Long-Term Impacts of Childhood Medicaid Expansions on Outcomes in Adulthood*

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Abstract

We use administrative data from the IRS to examine long-term impacts of childhood Medicaid eligibility expansions on outcomes in adulthood at each age from 19–28. Greater Medicaid eligibility increases college enrollment and decreases fertility, especially through age 21. Starting at age 23, females have higher contemporaneous wage income, although male increases are imprecise. Together, both genders have lower mortality. These adults collect less from the earned income tax credit and pay more in taxes. Cumulatively from ages 19–28, at a 3% discount rate, the federal government recoups 58 cents of each dollar of its "investment" in childhood Medicaid.

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1 Introduction

In the United States, several elements of the social safety net target children. One rationale for targeting children is that the childhood years are formative. In addition to delivering short-term gains, programs targeted at children have the promise of improving human capital formation, health, and economic outcomes. We assess and compare the age profiles of such long-term gains by examining the impact of policies that occurred in the past.

Using data from the Internal Revenue Service (IRS), we examine long-term impacts of previous expansions to childhood Medicaid on several outcomes during adulthood. Medicaid, an important element of the U.S. social safety net that provides health insurance to low-income individuals, began over 50 years ago in 1965. It expanded dramatically in the 1980s and again in the 1990s with the establishment of the State Children's Health Insurance Program (SCHIP) in 1997. These combined "Medicaid" expansions resulted in a tremendous amount of variation in health insurance eligibility for similar children born in different months residing in different states. We focus on children born from January 1981 to December 1984, as these children were exposed to many expansions, and we can observe their outcomes in each year of adulthood from age 19 to 28. Our main outcomes include college enrollment, fertility, mortality, wage income, earned income tax credit (EITC) receipts, and tax payments.

One reason why we might expect to observe long-term impacts of Medicaid eligibility on children is that a very large literature demonstrates robust short-term impacts on children and other groups. Seminal papers examine a doubling of eligibility for children from 1984 to 1992 and increases in eligibility for pregnant women from 1979 to 1992 (Cutler and Gruber, 1996; Currie and Gruber, 1996a,b). Pioneering the use of a simulated instrument methodology that we adapt to our application, they find increases in Medicaid coverage and utilization of medical care, as well as reductions in childhood and infant mortality. Card and Shore-Sheppard (2004) use a regression discontinuity design to examine two childhood eligibility increases examined by the previous literature, and they find modest increases in coverage. Several other papers revisit Medicaid expansions and later SCHIP expansions, generally finding Medicaid takeup rates from 5 to 24 percent.[1]

Building on the early literature, several papers have found short-term impacts of Medicaid on outcomes that could serve as mechanisms for long-term impacts. These outcomes include child and infant mortality (Goodman-Bacon, 2018), doctor visits (Lurie, 2009), births (Lindrooth and McCullough, 2007), vaccination rates (Joyce and Racine, 2003), assets (Gruber and Yelowitz, 1999), marriage (Yelowitz, 1998), and abortions (Blank et al., 1996). Findings from the Oregon Health Insurance Experiment demonstrate short-term impacts on a wide

[1]See Blumberg et al. (2000); Rosenbach et al. (2001); Zuckerman and Lutzky (2001); Cunningham et al. (2002); Cunningham et al. (2002); Lo Sasso and Buchmueller (2004); Ham and Shore-Sheppard (2005); Hudson et al. (2005); Bansak and Raphael (2006); Buchmueller et al. (2008); and Gruber and Simon (2008).

variety of other outcomes (Finkelstein et al., 2012; Taubman et al., 2014; Baicker et al., 2013, 2014; Finkelstein et al., 2016).

A small number of papers find long-term impacts of Medicaid on health and health care utilization. Sommers et al. (2012) finds impacts of recent Medicaid expansions on mortality up to five years later. Revisiting one of the expansions examined by Card and Shore-Sheppard (2004), Wherry and Meyer (2016) find a decrease in disease-related mortality for black teens between ages 15 and 18, and Wherry et al. (2015) find decreases in hospital and emergency department visits for black adults, but neither paper can reject decreases for whites. Other work by Miller and Wherry (2016) finds that *in utero* exposure to Medicaid decreases obesity as well as some types of hospitalizations in adulthood. Earlier work by Currie et al. (2008) finds evidence that children living in states with greater Medicaid eligibility in early childhood have better health outcomes later in childhood.

Other papers set the stage for why we might find long-term impacts of Medicaid on economic outcomes in adulthood. Levine and Schanzenbach (2009) and Cohodes et al. (2016) find long-term impacts of childhood Medicaid expansions on human capital formation. Boudreaux et al. (2016) find impacts of the initial adoption of Medicaid on an index of health outcomes, but they do not have enough power to detect meaningful impacts on economic outcomes. A growing literature finds impacts on the long-term economic outcomes of children exposed to other elements of the U.S. social safety net, including disability insurance (Deshpande, 2016), the Food Stamp program (Hoynes et al., 2016), and housing policy (Chetty et al., 2016). A related growing literature finds long-term impacts of childhood interventions outside of the United States, including child care in Norway (Havnes and Mogstad, 2011), well-child visits in Norway (Butikofer et al., forthcoming), medical care at birth for very low birth weight infants in Norway and Chile (Bharadwaj et al., 2013), and a deworming program in Kenya (Baird et al., 2016).

Using administrative data from the IRS, we can examine long-term impacts of Medicaid on outcomes that have not been examined by the Medicaid literature, and we can compare how several outcomes evolve with each year of age. The tax data include all individuals with any interaction with the U.S. tax system starting in 1996, yielding a very large sample size. We focus on all children born from 1981 to 1984. Given the time span of our data, these children are young enough for us to link them to their parents to determine Medicaid eligibility during childhood, and they are old enough for us to observe their outcomes from ages 19 to 28. By comparing outcomes for the same cohorts over a range of adult ages, we can discern relationships between human capital formation, fertility, and earnings.

The tax data do not contain information on Medicaid directly, but we simulate Medicaid eligibility in our data using an eligibility calculator that we developed from federal and state policies, which we distribute online.[2] We also examine robustness to simulating Medicaid eligibility in the Current Population Survey (CPS). We focus on Medicaid eligibility rather than takeup or spending because policymakers can manipulate eligibility thresholds directly. However, we also examine measures of Medicaid takeup and spending derived from the Medicaid Statistical Information System (MSIS).[3] When we add external sources of data, we still take advantage of our longitudinal tax data to assign childhood states of residence.

Our baseline specification harnesses variation across children born in the same state in different birth month cohorts and across children born in different states in the same birth month cohort. While our specification is subject to similar concerns as other specifications that harness state-level policy variation, we conduct exercises that alleviate some concerns. Of particular note, we conduct a dose-response exercise made possible by our longitudinal data. The foundation for the dose-response exercise is that poorer children are more likely to be eligible for Medicaid, so we should see greater impacts of Medicaid on children who resided in poorer households during childhood. The results of our dose-response exercise show that factors at the state and birth month cohort level that affect all children regardless of household income do not drive our results.

Our results show long-term impacts of Medicaid eligibility from birth to age 18 on several outcomes in adulthood. Children with more years of Medicaid eligibility during childhood enroll in college at higher rates, especially through age 22, and they still have a higher probability of having ever enrolled in college by age 26. These children are less likely to have their first dependent child in their teenage years, but impacts on this measure of fertility are most pronounced from ages 18–21, overlapping with the ages of greatest impact on college enrollment. After age 21, as individuals who delayed their fertility have their first child, impacts on fertility decrease, but an absolute decrease is still apparent at age 28. Temporal patterns in adult mortality are harder to discern, but cumulative adult mortality rates are lower for individuals who had greater Medicaid eligibility as children.

Turning to economic outcomes, females with more years of Medicaid eligibility during childhood have higher wage income starting at age 23, and the increases get larger with

[2] Several individuals contributed to the development of the calculator, and we acknowledge them in the documentation for the calculator available at http://users.nber.org/~kowalski/BKL.Medicaid.Calculator.Documentation.pdf. The full calculator is available for download at http://users.nber.org/~kowalski/BKL.Medicaid.Calculator.zip. The Medicaid calculator computes monthly Medicaid eligibility through age 18 for birth month cohorts born from January 1981–December 1984. The calculator consists of the federal poverty level (FPL) eligibility thresholds that each state and Washington, D.C., used to means-test Medicaid over this period. The calculator takes as inputs the following data which are sufficient to determine if a child was eligible for Medicaid: birth month and birth year, state of residence, and income as a percentage of the FPL (a statutory function of family income, state of residence, and household size). Along with the calculator itself, we provide detailed documentation on each source. We also distribute simulated Medicaid eligibility series that we constructed by applying our calculator to our tax data and to the Current Population Survey (CPS).

[3] We distribute these data with the Medicaid eligibility calculator.

age. By age 28, each additional year of simulated childhood Medicaid eligibility results in an increase of $1,784 in cumulative wage income on a base of $136,600. Male increases are smaller and imprecise. However, both genders collect less from the earned income tax credit (EITC) at each age from 19–28. Cumulatively by age 28, for each additional year of simulated childhood Medicaid eligibility, they collect $182 less on a base of $3,044. The increase in their total tax payments grows with age. Cumulatively by age 28, they pay $533 more in total taxes on a base of $20,623 for each additional year of simulated childhood Medicaid eligibility. Each additional year of simulated childhood Medicaid eligibility results in an additional 0.59 years of coverage and costs the government $593. Discounted to birth at a 3% rate, each additional year of simulated Medicaid eligibility increases spending by $404 and taxes by $233. The ratio of $233 to $404 implies that the government recoups 58 cents of each dollar it spends on childhood Medicaid by age 28.

In the next section, we discuss our data and methodology. In Section 3, we present our main results on the long-term impact of Medicaid. We examine heterogeneity in our results and the robustness of our results in Section 4. In Section 5, we examine Medicaid takeup and spending, and we calculate the implied fiscal return on investment in Medicaid. We conclude in Section 6.

2 Data and Methodology

2.1 Sample Selection

Our primary source of data comes from administrative tax records obtained from the Internal Revenue Service (IRS). These data span 1996 to the present and include all individuals who interacted with the tax system in those years. With access to an array of tax forms, we can examine effects for a variety of outcomes with a high level of precision and generality. These data have been used in few studies because of extremely limited accessibility due to their confidential nature. Examples of studies that have used these data include Chetty et al. (2011), Chetty et al. (2013), and Yagan (2016). Our project is one of the first to use the population of administrative tax data to evaluate the intersection of health policy and tax administration, alongside other work coauthored by members of our team (Helmchen et al., 2015; Heim et al., 2017)

We focus on children born from 1981 to 1984 because these children are old enough for us to observe their adult outcomes from ages 19 to 28, and they are young enough for us to link them to their parents so that we can estimate their Medicaid eligibility during childhood. We restrict analysis to children that we can link to their parents using Form 1040 in 1997, the earliest year in which we are confident in the linkage. We do not require parents to claim the children in any year other than 1997, but we do require parents to file a Form 1040 in each tax year from 1996 (the first year of our data) through the year in which the child turns 18 to increase the accuracy of our Medicaid eligibility estimates. After imposing other minor restrictions, the filing restriction eliminates about 20% of children, yielding a main sample of 10,045,162 children.[4] We examine robustness to this restriction by imputing Medicaid eligibility for children whose parents do not file in years other than 1997. In any given year, the vast majority of low-income parents file because the EITC and the child tax credit are refundable, providing an incentive to file even if the taxpayer faces no tax liability. Taxpayers whose employers file Form W-2 have another incentive to file because if they do not, they forfeit any excess federal income tax that has been withheld.

Even if children in our sample do not file in every year of adulthood, we can observe our six main outcomes—college enrollment, fertility, mortality, wage income, earned income tax credit (EITC) receipts, and tax payments—given a rich set of returns filed by other parties and the longitudinal nature of our data. For example, colleges file Form 1098-T, from which we derive college enrollment. The Social Security Administration maintains death records that have been linked to the administrative tax records. Employers file Form W-2, which provides information on wage income, payroll taxes, and federal income tax withholding. If individuals do not file, their EITC receipts are zero. Our measure of fertility only requires individuals in our sample to claim a child on a Form 1040 in at least one year of our data. From a single filing, we can infer the age of the individual when their child was born.

