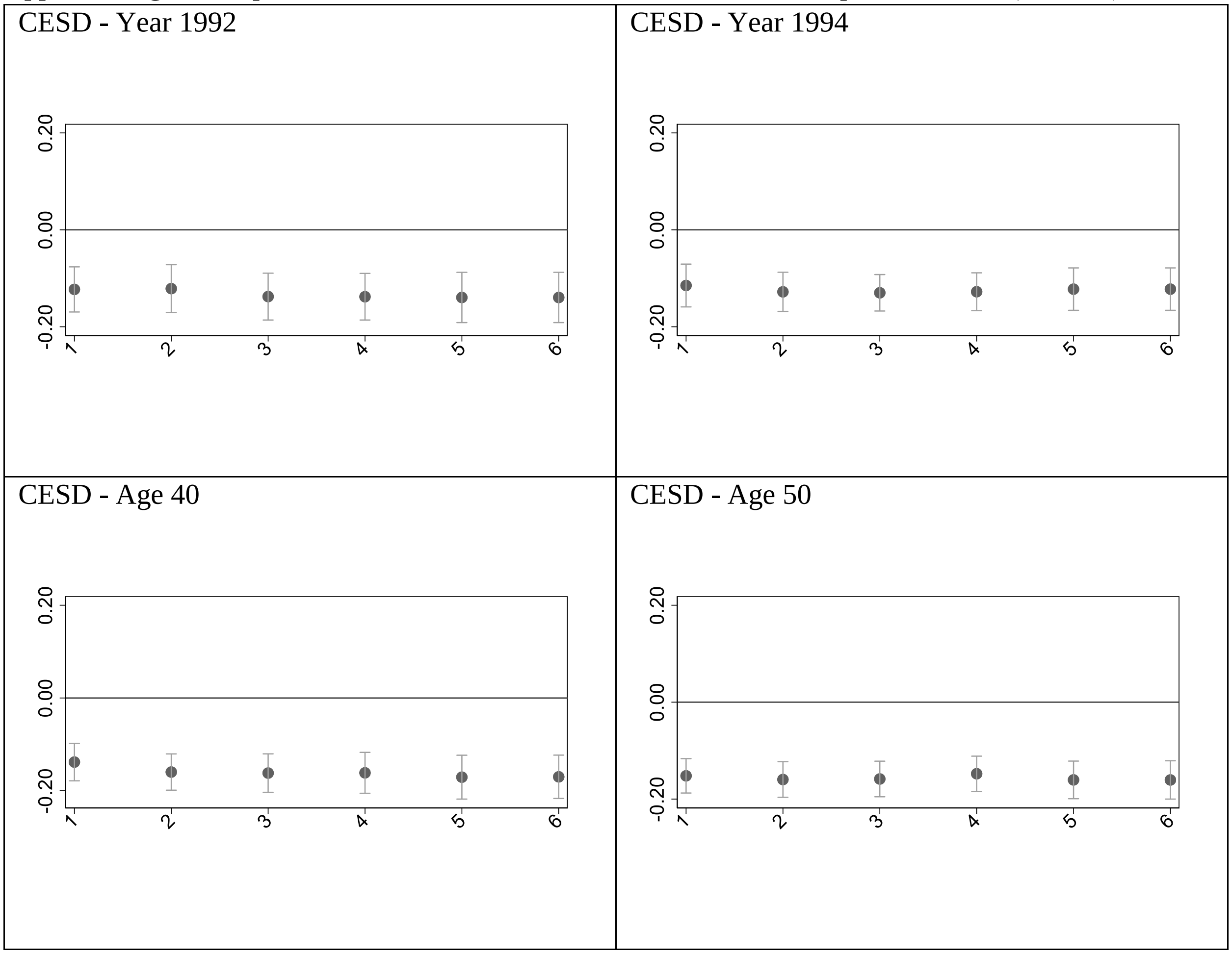
Notes: The y-axis is the simulated eligibility over time. The black line is for the full sample, and the gray lines are for each state.