2.2 Medicaid Eligibility

Our administrative tax data do not contain information on Medicaid directly, but we calculate Medicaid eligibility in our data using a calculator that we developed and distribute online. The calculator incorporates many federal and state policies that affected Medicaid eligibility for the children in our sample. In the early 1980s, children eligible for Medicaid mainly resided in low-income single-parent households. However, the federal government enacted several policies that first permitted and then required states to extend Medicaid eligibility to larger groups of children. For example, the Medicare Catastrophic Coverage Act of 1988 allowed states the option to extend coverage to children in households with higher incomes, and the Omnibus Budget Reconcilliation Acts (OBRAs) of 1989 and 1990

[4] Census estimates show that approximately 14.6 million children were born in 1981–1984. In the tax data, we begin with 13,834,198 dependents claimed on Form 1040 in 1997 that were born in 1981–1984 (we rely upon the date of birth (DOB) maintained by the Social Security Administration linked to the dependent's social security number rather than taxpayer-provided DOB on Form 1040). However, some of these dependents are duplicates claimed on more than one return. Addressing this issue by randomly selecting one return for duplicates, we arrive at 13,113,433 children matched as dependents in 1997. We lose additional children for whom we cannot identify a state of residence in each filing year from 1996 through age 18, arriving at 12,852,988 children. Restricting the sample to children whose parents file in every tax year from 1996 until the child turns 18, we arrive at our main estimation sample of 10,045,162 children: 4,913,139 females and 5,132,023 males. Part of the reason why we lose sample size in the last selection step is that 3,429,112 Form 1040 records are missing from our data in Florida in 1999 (some of the missing records are for parents of children who would otherwise be in our main sample).

required states to extend coverage to some groups of children based on their month of birth and household income. Because state legislation responded to federal legislation with various lags and established various eligibility thresholds, the combination of state and federal legislation induced a great deal of variation in Medicaid eligibility for children.

To determine Medicaid eligibility for an individual at a given age, we first calculate "household FPL," household income as a percent of the federal poverty level (FPL). The FPL is a statutory function of household size, household income, year, and state of residence; all states except Alaska and Hawaii share the same FPL. For years prior to when our data start in 1996, we hold household FPL constant using household FPL in the year of parent-child linkage. We then compare household FPL to the eligibility threshold in the calculator that corresponds to the household's state of residence, the month of eligibility, and the child's age in December.[5]

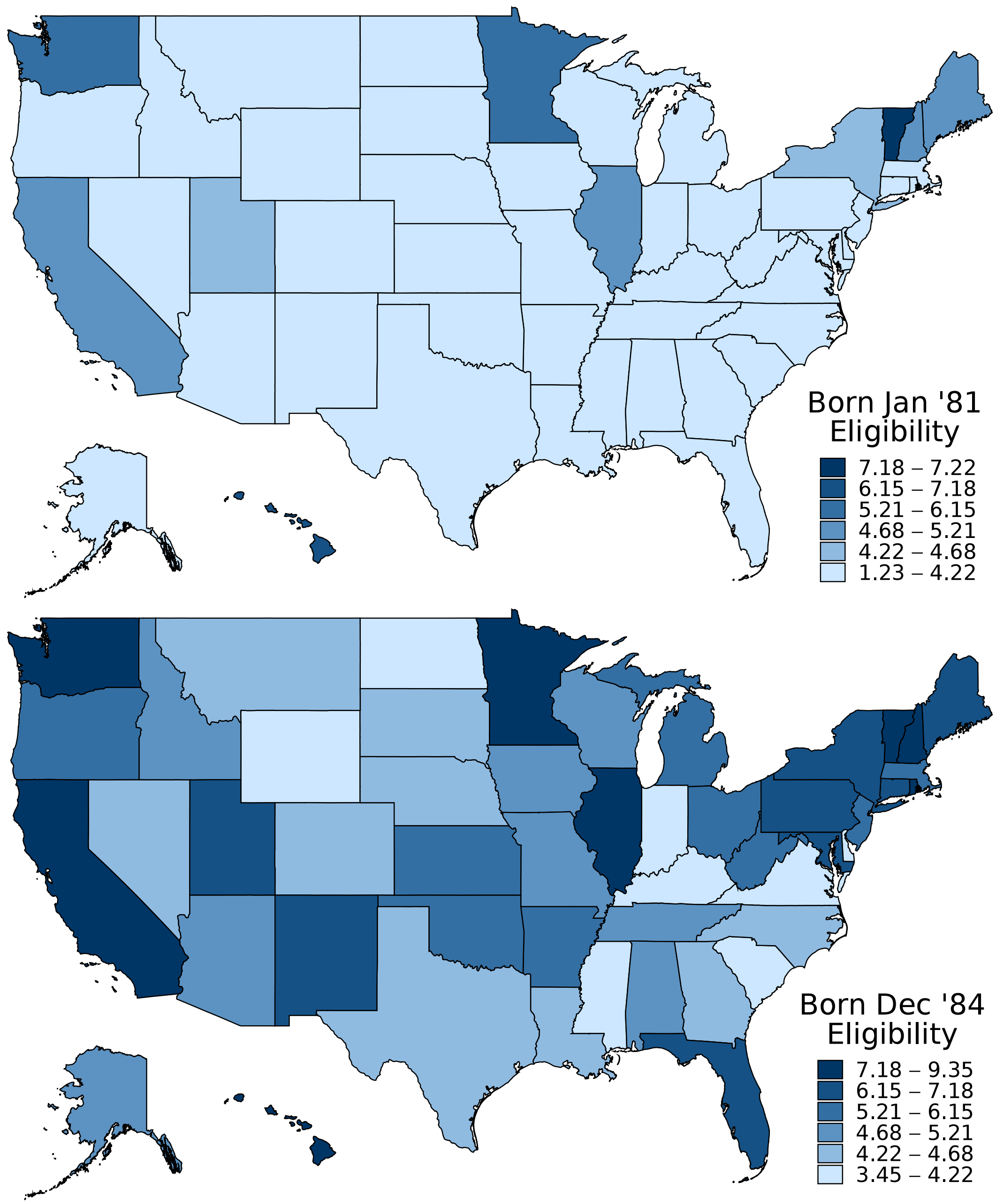
Since we are interested in the long-term impact of Medicaid eligibility, we construct measures of cumulative eligibility during childhood. We do so by summing Medicaid eligibility at each age from birth to age 18. To calculate Medicaid eligibility at ages before our data begin (before age 12 for our youngest cohort and age 15 for our oldest cohort), we assume that the child resides in the state of residence observed in the year of linkage (1997).

To address measurement error and to isolate policy-induced variation in Medicaid eligibility, we construct simulated measures of Medicaid eligibility in the tradition of Currie and Gruber (1996b). To construct simulated Medicaid eligibility in our data, we first extract a national sample of 200,000 dependents from 1997. For each eligibility year and state, we use our calculator to compute the share of children born in each month of the simulation sample who are eligible for Medicaid. To take into account trends in income over time, we also examine robustness to simulating Medicaid eligibility using a national sample drawn from the CPS in each year. We construct our main measure of simulated Medicaid eligibility during childhood by summing the assigned simulated Medicaid eligibility from birth to age 18 for each individual in our data. Simulated eligibility varies with the vector of states in which we observe the child residing in our longitudinal data.

Overall, individuals in our sample were eligible for Medicaid from birth to age 18 for an average of 3.77 years, with a standard deviation of 5.61 years. Simulated Medicaid eligibility is 4.49 years on average, with a standard deviation of 1.60 years. Figure 1 shows cross-state variation in simulated Medicaid eligibility during childhood for children born in our oldest and youngest cohorts, assuming that they resided in the same state from birth to age 18, so simulated eligibility does not vary within a state. As shown in the top panel, children born in January 1981 had just over one year of simulated eligibility from birth to age 18

[5]We only use the eligibility threshold from December of each year because we only observe the information needed for the calculator once per year (after the tax year is complete). Our focus on December eligibility should overstate our Medicaid eligibility levels because eligibility generally increased over time.

Figure 1: State Variation in Simulated Years Eligible for Medicaid, Ages 0–18



Note. Bins reflect the sextiles of the distribution for the cohort born in December 1984. We present the January 1981 and December 1984 cohorts because they are the oldest and youngest cohorts in our sample.

in Mississippi and more than six years in Vermont. As shown in the bottom panel, there is still a considerable amount of variation across states for children born in December 1984. However, individuals in this youngest cohort have a population-weighted average of 1.85 additional years of simulated eligibility relative to individuals in the oldest cohort. There is also variation in simulated Medicaid eligibility across individuals born in different months of the same calendar year that is not visible in this figure.

2.3 Methodology

To estimate the effect of Medicaid eligibility during childhood on long-term outcomes by age, we estimate the following main reduced form specification:

$$Y_{i,a} = \beta_a \sum_{t=0}^{18} Z_{i,t} + \gamma_c + \gamma_s + \varepsilon_{i,a}, \qquad (1)$$

where $\sum_{t=0}^{18} Z_{i,t}$ represents our "simulated instrument" simulated years eligible for Medicaid from birth to age 18 for individual i, where t denotes childhood age. We interpret the coefficient β_a as the effect of an additional year of Medicaid eligibility during childhood on an outcome $Y_{i,a}$ measured at adult age a. We estimate equation (1) for each adult age from 19 to 28 for two measures of each main outcome: (i) a contemporaneous measure at the given age, which we use to discern temporal patterns in the effect of Medicaid eligibility, and (ii) a cumulative measure from age 19 to the given age, which we use to measure an aggregate effect of Medicaid eligibility. We estimate equation (1) in the full sample and separately for females and males.

Equation (1) incorporates fixed effects for birth month cohort c and fixed effects for state of residence s at age 15 (the youngest age at which we observe all individuals in our sample). These fixed effects control for time-invariant state characteristics and state-invariant birth month cohort characteristics. The specification harnesses variation in Medicaid eligibility across birth month cohorts within a state and across states within a birth month cohort.[6] We examine robustness to the inclusion of income controls, but we exclude income controls from the main specification because household income at age 15 could be a function of Medicaid eligibility for children at previous ages, which would lead to an attenuation of our estimates. We cluster standard errors by state of residence at age 15 to account for arbitrary

[6] For robustness, we also conduct an exercise that harnesses only variation from OBRA 90, a federal policy that selectively applied to children born in different months of the same year. We estimate a regression discontinuity specification with a discontinuity at September 30, 1983, following Card and Shore-Sheppard (2004), Wherry and Meyer (2016), and (Wherry et al., 2015). Although the results are qualitatively similar to our main results, they are much noisier, so we report them and discuss their limitations relative to our preferred specification in Online Appendix 1. While Card and Shore-Sheppard (2004) also examine the OBRA 89 expansion, which started in 1990 and applied to children under six, we do not use this source of eligibility because the youngest children in our sample were six years of age by December 1990.

correlations within states over time.

While our specification is subject to similar concerns as other specifications that harness policy variation by state and cohort, the longitudinal nature of our data allows us to conduct a dose-response exercise that alleviates some concerns. The foundation for the dose-response exercise is that poorer children are more likely to be eligible for Medicaid, so we should see greater impacts of Medicaid on adults who resided in poorer households during childhood. To implement the exercise, we estimate equation (1) on samples stratified by household FPL during childhood for each of our main outcomes. To the extent that we see a dose-response relationship between household FPL during childhood and long-term impacts, we can be confident that policies or economic changes coincident with Medicaid expansions that affected all children regardless of household FPL do not drive our main results. Remaining threats to our design include factors coincident with Medicaid expansions that differentially affected *poor* children (i) born in different birth month cohorts who reside in the same state, or (ii) born in the same birth month cohort who reside in different states.

For several reasons, we focus on the reduced form specification given by equation (1) rather than a traditional instrumental variable (IV) specification that instruments Medicaid eligibility with simulated eligibility. First, the reduced form is simpler and more transparent. To estimate the reduced form, we use longitudinal data on state of residence during childhood to determine simulated Medicaid eligibility. To estimate the IV, we also need longitudinal data on household FPL to determine endogenous Medicaid eligibility. Second, the reduced form and IV are quantitatively similar since the first stage is close to one, as we show in the first column of Table 1. Third, a dose-response relationship between childhood poverty and outcomes should only be visible in the reduced form (the first stage should be close to zero for children far from poverty, so the IV estimate, which is equal to the reduced form estimate divided by the first stage estimate, is not well-defined). Although we focus on reduced form estimates, readers can construct IV estimates by dividing the reduced form estimates by the first stage estimate, and we also report ordinary least squares (OLS) estimates.

3 Results

3.1 College Enrollment

We measure college enrollment using Form 1098-T, which educational institutions send to the IRS regardless of whether the enrollee files a return or claims a tax credit. The 1098-T is used to administer educational incentives such as the American Opportunity Tax Credit and the Lifetime Learning Credit. From the 1098-T, we derive our main measures of college enrollment: (i) a contemporaneous measure that indicates whether an individual is currently enrolled at a given age, and (ii) a cumulative measure that indicates whether an individual has ever enrolled from age 19 to a given age. We do not consider cumulative years of enrollment because five years of college is not necessarily better than four. The 1098-T does not include an indicator for college completion. Using the 1098-T, Chetty et al. (2014, 2016) measure contemporaneous college enrollment as we do. Chetty et al. (2014) report a correlation greater than 0.95 between enrollment counts using the 1098-T and a corresponding measure from the Integrated Postsecondary Education Data System (IPEDS).

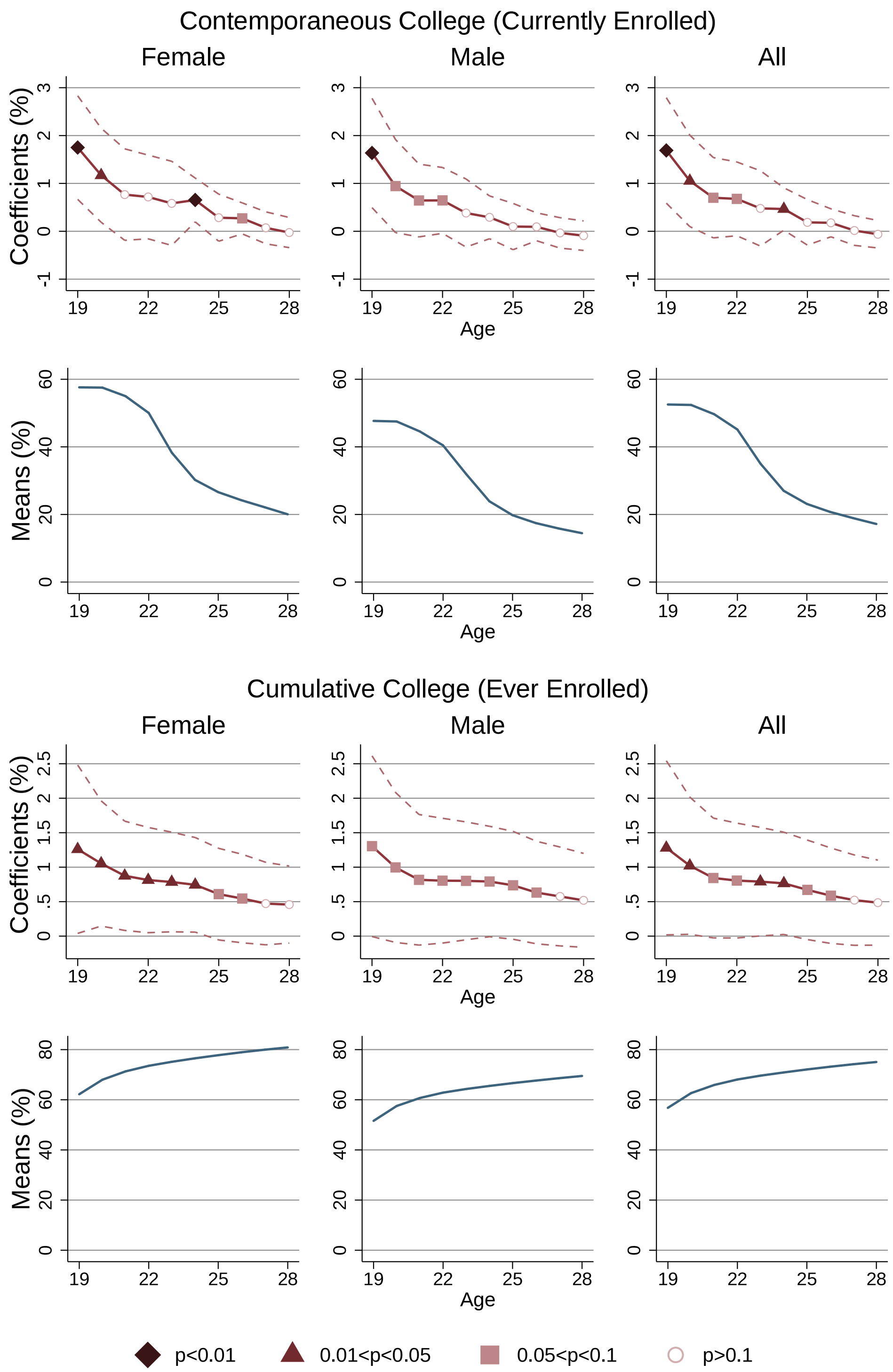
Figure 2a reports contemporaneous results in the top panel and cumulative results in the bottom panel. Within each panel, the top subfigures plot the coefficient β_a from equation (1), estimated at each age a from 19 to 28. The columns report results within the female, male, and full samples. The bottom subfigures in each panel plot the mean of the dependent variable within each sample at each age. We report the values from Figure 2a in tabular form in Table OA.2 of Online Appendix 2. To facilitate comparisons across outcomes, we also report coefficients for all of our main outcomes—college enrollment, fertility, mortality, wage income, earned income tax credit (EITC), and total taxes—at ages 19, 22, and 28 in Table A.1, which presents contemporaneous coefficients, and A.2, which presents cumulative coefficients.

The contemporaneous means in Figure 2a show strong temporal patterns in college enrollment; from age 19 to age 28, annual college enrollment falls from 53% to 17%. At every age, females enroll in college at higher rates than males. The cumulative means show that 81% of women and 70% of men ever enroll by age 28. Despite the differences in means across genders, the magnitudes of the coefficients are indistinguishable. At age 19, the coefficient in the full sample indicates that each additional year of Medicaid eligibility increases college enrollment by 1.69 percentage points on a base of 53%. The results are largest in magnitude through age 22. At older ages, as college enrollment decreases, so does the impact of Medicaid.

The cumulative coefficients show that Medicaid shifts the timing of college enrollment to younger ages. Additionally, the coefficients suggest that Medicaid increases college enrollment in general since the cumulative coefficients remain positive at older ages, though they are not statistically significant at conventional levels after age 26. By age 28, each additional year of Medicaid eligibility during childhood increases the probability of having ever enrolled in college by 0.49 percentage points on a base of 75%.

To put our estimates in context, Cohodes et al. (2016) find that a 10 percentage point increase in Medicaid eligibility during childhood decreases the high school dropout rate by 4%, increases college enrollment by 0.5%, and increases college completion by 2.5%. Their 10 percentage point increase in Medicaid eligibility from birth to age 17 translates into 1.8 (=0.1*18) additional years of eligibility. Our cumulative coefficient implies that a 1.8 year increase in Medicaid eligibility during childhood increases the likelihood of having ever enrolled in college by 1.17% (=0.486*1.8/0.75) at age 28, which is larger than their estimate

Figure 2a: Contemporaneous and Cumulative College Enrollment (%)



Note. Contemporaneous college enrollment indicates current enrollment in college at a given age, observed through Form 1098-T, filed by educational institutions. Cumulative college enrollment indicates ever having enrolled in college by a given age, starting at age 19. Coefficients for each age are obtained from separate reduced form regressions of college enrollment on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state. Dashed lines show 95% confidence intervals. Table OA.2 contains corresponding results.

for college enrollment but smaller than their estimate for college completion.

3.2 Fertility

We observe fertility if any individual in our sample ever claims a dependent child on a Form 1040. For each dependent child claimed, we use SSA records to obtain the DOB of the child and thereby the age of the parent when the child is born, even if the parent does not claim the child until a subsequent year.[7] Contemporaneous fertility indicates if a first dependent child is born at a given age, and cumulative fertility indicates if a dependent child is ever born by a given age. While these measures of fertility depend on filing and claiming behavior, the vast majority of children are claimed as dependents at some point early in their lives. Further, claiming a dependent child is interesting in its own right, as it determines EITC eligibility and reflects the unequal costs of fertility borne by females.

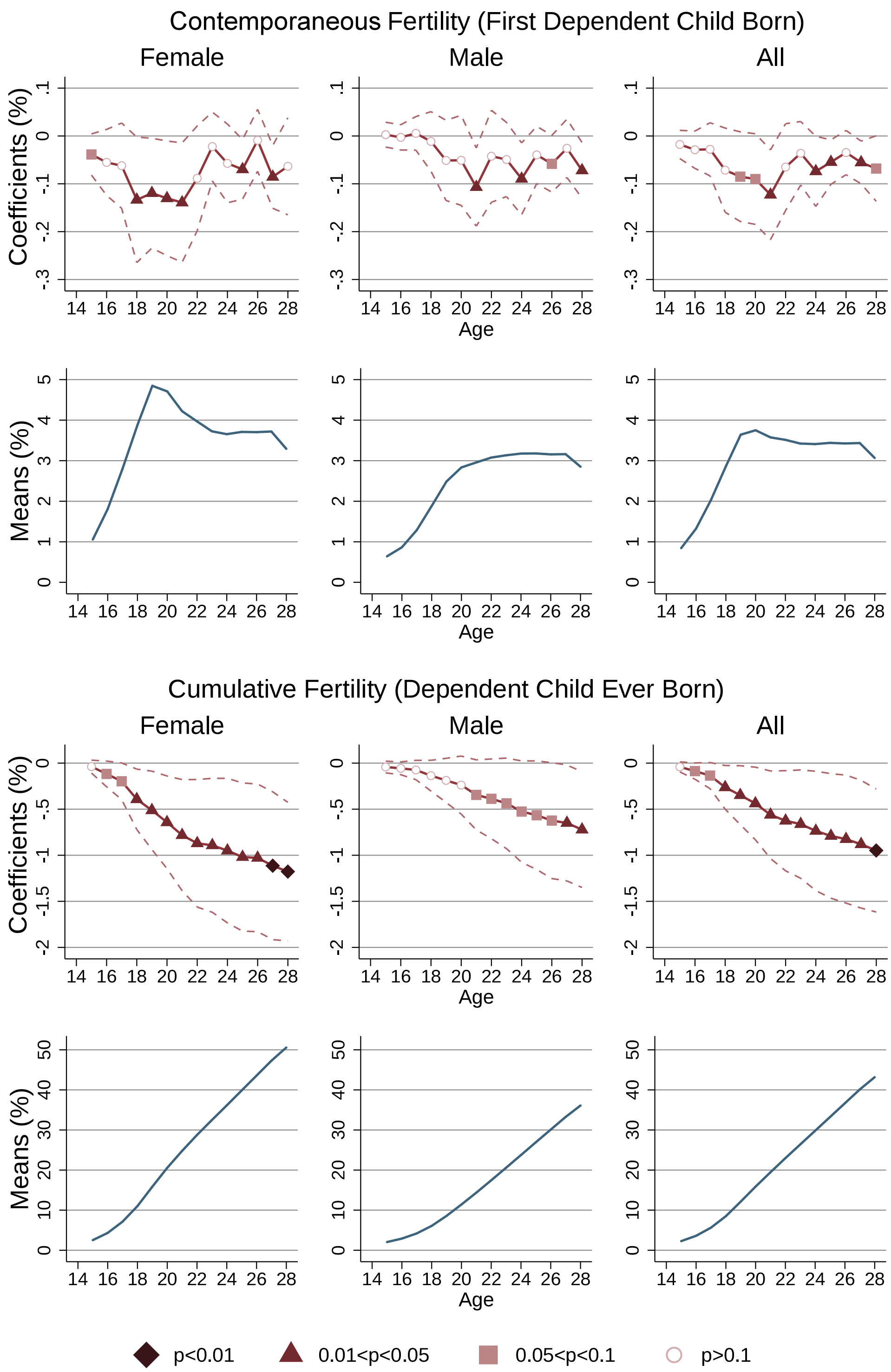
We focus on the first birth since the first child is likely to cause earlier disruptions in human capital investment and labor force participation, resulting in greater effects on labor market outcomes later in life. Furthermore, the first birth has a greater impact on EITC eligibility and benefit levels than subsequent births. To capture first births that occur during teenage years, we estimate impacts on fertility starting at age 15, the first year that we have reliable data on Medicaid eligibility and covariates for all individuals in our sample. We measure Medicaid eligibility through the age of the outcome or through age 18, whichever is younger. We observe births before age 15, and we incorporate them into our cumulative outcomes. Therefore, our cumulative outcome at age 19 should capture all births during the teenage years.