Appendix Figure 2: Specification robustness, how additional controls impact estimates



Notes: * p < 0.05, ** p < 0.01, *** p < 0.001.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother-by-year level. The main X variable has a range of 0-to-1 so changes represent a 100 ppt change in eligibility affects Y by beta.
Model: Specification 1 includes Individual FE and Age. Specification 2 adds Current Year FE. Specification 3 adds Current state FE. Specification 4 adds Current number of children FE. Specification 5 adds Year of birth FE. Specification 6 adds Current state-by-year of birth FE. Specification 7 adds Current number of children-by-current year FE.
Regressions weighted by sample weight provided by NLSY.

Appendix Figure 3: Specification robustness, how additional controls impact estimates (controls)



Notes: * p < 0.05, ** p < 0.01, *** p < 0.001.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother level. The main X variable has a range of 0-to-1 so changes represent a 100 ppt change in eligibility affects Y by beta.
Model: Specification 1 includes Age. Specification 2 adds Current state FE and Current Year FE (if applicable). Specification 3 adds Current number of children FE. Specification 4 adds Year of birth FE. Specification 5 adds Current state-by-year of birth FE. Specification 6 adds Current number of children-by-current year FE.
Regressions weighted by sample weight provided by NLSY.

Appendix Table A1: Regression on Main Time-Varying Outcomes including EITC

Panel A: Main Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.187***	-0.158***	-0.0501*	0.152*	-0.104	-0.0468*
	(0.0406)	(0.0382)	(0.0229)	(0.0583)	(0.0581)	(0.0219)
N	54,523	54,523	54,523	43,307	43,307	43,307
Dep. Var. Mean	0.698	0.191	0.103	0.314	0.628	0.058

Panel B: Including EITC State Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.158***	-0.140***	-0.0388	0.101	-0.0580	-0.0421
	(0.0396)	(0.0398)	(0.0205)	(0.0506)	(0.0494)	(0.0220)
N	45,227	45,227	45,227	34,013	34,013	34,013
Dep. Var. Mean	0.705	0.198	0.088	0.290	0.661	0.049

Note Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Appendix Table A2: Regression on Main Time-Varying Outcomes, Addressing Maternal Medicaid Eligibility (Dropping mothers with children age 0)

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.198***	-0.175***	-0.0462	0.171*	-0.128*	-0.0420
	(0.0446)	(0.0416)	(0.0235)	(0.0665)	(0.0621)	(0.0224)
N	48,053	48,053	48,053	36,946	36,946	36,946
Dep. Var. Mean	0.685	0.205	0.101	0.289	0.652	0.058

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Appendix Table A3: Regression on Main Cross-Sectional Outcomes; CES-Depression Scale, Addressing Maternal Medicaid Eligibility (Dropping mothers with children age 0)

	(1)	(2)	(3)	(4)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-7.303***	-4.400***	-5.636***	-5.596***
	(1.072)	(1.064)	(0.827)	(0.667)
N	2,834	3,072	3,476	3,218
Dep. Var. Mean	4.69	4.44	3.60	4.49

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE, Current number of children FE and Race FE. Regressions weighted by sample weight provided by NLSY.
Sample code: `reghdfe cesd_7item_40 Zany1_40 i.year AGEATINT [aw=SAMPWEIGHT] if firstyearabove40==1 & fips>0, vce(cluster fips) a(i.fips##i.yob i.numkid  i.SAMPLE_RACE_78SCRN)`

Appendix Table A4: Regression on Main Time-Varying Outcomes by Number of Children

Panel A: Less than 3 children

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.134**	-0.124**	-0.0401	0.0640	-0.0140	-0.0496
	(0.0484)	(0.0449)	(0.0309)	(0.0675)	(0.0707)	(0.0258)
N	37,779	37,779	37,779	31,444	31,444	31,444
Dep. Var. Mean	0.702	0.181	0.110	0.288	0.655	0.056

Panel B: 3 or more Children

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.106	-0.106	-0.0105	0.190	-0.167	-0.0216
	(0.0683)	(0.0677)	(0.0259)	(0.109)	(0.108)	(0.0518)
N	16,549	16,549	16,549	11,548	11,548	11,548
Dep. Var. Mean	0.686	0.216	0.086	0.389	0.546	0.065

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Appendix Table 5: Regression on Main Cross-Sectional Outcomes; CES-Depression Scale by Number of

Panel A. Less than 3 children

	(1)	(2)	(3)	(4)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-5.548***	-4.032***	-5.297***	-4.908***
	(0.971)	(1.081)	(0.971)	(0.837)
N	2,167	2,166	2,097	1,886
Dep. Var. Mean	4.50	4.25	3.51	4.42