As shown in Figure 2b and Table OA.3, our mean fertility outcomes are larger for women than for men at all ages. By age 28, 51% of women and 36% of men have dependents that have already been born (our specification includes children claimed as dependents before, during, or after age 28). There are a variety of reasons why we could observe larger fertility outcomes for women. For example, women could be more likely to claim children as single parents, women could have children with older men, and women could have children with men who also have children with other women. Despite the apparent differences in means, the coefficients are only slightly larger for women than they are from men, and the magnitudes are statistically indistinguishable across genders.

The coefficients show that children eligible for Medicaid are less likely to have their first dependent child in their teenage years. Each additional year of Medicaid eligibility during childhood decreases the cumulative probability that the first dependent child has been born

[7] Chetty et al. (2016) directly observe fertility in the tax data using the Kidlink (DM-2) database from the SSA, made available at the IRS. We cannot use this database to measure fertility in our sample because it begins in 1983. However, similar to Kidlink (DM-2), our measure uses SSA records linked through the social security number (SSN) to determine the time of fertility. It differs from Kidlink (DM-2) only in that we establish fertility through claiming behavior over a wide range of filing years.

Figure 2b: Contemporaneous and Cumulative Fertility (%)



Note. Contemporaneous fertility indicates if a first dependent child is born at a given age, and cumulative fertility indicates if a dependent child is ever born by a given age, starting at age 19. If an individual ever claims a dependent child on a Form 1040, SSA records yield age at birth. Coefficients for each age are obtained from separate reduced form regressions of fertility on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state. Dashed lines show 95% confidence intervals. Table OA.3 contains corresponding results.

by age 19 by 0.35 percentage points on a base of 12.1%. The contemporaneous coefficients show that Medicaid eligibility has the most pronounced impacts on fertility from ages 18–21, overlapping with the ages of greatest impact on college enrollment. After age 21, as individuals who delayed their fertility have their first child, impacts on fertility decrease, but an absolute decrease is still apparent at age 28. By age 28, a dependent child has been born to 43% of our sample, and each additional year of Medicaid eligibility during childhood decreases the probability that the first dependent child has been born by 0.95 percentage points.

Delays in fertility could serve as a mechanism through which Medicaid affects later-life economic outcomes. Hotz et al. (2005) and Hotz et al. (1997) find that would-be teen mothers who have miscarriages have lower annual hours of work and earnings as adults. However, we generally expect reductions in fertility to improve economic outcomes, since our focus is broader than teen motherhood and since we see decreases in fertility at ages where also see increases in college enrollment.

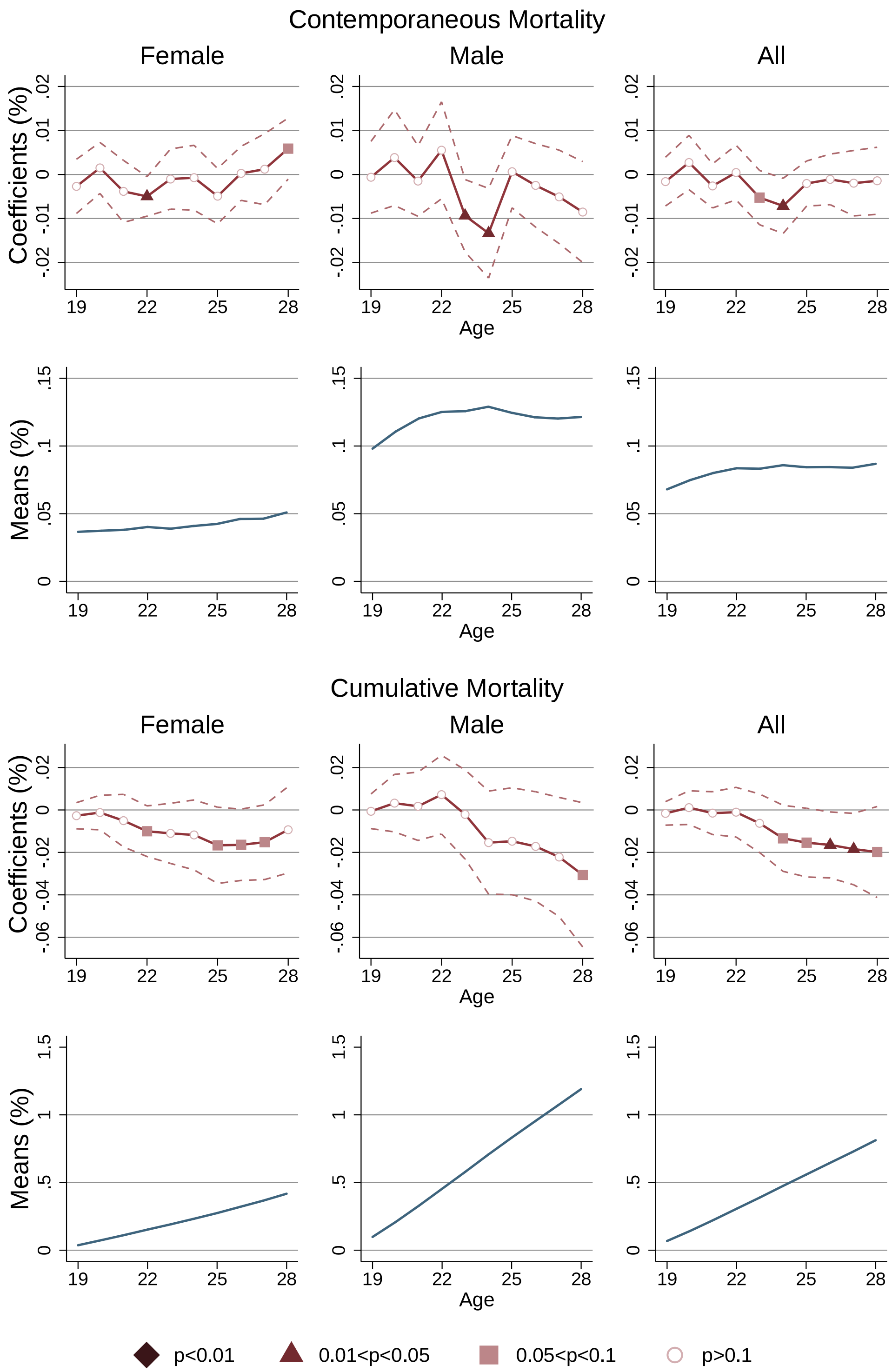
3.3 Mortality

We observe mortality regardless of filing behavior using Social Security Administration (SSA) death records. We focus on mortality from age 19 to age 28 so that we can assess temporal patterns in mortality relative to other outcomes, holding the sample constant. Though examining fertility before age 19 does not require us to change our sample, examining mortality before age 19 would require us to expand our sample to include children who died during childhood. Because we have limited administrative tax data on children who die at young ages, including them would necessitate changes to our instrument and specification that would inhibit comparability with our main results.

As shown in Figure 2c and Table OA.4, the contemporaneous mortality coefficients are generally imprecise, and it is hard to discern temporal patterns. However, we observe cumulative mortality reductions over adulthood that are statistically significant at least at the 10% level from ages 25–28 and at the 5% level from ages 26–27. We focus on the point estimate at age 28 for comparison to other outcomes. On a base of 81.2 cumulative deaths per 10,000 from ages 19–28, each additional year of childhood Medicaid eligibility saves 2.0 lives per 10,000 in aggregate, an average of 0.20 lives per 10,000 each year.

The magnitude of our adult mortality estimate is plausible in the context of previous infant, child, and teen mortality estimates from the Medicaid literature. Currie and Gruber (1996b) find a large infant mortality impact; an additional year of eligibility at birth saves 30.31 infant lives per 10,000. Considering children, who have lower death rates, Currie and Gruber (1996a) find that each additional year of Medicaid eligibility during childhood saves 1.28 child lives per 10,000. Considering teens, who have higher death rates, Wherry and Meyer (2016) find that each additional year of Medicaid eligibility during childhood saves

Figure 2c: Contemporaneous and Cumulative Mortality (%)



Note. Contemporaneous mortality indicates mortality at a given age, measured using SSA death records. Cumulative mortality indicates mortality by a given age, starting at age 19. Coefficients for each age are obtained from separate reduced form regressions of mortality on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state. Dashed lines show 95% confidence intervals. Table OA.4 contains corresponding results.

0.16 teens per 10,000 per year from ages 15–18. As we show in Section 5.1, even though the absolute number of lives saved varies across studies, estimates of cost per life saved are similar.

3.4 Wage Income

We measure wage income using Line 1 of Form W-2, summed over all employers in a given tax year and adjusted to 2011 dollars using the CPI-U. Individuals who file without Form W-2 have zero wage income. The frequency of zero contemporaneous wage income ranges from 12.4% at age 23 to 17.9% at age 28. Chetty et al. (2011) show that wages at age 28 are a good predictor of future wages, which supports our focus on wage income at age 28.

As shown in Figure 2d and Table OA.5, average wage income grows with age, and the impact of Medicaid on wage income also tends to grow with age. At a few ages, estimates are statistically significant at the 10% level in the full sample. Females with more years of Medicaid eligibility during childhood have higher contemporaneous wage income starting at age 23, and the increases get larger with age. Cumulative impacts on wage income magnify contemporaneous impacts, gaining magnitude with age. By age 28, each additional year of childhood Medicaid for females results in $1,784 of cumulative wage income on a base of $136,600. Male increases are smaller and imprecise.

It is unclear why wage income gains are larger for females. Increases in college enrollment and decreases in fertility are indistinguishable for females and males. However, it is possible that these factors have a disproportionate impact on wage income for females, especially since we start to see gains in wage income around age 23, presumably after graduation from college.

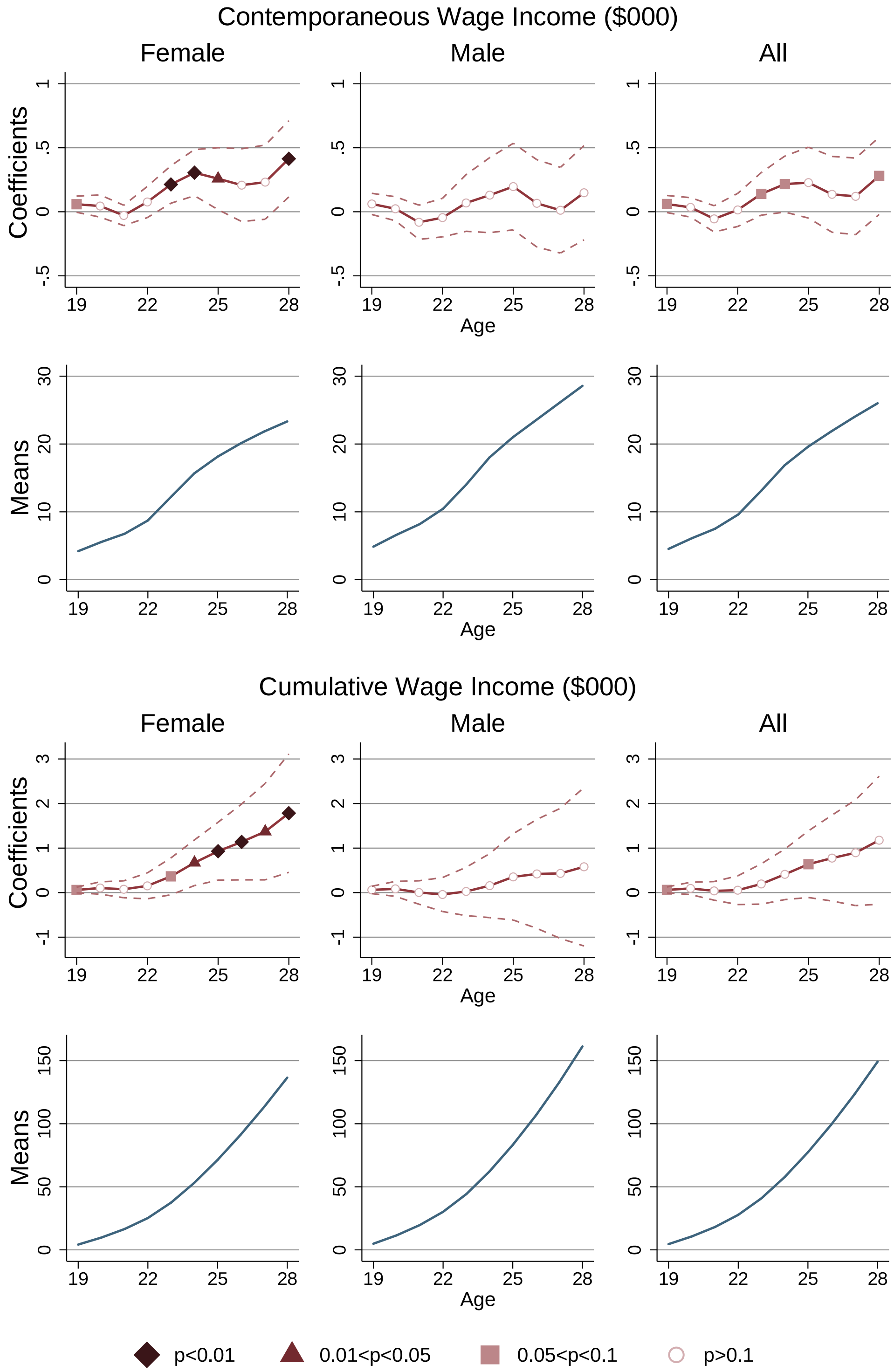
To put our wage results in the context of a finding from the small existing literature on long-term wage impacts of interventions during childhood, Chetty et al. (2011) find that a one standard deviation increase in teacher value-added in a given grade increases earnings at age 28 by 1.3%. Our estimate is of the same order of magnitude. In the full sample, a one standard deviation increase in Medicaid eligibility (5.59 years) results in a 6.0% increase (=(280*5.59)/26,013) in wage income at age 28.

3.5 Earned Income Tax Credit (EITC)

Since the EITC is administered through the tax system, we measure EITC receipt directly using Form 1040. We examine EITC receipt at the household level, as eligibility and benefit levels are determined at that level. EITC receipt is zero for a large fraction of the sample, so we examine EITC participation as a supplemental outcome. Although EITC generosity expanded during the period of study, we do not adjust our estimates because actual EITC receipts are relevant for the fiscal return to Medicaid spending.

The coefficients shown in Figure 2e and Table OA.6 show that individuals with greater

Figure 2d: Contemporaneous and Cumulative Wage Income ($000)



Note. Contemporaneous wage income indicates wages earned at a given age, obtained from Form W-2, adjusted to 2011 dollars and censored at $10 million. Cumulative wage income indicates wage income earned by a given age, starting at age 19. Coefficients for each age are obtained from separate reduced form regressions of wage income on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state. Dashed lines show 95% confidence intervals. Table OA.5 contains corresponding results.

Medicaid eligibility during childhood collect less from the EITC at all ages from 19–22, and the decreases generally get more pronounced over time. Cumulatively by age 28, for each additional year of Medicaid eligibility during childhood, adults collect $182 less on a base of $3,044. In addition to reducing EITC benefits, Table OA.8 in Online Appendix 3 shows that each additional year of Medicaid eligibility reduces the probability of EITC participation from ages 19–28 by 0.69 percentage points on a base of 47.5%. These decreases are particularly notable given that EITC benefits tend to grow with age within our data.

The effect of Medicaid eligibility on EITC receipts is approximately twice as large for women, and the 95% confidence intervals for women and men shown in Figure 2e often do not overlap. EITC eligibility does not explicitly depend on gender—it only depends on income, number of children, and marital status. Therefore, our wage income and fertility and results provide potential mechanisms through which Medicaid affects EITC receipt.

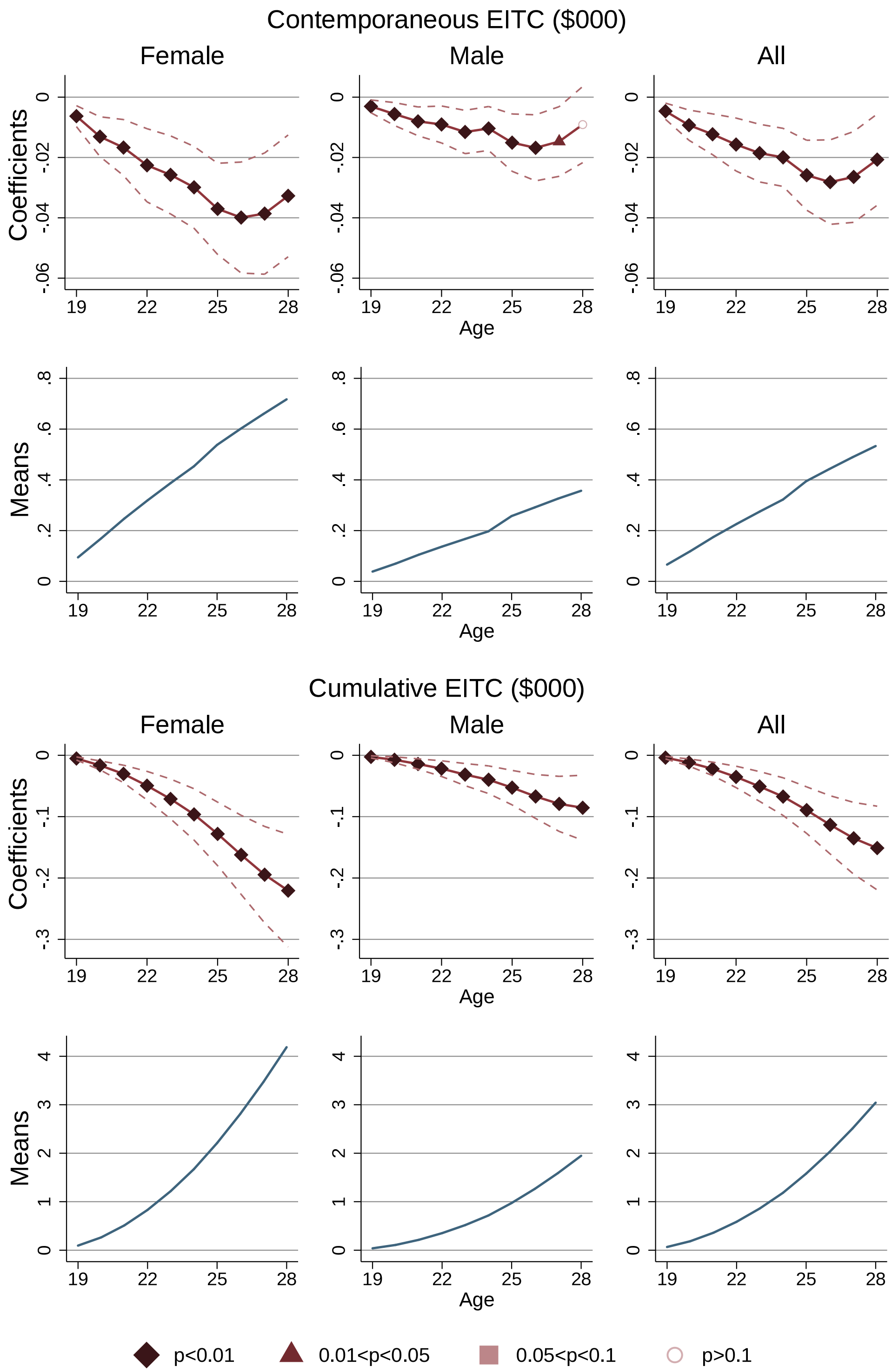
3.6 Total Taxes

Our administrative tax data are especially well-suited to the examination of tax payments. Tax payments are relevant for the fiscal return to Medicaid spending, and they are also relevant as a summary measure that reflects the other five main outcomes (college enrollment, fertility, mortality, wage income, and EITC). We construct a measure of total federal income and payroll taxes at the household level. We start with tax payments reported on Form 1040 for the household, from which we deduct refundable tax credits—such as the Earned Income Tax Credit (EITC), the Additional Child Tax Credit, and credits refundable through the American Opportunity Tax Credit. Next, for each individual in the household, we add payroll tax payments reported by employers on Form W-2 and by the self-employed on Schedule SE. We adjust total taxes to 2011 dollars using the CPI-U.

The results in Figure 2f and Table OA.7 show that the positive impact of Medicaid on total taxes increase with age. Cumulatively by age 28, each additional year of Medicaid eligibility during childhood increases total taxes by $533 on a base of $20,623. Therefore, a one standard deviation increase in Medicaid eligibility during childhood (5.61 years) increases total taxes by $2,990 (=533*5.61), a 14.5% increase (=2,990/20,623). Cumulative coefficients are significant at the 5% level at ages 19–22 and the 1% level at ages 23–28. Female coefficients are slightly larger and more precise than male coefficients.

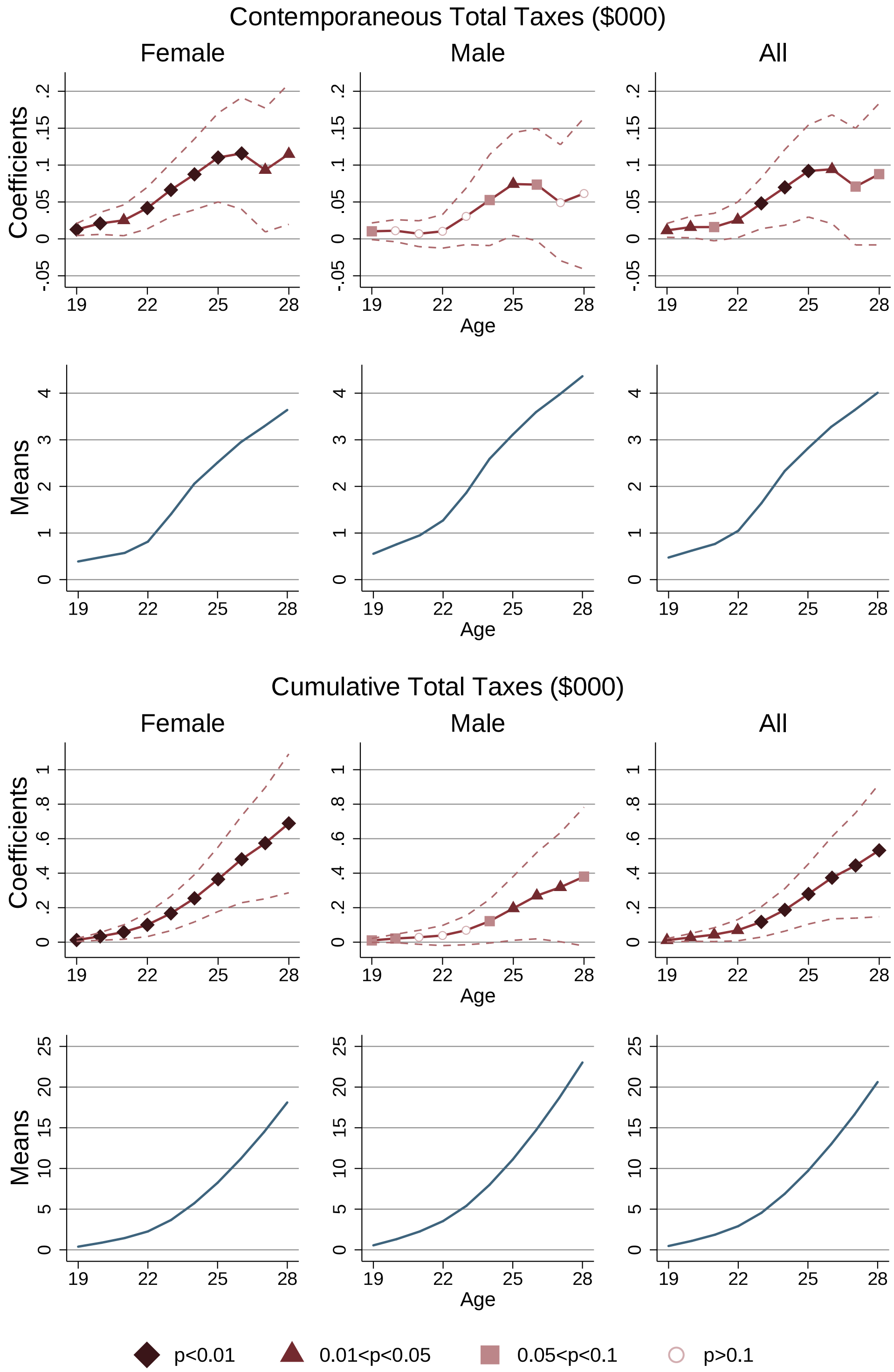
A natural question is how the increase in total taxes relates to our findings of an increase in wage income and a decrease in EITC receipts. More broadly, we are interested in how much of the increase in total taxes stems from changes in payments to vs. from the government. It is hard to separate these factors from a causal perspective because income affects EITC receipts, but we can separate them from an accounting perspective. We decompose total taxes into three components: EITC, payroll taxes (a transformation of wage income), and income taxes plus EITC (gross income taxes). Total taxes are equal to payroll taxes plus