Panel B. 3 or more children

	(1)	(2)	(3)	(4)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-12.67**	-10.27***	-6.950***	-8.228***
	(3.535)	(2.295)	(1.519)	(1.843)
N	937	1,104	1,359	1,228
Dep. Var. Mean	4.86	4.64	3.78	4.58

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children FE and Race FE. Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe cesd_7item_40 Zany1_40 i.year AGEATINT [aw=SAMPWEIGHT] if firstyearabove40==1 & fips>0, vce(cluster fips) a(i.fips##i.yob i.numkid  i.SAMPLE_RACE_78SCRN)
```

Appendix Table A6: Regression on Main Time-Varying Outcomes Split by Time Period

Panel A: 1990 and after

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.158***	-0.144**	-0.0370	0.131*	-0.0853	-0.0451
	(0.0445)	(0.0438)	(0.0208)	(0.0507)	(0.0586)	(0.0246)
N	32,647	32,647	32,647	21,426	21,426	21,426
Dep. Var. Mean	0.709	0.205	0.076	0.266	0.689	0.045

Panel B: Before 1990

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.379**	-0.262*	-0.115	0.339*	-0.248	-0.0907
	(0.114)	(0.108)	(0.0639)	(0.158)	(0.154)	(0.0617)
N	21,512	21,512	21,512	21,514	21,514	21,514
Dep. Var. Mean	0.670	0.161	0.165	0.381	0.541	0.078

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.
Regressions weighted by sample weight provided by NLSY.
Sample code: `reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)`

Appendix Table A7: Regression on Main Time-Varying Outcomes, Random Inference P-values

	(1)	(2)	(3)	(4)	(5)	(6)
	Married	Divorced	Never Married	Out of Labor Force	Employed	Unemployed
Simulated Elig.	0.187***	-0.158***	-0.0501*	0.152*	-0.104	-0.0468*
	(0.0406)	(0.0382)	(0.0229)	(0.0583)	(0.0581)	(0.0219)
Original P-value	<0.003	<0.003	0.033	0.012	0.078	0.037
P-value from Randomized Inference	<0.003	<0.003	<0.003	0.003	0.017	0.033
N	54,523	54,523	54,523	43,307	43,307	43,307
Dep. Var. Mean	0.698	0.191	0.103	0.314	0.628	0.058

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Standard errors are in parentheses and are clustered at the state level.

Interpretation: Regressions are run at the mother-by-year level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so the estimated β represents a 100 ppt change in eligibility.

Model: Model includes Age, Current state-by-year of birth FE, Current number of children-by-current year FE, and Individual FE.

Regressions weighted by sample weight provided by NLSY.

Sample code:
```
reghdfe yvar Zany_time AGEATINT [aw=SAMPWEIGHT] if fips>0 & AGEATINT>0 & numkid>0, vce(cluster fips)  a(id i.fips##i.yob i.numkid##i.year)
```

Appendix Table A8: Regression on Main Cross-Sectional Outcomes; CES-Depression Scale, Random Inference P-values

	(1)	(2)	(3)	(4)
	Year 1992	Year 1994	Age 40	Age 50
Simulated Elig.	-5.810***	-4.721***	-5.570***	-5.619***
	(1.092)	(0.910)	(0.804)	(0.674)
Original P-value	<0.003	<0.003	<0.003	<0.003
P-value from Randomized Inference	<0.003	<0.003	<0.003	<0.003
N	3,186	3,339	3,515	3,165
Dep. Var. Mean	4.63	4.40	3.63	4.46

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.
Standard errors are in parentheses and are clustered at the state level.
Interpretation: Regressions are run at the mother level. The main explanatory variable (Simulated Instrument) has a range of 0-to-1 so β represents a 100 ppt change in eligibility.
Model: Model includes Age, Current state-by-year of birth FE, Current number of children FE and Race FE. Regressions weighted by sample weight provided by NLSY.
Sample code: `reghdfe cesd_7item_40 Zany1_40 i.year AGEATINT [aw=SAMPWEIGHT] if firstyearabove40==1 & fips>0, vce(cluster fips) a(i.fips##i.yob i.numkid  i.SAMPLE_RACE_78SCRN)`