Figure 2e: Contemporaneous and Cumulative EITC ($000)



Note. Contemporaneous EITC indicates EITC earned at a given age, obtained from Form 1040, adjusted to 2011 dollars. Cumulative EITC indicates EITC earned by a given age, starting at age 19. Coefficients for each age are obtained from separate reduced form regressions of EITC on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state. Dashed lines show 95% confidence intervals. Table OA.6 contains corresponding results.

Figure 2f: Contemporaneous and Cumulative Total Taxes ($000)



Note. Contemporaneous total taxes indicate taxes paid at a given age, defined as household federal tax payments plus individual payroll tax payments less EITC, adjusted to 2011 dollars. Cumulative total taxes indicate taxes paid by a given age, starting at age 19. Coefficients for each age are obtained from separate reduced form regressions of total taxes on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state. Dashed lines show 95% confidence intervals. Table OA.7 contains corresponding results.

gross income taxes minus EITC. We perform the decomposition in this way so that the EITC results have the same sign in the main results, even though EITC receipts enter negatively into the government budget. Online Appendix 4 presents results that examine each component of total taxes as separate outcomes in equation (1). As shown in Figure OA.4 and Table OA.9, at age 19, each additional year of Medicaid eligibility during childhood decreases EITC by \$5 and increases total taxes by \$12. Therefore, 42% (=-(-5)/12) of the change in cumulative total taxes is due to a decrease in EITC. By similar calculations, the increase in payroll taxes explains 25%, and the increase in gross income taxes explains the remaining 33%. Further into adulthood, the absolute impact of each component on total taxes grows, but the decomposition shows that the relative impact changes—the role of EITC decreases dramatically and the role of income taxes increases dramatically. At age 28, 24% of the \$88 increase in contemporaneous total taxes is due to a decrease in EITC and 83% is due to an increase in gross income taxes.

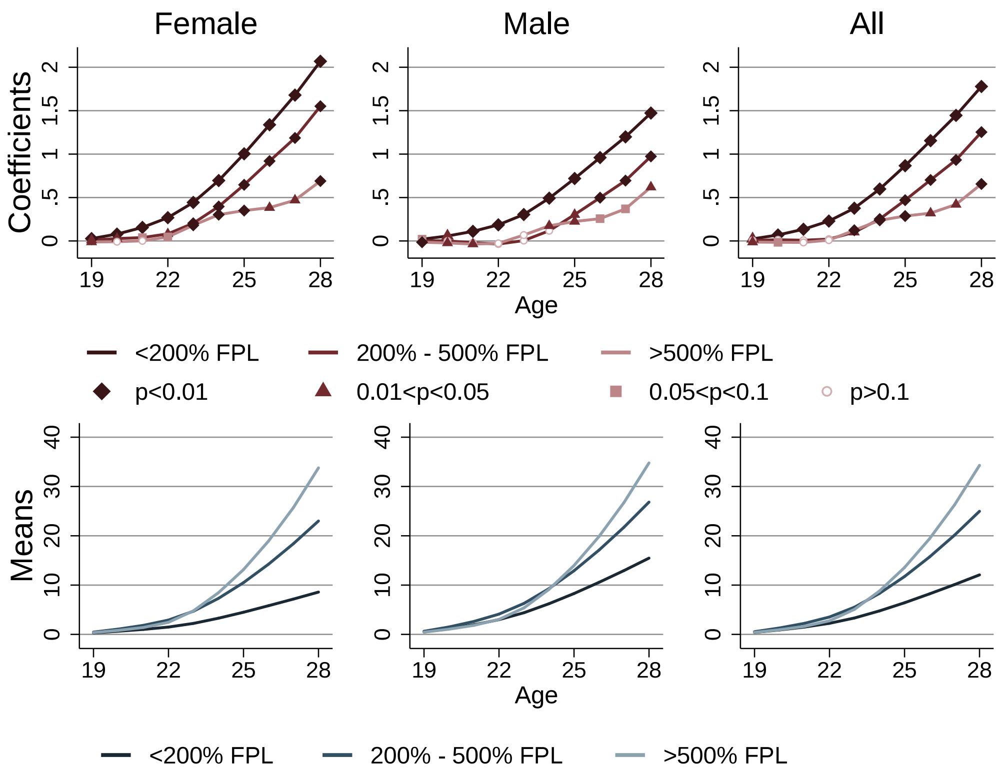
4 Heterogeneity and Robustness

4.1 Heterogeneous Effects by Childhood Household FPL: Dose-Response

Medicaid is targeted at the poor. Therefore, we should see the greatest impact of Medicaid on individuals who lived in the poorest households during childhood. We examine the reduced form impact of simulated Medicaid eligibility on our main outcomes in three samples: a "high impact" sample of children whose families were below 200% of the Federal Poverty Level (FPL) in every year of our longitudinal data during childhood, an "intermediate impact" sample between 200% and 500% FPL, and a "low impact" sample greater than 500% FPL. We exclude 32.2% of the sample belonging to multiple FPL categories in the longitudinal data. Because children are often born poor, and their household income increases over time, we cannot be sure that children in our "low impact" sample had no exposure to Medicaid during their childhoods before our sample begins in 1996, but we expect that there should be a dose-response relationship whereby individuals with lower observed household FPL as children should experience greater benefits from Medicaid. Boudreaux et al. (2016) and Hoynes et al. (2012) also stratify their samples to examine dose-response relationships in their settings.

We see a general dose-response relationship for cumulative total taxes in Figure 3, and for all other main outcomes in Online Appendix 5. In our exercises that examine heterogeneity and robustness, we focus on cumulative total taxes because it captures impacts on our other main outcomes and because it directly affects the fiscal return on investment in Medicaid. For each additional year of Medicaid eligibility during childhood, cumulative total taxes by age 28 increase by \$1,779 in the high impact sample, \$1,253 in the intermediate impact sample, and \$656 in the low impact sample. The dose-response relationship in the coefficients is especially striking given that the means show the opposite relationship, consistent with inter-generational persistence in household FPL absent Medicaid eligibility.[8]

Figure 3: Cumulative Total Taxes ($000) by Family FPL at Ages 15–18



Note. Cumulative total taxes indicate taxes paid by a given age starting at age 19, defined as household federal tax payments plus individual payroll tax payments less EITC, adjusted to 2011 dollars. Coefficients for each age are obtained from separate reduced form regressions of total taxes on simulated years eligible, ages 0–18. Children are assigned to an % FPL bin if their household remained in that bin at every age from 15–18. We exclude children with heterogeneity in their observed % FPL bin (32.2% of the sample). The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). Standard errors are clustered by state.

4.2 Heterogeneous Distributional Effects Within the High Impact Sample

To examine the impact of Medicaid on upward mobility, we focus on the high impact sample of children with low household FPL during childhood. On this sample, we estimate versions of equation (1) with outcomes representing the quartiles of the distribution of total taxes and wage income in the full sample. The means in Table OA.10 show that 17% of children from below 200% of the FPL end up in the top quartile of the distribution of cumulative total taxes at age 28. For comparison, if there were no inter-generational persistence, 25%

[8]In Online Appendix 6, we examine heterogeneous impacts of Medicaid using filing status as a proxy for whether children resided in one vs. two parent households. This exercise is directly related to our dose-response exercise insofar as household FPL is higher for children whose parents file jointly. The results tell a similar story.

of children would end up in the top quartile.[9] The coefficients increase as the quartiles increase, suggesting that Medicaid eligibility induces upward mobility among some children in the high impact sample. The coefficients in Table OA.10 show that an additional year of Medicaid eligibility during childhood increases the probability of being in the highest quartile of total taxes by age 28 by 1.6 percentage points. Therefore, a one standard deviation increase in Medicaid eligibility (5.61 years) closes the gap between the underlying rate of inter-generational persistence and zero inter-generational persistence ((1.6*5.61)>(25-17)). The wage income results tell a similar story.

4.3 Heterogeneous Effects of Medicaid Eligibility at Different Ages

Examining which periods of childhood Medicaid eligibility drive our results, we find that Medicaid eligibility from ages 15 to 18 results in the largest increase in cumulative total taxes starting at age 22.[10] Though eligibility during teenage years seems to drive our results, we also find positive though imprecise results for Medicaid eligibility from ages 0–3 starting after age 25. These results align with results from the literature that emphasize the importance of intervening early in childhood and results from Cohodes et al. (2016) that find that Medicaid eligibility during teenage years has the most important impact on college completion. However, we interpret our results with caution because eligibility in any of the age bins could be collinear with eligibility at other ages. Furthermore, ages 15–18 are the only ages at which we observe longitudinal data on all children in our sample.

4.4 Robustness to Assumptions in Early Childhood

Because our data do not begin until 1996, we make assumptions about household FPL and state of residence in early childhood; we impute household FPL using household FPL in the year of parent-child linkage, and we assume that the child resides in the first observed state of residence. We are not particularly concerned about the imputation of household FPL before the tax data begin because we focus on reduced form estimates, which rely on simulated Medicaid eligibility but do not rely on actual Medicaid eligibility. We construct simulated eligibility by running a nationally-representative sample through our Medicaid calculator, so measurement error that results from holding FPL constant in years before the tax data began should be addressed by cohort fixed effects. However, to be sure that national trends in household FPL that occurred before our tax data begin do not drive our results, we construct simulated Medicaid eligibility in the CPS using a different national sample in each year. We estimate reduced form specifications following equation (1) with

[9] For another comparison, Chetty et al. (2014) find a 7.5% probability that a child from the bottom *quintile* of the income distribution will end up in the top *quintile*.

[10] We divide Medicaid eligibility into four ranges—ages 0–3, 4–7, 8–14, and 15–18. We then estimate equation (1), replacing simulated Medicaid eligibility from birth to age 18 with a vector of simulated Medicaid eligibilities for each age range. We present the results in Online Appendix 7.

simulated eligibility from the CPS in lieu of simulated eligibility from the tax data, assigning longitudinal state of residence during childhood from the tax data. We report the results for cumulative total taxes in Figure OA.13. We also report the results at ages 19, 22, and 28 in Table A.3, which facilitates comparisons across various robustness specifications. As shown, results that use the CPS to simulate Medicaid eligibility are very similar to our main results, suggesting that our tax data are broadly representative compared to the nationally representative CPS and that the inability to observe longitudinal household FPL in the tax data before 1996 does not drive our results.

To address our inability to observe state of residence before the tax data begins, we examine how important interstate moves that we can observe during childhood are to our results. Figure OA.14 presents results separately for children who reside in one state from ages 15–18 and children who reside in multiple. Results in the sample of children who reside in only one state tell a similar story, although the coefficients are less precise and smaller in magnitude.

We also implement two exercises that use variation in sibling Medicaid eligibility to control for potential unobserved characteristics across households, where one potential unobserved characteristic is household state of residence before the tax data begin.[11] The first exercise controls for the sibling's outcome. As shown in Figure OA.15, this exercise generates estimates that are very similar to those from our main specification. The estimates are slightly attenuated, which we expect because Medicaid eligibility is correlated across siblings, such that controlling for the sibling's outcome is conceptually similar to controlling for a lagged dependent variable. The second exercise, which is more restrictive than controlling for the sibling's outcome, incorporates family fixed effects. Estimates from the second exercise, presented in Figure OA.15, are attenuated further and are no longer statistically significant, but they remain positive and display a similar age profile as our main results. Households included in this specification had to have more than one child born in the years 1981 to 1984. Since this specification exploits differential variation in eligibility across children within these households, the remaining variation in eligibility is low, and the 95% confidence intervals contain our main coefficients at each age in adulthood. The attenuation is also consistent with Medicaid serving as a treatment for the whole household, which amounts to a treatment spillover that would bias our coefficients to zero. Consistent with a treatment spillover, parental investments could compensate for differences in Medicaid

[11] We perform these exercises in the subsample of households with two children born in our sampling window from 1981 to 1984, and we pool across genders to allow for comparison of siblings of different genders. The estimates attenuate to zero for households with three or more children (N=208,035), potentially due to the small sample size and to the unobserved characteristics of households who had three-or-more children in our short four-year sampling window. We therefore focus on the sample of two-children households, which makes controlling for sibling outcomes easier and makes the identification of our specifications more transparent.

eligibility across children.

4.5 Robustness to Sample Selection

Our main sample only includes children whose parents claim them in 1997 and file in each year from 1996 (the first year of our data) until the year in which the child turns 18. We examine robustness of our results to the inclusion of children whose parents claim them in 1997 but do not file in every year from 1996 through age 18. In our expanded sample that includes non-filers, we impute income and state of residence using the nearest filing year. Figure OA.16 compares results from our main sample to results from the expanded sample. Impacts on cumulative total taxes by age 28 are nearly indistinguishable for the children in our sample, regardless of whether their parents filed in each year.

4.6 Robustness to OLS and Income Controls

We compare OLS and reduced form specifications with and without income controls in Figure OA.17. We do not control for household income in equation (1) because household income at age 15, the earliest age we observe it for all children, could reflect Medicaid eligibility at earlier ages. However, we examine robustness to the inclusion of income controls. OLS estimates without income controls show that individuals with greater Medicaid eligibility during childhood have lower cumulative total taxes in adulthood, which is to be expected because Medicaid is targeted at the poor. Controlling for income attenuates the OLS estimates, but they remain negative. In contrast, the reduced form estimates show positive impacts of Medicaid eligibility on cumulative total taxes in adulthood regardless of income controls. The inclusion of income controls attenuates the reduced form estimate of the impact of an additional year of Medicaid eligibility on cumulative total taxes by age 28 from \$533 to \$326. This attenuation is to be expected if household income reflects Medicaid eligibility at earlier ages.

4.7 Robustness to State-Specific Linear Time Trends

In Figure OA.18, we compare reduced form results from our main specification with results that include state-specific linear time trends in equation (1). State-specific linear time trends control for confounders that evolve linearly within states over time. In specifications that examine cumulative total taxes, the inclusion of these trends slightly increases the magnitudes of the coefficients and generally decreases their precision.

5 Medicaid Takeup, Spending, and Fiscal Return on Investment

5.1 Medicaid Takeup and Spending

We supplement the tax data with administrative data on Medicaid takeup and spending obtained from the Medicaid Statistical Information System (MSIS). Because our MSIS data are aggregated over all children under twenty-one at the state-by-year level, we incorporate additional data and assumptions to further disaggregate the data by age.[12] For each individual in our tax data, we assign cumulative measures of Medicaid takeup and spending from birth to age 18 as outcomes in our main specification.

Column 2 of Table 1 shows that each additional year of Medicaid eligibility during childhood increases Medicaid takeup by almost seven months (0.59 years) on a base of almost three years. The implied 59% takeup per year of eligibility is higher than almost all of the estimates from the literature discussed in Section 1, which generally range from 5 to 24 percent. However, studies that use different sources of variation and different covariates will find different estimates if there is heterogeneity in takeup rates. Card and Shore-Sheppard (2004) even find different takeup rates for the two expansions that they examine within the same study. Furthermore, our takeup estimate differs from those in the literature because we consider aggregate takeup over childhood, rather than contemporaneous takeup.

We do our best to identify takeup using the same variation that we use to identify our other outcomes because heterogeneity in takeup is likely related to heterogeneity in other outcomes. By scaling estimates for other outcomes by similarly obtained estimates of takeup, we can assess the impact of enrollment rather than eligibility, assuming that impacts of Medicaid are zero for those who are not enrolled. For example, using our reduced form coefficient for total taxes, we find that each additional year of Medicaid enrollment from birth to age 18 increases cumulative total tax payments by age 28 by $903 (=533/0.59). If we had simply scaled by a takeup estimate from the literature instead of estimating takeup using the same variation, we would have obtained a much larger enrollment impact (through division by a smaller number).

Column 3 of Table 1 shows that Medicaid spending during childhood increased by $593 on a base of $1,804 for each year of simulated eligibility. The comparison of spending and takeup means implies that each year of enrollment costs $623 (=1,804/2.894) on average, and the comparison of spending and takeup coefficients shows that each additional year of simulated enrollment costs $1,005 (=593/0.59). Therefore, the additional children who enroll due to the expansions that we study cost more to cover than the previously enrolled children.

We can also compare the impact on Medicaid spending with the impact on another outcome to obtain the cost of achieving that outcome through Medicaid, assuming that no benefits accrue through other outcomes. For example, the considering mortality as an out-

[12]To disaggregate the MSIS data, we apply our calculator to the Current Population Survey (CPS) to determine the share of children eligible for Medicaid by year, state, and age. We apply these shares to intercensal population estimates by year, state, and birth year to obtain the population of eligibles by year, state, and age. We allocate takeup and spending in proportion to eligibility. Finally, we adjust spending to 2011 dollars using the CPI-U.

Table 1: First Stage, Takeup, Spending, Taxes, and Fiscal Return on Investment (ROI)

	(1) Years Eligible for Medicaid, Age 0-18	(2) Years of Medicaid Takeup, Age 0-18	(3) Medicaid Spending ($000), Age 0-18	(4) Cumulative Total Taxes ($000), Age 19-28	(5) Fiscal ROI by Age 28 = (3)/(2) - 100%
Discount rate = 0%					
Simulated Years Eligible, Age 0-18	0.937***	0.591***	0.593***	0.533***	-10.20%
	(0.077)	(0.037)	(0.065)	(0.192)	
Mean	3.767	2.894	1.804	20.623	
Discount rate = 1%					
Simulated Years Eligible, Age 0-18	-	-	0.520***	0.403***	-22.48%
			(0.057)	(0.145)	
Mean			1.584	15.609	
Discount rate = 2%					
Simulated Years Eligible, Age 0-18	-	-	0.457***	0.306***	-33.11%
			(0.050)	(0.110)	
Mean			1.396	11.846	
Discount rate = 3%					
Simulated Years Eligible, Age 0-18	-	-	0.404***	0.233***	-42.32%
			(0.045)	(0.837)	
Mean			1.234	9.014	
Observations	10,045,162	9,876,591	9,876,591	10,045,162	

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses are clustered by state. Cumulative Medicaid takeup and spending for ages 0–18 are estimated in the full sample using administrative data from the Medicaid Statistical Information System (MSIS), adjusted to 2011 dollars. Cumulative total taxes indicate taxes paid in the full sample from ages 19–28, defined as household federal tax payments plus individual payroll tax payments less EITC, adjusted to 2011 dollars. Coefficients are obtained from a reduced form regression of the given outcome on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). We exclude Arizona from the spending and takeup specifications due to missing MSIS data. The fiscal ROI by age 28 excluding Arizona from the cumulative total taxes specification is -8.23% (0% discount), -21.01% (1% discount), -31.72% (2% discount), and -41.17% (3% discount).

come, Table OA.4 shows that each year of simulated Medicaid eligibility during childhood saves 2.0 lives per 10,000 (0.020 percentage points) from ages 19–28. Therefore, the cost per life saved through expanded childhood Medicaid eligibility is approximately $3.0 million (=593/0.020%), which is at the lower bound of the traditional $3–7 million value of a statistical life (Cutler, 2005). Our estimate for cost per life saved is similar to estimates from the Medicaid literature.[13] However, as we have shown, decreased mortality is not the only benefit of childhood Medicaid, so the effective cost of saving these lives is likely much lower.

[13] Currie and Gruber (1996b) report a $840,000 (in 1986 dollars, $1.7 million in 2011 dollars) cost per life saved through targeted eligibility changes but a much higher $4.2 million (in 1986 dollars, $8.6 million in 2011 dollars) cost per life saved through broad eligibility changes. Currie and Gruber (1996a) report a cost per life saved of $1.61 million (in 1992 dollars, $2.58 million in 2011 dollars). Similarly, Wherry and Meyer (2016) report a $1.77 million (in 2011 dollars) cost per life saved, and Goodman-Bacon (2018) report a cost per life saved of $1.83 million (in 2012 dollars, $1.79 million in 2011 dollars).

5.2 Fiscal Return on Investment

Increased tax revenue lowers the effective cost of childhood Medicaid. Our estimates show that each additional year of simulated Medicaid eligibility during childhood costs $593 and yields $533 in future tax revenue by age 28, suggesting that the government recoups 0.90 cents on each dollar (=533/593) spent on childhood Medicaid by age 28. However, to take into account that the spending occurs well before the tax payments, we discount both to birth at 1%, 2%, and 3% rates in the data before estimating the reduced form results presented in Table 1.[14] At a 3% discount rate, each additional year of simulated Medicaid eligibility increases spending by $404 and taxes by $233. The ratio of $233 to $404 implies that the government recoups 58 cents of each dollar it spends on childhood Medicaid by age 28. Therefore, the fiscal return on investment in childhood Medicaid is -42% (=0.58-1) by age 28.

The actual return to Medicaid is likely much larger. From the perspective of the federal government, the fiscal return is larger because approximately 50% of Medicaid spending was done by states in the period under consideration (Centers for Medicare & Medicaid Services, 2015). The actual return is also larger if we consider benefits that accrue to the children themselves. For example, if we add an implied value of life saved to the fiscal return, Medicaid delivers benefits equal to three times its costs by age 28.[15]

6 Conclusion

Looking forward to future decisions regarding whether to expand Medicaid, our research shows that Medicaid generally has favorable long-term impacts on children. Using administrative data from the IRS, we see that children with greater exposure to Medicaid enroll in college at higher rates, delay their fertility, and have lower rates of adult mortality. Females have higher wage income, and both genders collect less from the earned income tax credit. Moreover, the government recoups much of its investment in childhood Medicaid over time in the form of higher future tax payments.

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[14] The Office of Management and Budget recommends a real discount rate of 0.8% for cost-effectiveness projects of a 30-year duration (US Office of Management & Budget, 2016), which is within the range of our 0% and 1% discount rates. The Department of Commerce recommends a 3% real discount rate for use in life-cycle projects (Lavappa and Kneifel, 2016). We prefer 3% because it is the most conservative.

[15] Using a conservative $3 million dollar value of a statistical life from Cutler (2005) and our mortality result by age 28, we estimate that the value of life saved by each additional year of Medicaid eligibility during childhood is $600 (=0.020%*$3 million). Combining this estimate with our comparable tax revenue and spending estimates, the benefits ($533+$600) are roughly double the cost ($593), implying an ROI from increased tax revenue and decreased mortality by age 28 of 91% (=(533 + 600 - 593)/593).

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Appendix A Main Results Tables and Robustness, Selected Ages

Table A.1: Contemporaneous Outcomes at Age 19, 22, and 28

	(1) By Age 19			(2) By Age 22			(3) By Age 28		
	Female	*Male*	*All*	*Female*	*Male*	*All*	*Female*	*Male*	*All*
College (Currently Enrolled; %)									
Simulated Years	1.750***	1.637***	1.690***	0.718	0.646*	0.678*	-0.026	-0.092	-0.062
Eligible, Age 0-18	(0.539)	(0.568)	(0.549)	(0.435)	(0.342)	(0.384)	(0.157)	(0.154)	(0.143)
Mean	57.617	47.684	52.542	50.040	40.454	45.143	20.062	14.461	17.201
Fertility (First Had Dependent Child; %)									
Simulated Years	-0.119**	-0.051	-0.085*	-0.088	-0.042	-0.065	-0.063	-0.072**	-0.068*
Eligible, Age 0-18	(-0.057)	(-0.042)	(0.047)	(0.054)	(0.048)	(0.045)	(0.050)	(0.029)	(0.034)
Mean	4.848	2.488	3.642	3.971	3.077	3.514	3.294	2.852	3.068
Mortality (%)									
Simulated Years	-0.003	-0.001	-0.002	-0.005**	0.006	0.000	0.006*	-0.009	-0.001
Eligible, Age 0-18	(0.003)	(0.004)	(0.003)	(0.002)	(0.005)	(0.003)	(0.003)	(0.006)	(0.004)
Mean	0.037	0.098	0.068	0.040	0.125	0.084	0.051	0.121	0.087
Wage Income ($000)									
Simulated Years	0.059*	0.061	0.061*	0.077	-0.045	0.015	0.414***	0.149	0.280*
Eligible, Age 0-18	(0.031)	(0.041)	(0.033)	(0.061)	(0.075)	(0.064)	(0.148)	(0.183)	(0.150)
Mean	4.198	4.864	4.538	8.729	10.461	9.614	23.336	28.577	26.013
EITC ($000)									
Simulated Years	-0.006***	-0.003***	-0.005***	-0.023***	-0.009***	-0.016***	-0.033***	-0.009	-0.021***
Eligible, Age 0-18	(0.002)	(0.001)	(0.001)	(0.006)	(0.003)	(0.004)	(0.010)	(0.006)	(0.008)
Mean	0.095	0.039	0.066	0.319	0.137	0.226	0.717	0.357	0.533
Total Taxes ($000)									
Simulated Years	0.013***	0.010*	0.012**	0.042***	0.010	0.026**	0.115**	0.061	0.088*
Eligible, Age 0-18	(0.004)	(0.006)	(0.005)	(0.014)	(0.011)	(0.012)	(0.047)	(0.051)	(0.048)
Mean	0.391	0.555	0.475	0.815	1.271	1.048	3.640	4.364	4.010
Observations	4,913,139	5,132,023	10,045,162	4,913,139	5,132,023	10,045,162	4,913,139	5,132,023	10,045,162

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses are clustered by state. Contemporaneous college enrollment indicates current enrollment in college at a given age, observed through Form 1098-T, filed by educational institutions. Contemporaneous fertility indicates if a first dependent child is born at a given age. If an individual ever claims a dependent child on a Form 1040, SSA records yield age at birth. Contemporaneous mortality indicates mortality at a given age, measured using SSA death records. Contemporaneous wage income indicates wages earned at a given age, obtained from Form W-2, adjusted to 2011 dollars and censored at $10 million. Contemporaneous EITC indicates EITC earned at a given age, obtained from Form 1040, adjusted to 2011 dollars. Contemporaneous total taxes indicate taxes paid at a given age, defined as household federal tax payments plus individual payroll tax payments less EITC, adjusted to 2011 dollars. Coefficients for each age are obtained from separate reduced form regressions of the given outcome at that age on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample).

Table A.2: Cumulative Outcomes at Ages 19, 22, and 28

	(1) By Age 19			(2) By Age 22			(3) By Age 28		
	Female	*Male*	*All*	*Female*	*Male*	*All*	*Female*	*Male*	*All*
College (Ever Enrolled; %)									
Simulated Years	1.261**	1.305*	1.281**	0.813**	0.805*	0.806*	0.458	0.519	0.486
Eligible, Age 0-18	(0.608)	(0.652)	(0.629)	(0.380)	(0.450)	(0.415)	(0.278)	(0.339)	(0.307)
Mean	62.209	51.593	56.785	73.562	62.858	68.094	80.888	69.501	75.070
Fertility (Ever Had Dependent Child; %)									
Simulated Years	-0.512**	-0.187	-0.348**	-0.870**	-0.387*	-0.625**	-1.177***	-0.721**	-0.948***
Eligible, Age 0-18	(0.212)	(0.119)	(0.159)	(0.344)	(0.215)	(0.271)	(0.374)	(0.313)	(0.332)
Mean	15.863	8.572	12.138	28.763	17.442	22.979	50.573	36.103	43.180
Mortality (%)									
Simulated Years	-0.003	-0.001	-0.002	-0.010*	0.007	-0.001	-0.009	-0.031*	-0.020*
Eligible, Age 0-18	(0.003)	(0.004)	(0.003)	(0.006)	(0.009)	(0.006)	(0.010)	(0.017)	(0.011)
Mean	0.037	0.098	0.068	0.152	0.454	0.306	0.417	1.191	0.812
Wage Income ($000)									
Simulated Years	0.059*	0.061	0.061*	0.152	-0.042	0.055	1.784***	0.581	1.177
Eligible, Age 0-18	(0.031)	(0.041)	(0.033)	(0.145)	(0.189)	(0.160)	(0.662)	(0.885)	(0.715)
Mean	4.198	4.864	4.538	25.262	30.147	27.758	136.600	161.350	149.245
EITC ($000)									
Simulated Years	-0.006***	-0.003***	-0.005***	-0.059***	-0.026***	-0.042***	-0.263***	-0.103***	-0.182***
Eligible, Age 0-18	(0.002)	(0.001)	(0.001)	(0.015)	(0.008)	(0.011)	(0.063)	(0.034)	(0.046)
Mean	0.095	0.039	0.066	0.831	0.351	0.586	4.188	1.948	3.044
Total Taxes ($000)									
Simulated Years	0.013***	0.010*	0.012**	0.101***	0.039	0.069**	0.689***	0.380*	0.533***
Eligible, Age 0-18	(0.004)	(0.006)	(0.005)	(0.034)	(0.029)	(0.031)	(0.200)	(0.200)	(0.192)
Mean	0.391	0.555	0.475	2.263	3.535	2.913	18.115	23.025	20.623
Observations	4,913,139	5,132,023	10,045,162	4,913,139	5,132,023	10,045,162	4,913,139	5,132,023	10,045,162

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses are clustered by state. Cumulative college enrollment indicates ever having enrolled in college by a given age, starting at age 19, observed through Form 1098-T, filed by educational institutions. Cumulative fertility indicates if a dependent child is ever born by a given age, starting at age 19. If an individual ever claims a dependent child on a Form 1040, SSA records yield age at birth. Cumulative mortality indicates mortality by a given age, starting at age 19, measured using SSA death records. Cumulative wage income indicates wage income earned by a given age, starting at age 19, obtained from Form W-2, adjusted to 2011 dollars and censored at $10 million. Cumulative EITC indicates EITC earned by a given age, starting at age 19, obtained from Form 1040, adjusted to 2011 dollars. Cumulative total taxes indicate taxes paid by a given age, starting at age 19, defined as household federal tax payments plus individual payroll tax payments less EITC, adjusted to 2011 dollars. Coefficients for each age are obtained from separate reduced form regressions of the given outcome at that age on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample).

Table A.3: Robustness of Cumulative Total Tax ($000) Results at Ages 19, 22, and 28

	(1) By Age 19			(2) By Age 22			(3) By Age 28		
	Female	*Male*	*All*	*Female*	*Male*	*All*	*Female*	*Male*	*All*
Main Results									
Simulated Years Eligible,	0.013***	0.010*	0.012**	0.101***	0.039	0.069**	0.689***	0.380*	0.533***
Age 0-18	(0.004)	(0.006)	(0.005)	(0.034)	(0.029)	(0.031)	(0.200)	(0.200)	(0.192)
Mean	0.391	0.555	0.475	2.263	3.535	2.913	18.115	23.025	20.623
Instrument: Simulated Eligibility in the CPS									
Simulated Years Eligible	0.015***	0.012*	0.014**	0.114***	0.045	0.079**	0.731***	0.395*	0.560***
using CPS, Age 0-18	(0.005)	(0.006)	(0.005)	(0.039)	(0.033)	(0.035)	(0.216)	(0.220)	(0.208)
Mean	0.391	0.555	0.475	2.263	3.535	2.913	18.115	23.025	20.623
Sample: Constant State of Residence									
Simulated Years Eligible,	0.013**	0.015*	0.014**	0.078**	0.040	0.059	0.376**	0.164	0.269
Age 0-18	(0.006)	(0.008)	(0.007)	(0.038)	(0.035)	(0.036)	(0.172)	(0.180)	(0.167)
Mean	0.392	0.556	0.476	2.274	3.547	2.924	18.254	23.153	20.757
Specification: Inclusion of Sibling Controls									
Simulated Years Eligible,			0.013**			0.064*			0.312*
Age 0-18	-	-	(0.005)	-	-	(0.034)	-	-	(0.172)
Mean			0.494			3.029			21.537
Specification: Inclusion of Family Fixed Effects									
Simulated Years Eligible,			0.014			0.052			0.035
Age 0-18	-	-	(0.012)	-	-	(0.063)	-	-	(0.303)
Mean			0.494			3.029			21.537
Sample: Parents Filing Jointly									
Simulated Years Eligible,	0.009**	0.009	0.009*	0.065**	0.013	0.039	0.481**	0.222	0.350*
Age 0-18	(0.004)	(0.006)	(0.005)	(0.031)	(0.030)	(0.030)	(0.200)	(0.226)	(0.207)
Mean	0.436	0.595	0.517	2.680	3.865	3.288	22.396	26.452	24.477
Sample: Parents Not Filing Jointly									
Simulated Years Eligible,	0.020***	0.012**	0.016***	0.168***	0.084**	0.125***	0.854***	0.459***	0.651***
Age 0-18	(0.006)	(0.005)	(0.005)	(0.044)	(0.033)	(0.037)	(0.229)	(0.163)	(0.183)
Mean	0.276	0.451	0.364	1.203	2.669	1.944	7.234	14.036	10.671
Sample: Non-filers									
Simulated Years Eligible,	0.015***	0.012**	0.013**	0.109***	0.038	0.074**	0.669***	0.322*	0.494***
Age 0-18	(0.005)	(0.006)	(0.005)	(0.036)	(0.030)	(0.032)	(0.184)	(0.188)	(0.176)
Mean	0.369	0.538	0.455	2.102	3.419	2.773	16.365	21.612	19.037
Specification: Inclusion of Income Controls									
Simulated Years Eligible,	0.012***	0.010*	0.011**	0.082**	0.032	0.057*	0.451**	0.207	0.326*
Age 0-18	(0.004)	(0.006)	(0.005)	(0.031)	(0.028)	(0.029)	(0.170)	(0.187)	(0.172)
Mean	0.391	0.555	0.475	2.263	3.535	2.913	18.115	23.025	20.623

Note. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$. Standard errors in parentheses are clustered by state. Cumulative total taxes indicate taxes paid by a given age, starting at age 19, defined as household federal tax payments plus individual payroll tax payments less EITC, adjusted to 2011 dollars. Coefficients for each age are obtained from separate reduced form regressions of the given outcome at that age on simulated years eligible, ages 0–18. The specification includes fixed effects for birth cohort by month and for state of residence at age 15 (the youngest age at which we observe all individuals in our sample). The specifications that include sibling controls and family fixed effects are estimated in the sample of two-child households for the pooled-gender samples only. Observation counts for each specification are available in the Online Appendix.