Nudging Parents to Invest: Evidence from Children's Insurance

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Abstract

I study how parental investments respond to children's insurance exploiting the roll-out of Children's Health Insurance Program, which expanded public insurance for children in the US. In anticipation of the insurance, pregnant mothers exposed to the roll-out reduced present bias and increased private investments in utero. The investments increased the child's birth weight, and increased mother utility similar to expansions of her own insurance. In the long run, investments further increased college enrollment, predicting higher tax payments that offset 8.4% of the program cost in childhood. The results suggest that information outreach can encourage investments by adjusting parents' behavioral biases, resulting in greater parental utility and lower social costs of insurance.

Key words: Parental investments, Behavioral biases, Nudges, Social insurance, Children

JEL codes: I13, J13, I38, H75

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1 Introduction

A growing body of empirical literature has identified substantial benefits of early-life investments on the health, skill, and economic success of children over the life course. These benefits motivate social insurance to target children in low-income families, where private investments may be inadequate. While targeting children, the insurance relies on the behavior of parents to enroll and to invest in the child. However, parental behavior remains understudied in the literature on children's insurance. In particular, there is little evidence on how parents respond to children's insurance, and how their investments could impact child outcomes and the effectiveness of insurance.

This paper brings evidence to bear on these questions exploiting the roll-out of the Children's Health Insurance Program (CHIP) in the US. The program doubled the share of children eligible for public insurance from 15% to 30%, but did not expand insurance for pregnant mothers or their children in utero. As such, CHIP is unlikely to impact the birth outcomes of children. Nonetheless, birth outcomes may improve if pregnant mothers responded to the roll-out by increasing private investments in the child. Therefore, I examine the mother's in-utero investments and the child's birth weight in the roll-out of CHIP to understand parental responses to social insurance for children.

I have three main findings from the analysis. First, exposure to the roll-out significantly increased mother's investments in the child, and birth weight already improved for children with in-utero exposure to CHIP. Second, the exposure increased investments by reducing the present bias of mothers. Due to the large benefits of investments on birth weight, mothers valued the exposure similar to expansions of her own insurance. Third, investments increased the college enrollment rate for children, and predict higher earnings and tax payments that could lower the social cost of insurance by 8.4% in the long run.

Conceptually, expanding insurance for children could decrease parental investments in utero due to the incentive effect on ex-ante investments. By investing more in less healthy children, CHIP reduces the gap in child outcomes by child health. The insurance may lower parents' incentive to invest in child health in utero. Empirically, however, the roll-out of CHIP led to a substantial "crowd-in" of investments, suggesting the existence of additional mechanisms besides the incentive effect on investments. I motivate and show support for a behavioral effect on the present bias of mothers as the leading mechanism.

Empirically, I estimate parental responses exploiting the roll-out as an exogenous shock on mother's exposure to children's insurance. The roll-out increased the income limit of children's insurance across states. Within states, mothers exposed to CHIP early in the pregnancy had greater duration of exposure to the expansion. I capture the variations and construct mother's exposure as a weighted average of income limits before and after CHIP, with the weights equal to the share of pregnancy exposed to each limit. In the regressions, I exploit the within-state variation in the duration of exposure across cohorts to estimate parental responses to children's insurance.

I find that exposure to the roll-out significantly increased mother's investments in the child, resulting in earlier onset of pre-natal visits and less smoking in pregnancy. Specifically, the exposure reduced late care onset past the first trimester by 5.6%, reduced very late onset in the third trimester by 11.2%, and reduced smoking by 5.3%. The investments increased birth weight by 8.5 grams, and decreased low birth weight by 3.6%. These effects were fully concentrated among children of single mothers exposed to CHIP since the first trimester. By contrast, exposure had little effect on the investments of married mothers whose children had low predicted eligibility for CHIP.

To understand mechanisms, I examine whether the exposure to children's insurance increased mother's uptake of own insurance, or increased her incomes in pregnancy. Drawing data from the Survey of Income and Program Participation, I find that the exposure did not affect mother's insurance coverage, cash transfer incomes, borrowing from future incomes, or health spending in pregnancy. Moreover, mothers who invested more in utero also had substantially higher uptake of CHIP for their newborns, but these mothers did not indicate higher expected education for the child. This suggests that the investments were not motivated by the long-run effects of investments on education.

After ruling out mother's insurance, income, and the long-run effects of investments as mechanisms, I explore two behavioral mechanisms whereby the exposure may have adjusted mother's perception of investments. First, the exposure may have increased mother's utility weight on child outcomes relative to her own consumption in pregnancy, thus increasing her altruism for the child. Second, the exposure may have shifted mother's inter-temporal weights towards utility in future periods, resulting in less present bias and more forward thinking in pregnancy.

I investigate the behavioral mechanisms using a dynamic model of in-utero investments. In the model, mothers choose pre-natal visits and smoking each trimester to invest in the child's birth weight. Because investments occur over multiple periods, mothers with lower valuation of future utility may delay investments and end up investing less in the child. By reducing the present bias, the exposure could shift investments to early trimesters in pregnancy. It could further increase investments by increasing the altruism for the child. To quantify the behavioral effects, I exploit the exposure as a shifter of mother preferences and match investments across different exposure to CHIP. I estimate that exposure to the roll-out reduced present bias by 14.3%, with little effect on altruism.

Turning to welfare, I quantify mother's valuation of the exposure from her investment responses. Mother values the exposure because it reduces her behavioral biases and results in better outcomes for the child. In the roll-out of CHIP, the exposure increased mother utility by $0.31 due to the benefit of investments on birth weight. Compared to the program's spending on outreach, mother values the exposure at 76% of the spending, similar to her valuation of own insurance from Medicaid (Hendren and Sprung-Keyser, 2020). For children's insurance, this result suggests that outreach efforts engaging parents can increase parental utility as effectively as expansions of parents' own insurance.

In the long run, investments increased college enrollment by 8.7% for children of single mothers. This effect predicts higher tax payments which may lower the social cost of insurance. However, since mothers did not internalize the effects of investments on education, the fiscal externality is under-stated in mother's valuation of the exposure. To quantify the externality, I predict an increase in earnings by $1,101.1 for children of single mothers based on the effect on college enrollment. The resulting increase in tax payments recoups 8.4% of the program cost in childhood. Thus, parental investments can have large impacts on the social cost of insurance through the long-run effects on children.

These findings suggest that parental investments can powerfully impact the effectiveness of children's insurance. Positive investment responses not only improve child outcomes before the program onset, but also lower the social cost of insurance through the long-run effects in adulthood. Investigations into the mechanism of the responses reveal that parents may suffer from behavioral biases that limit their investments in children. By reducing the biases, the information of insurance can "nudge" investments and increase parental utility through the benefits to children. The impacts on children, parents, and the effectiveness of insurance motivate outreach efforts engaging parents in children's insurance programs.

This paper contributes to several strands of literature. First, although numerous studies have documented the beneficial impacts of insurance programs for children (Currie and Gruber 1996a; Currie and Gruber 1996b; Goodman-Bacon 2018), less is known about the parental responses to these programs, or whether parental investments could improve child outcomes over and above the direct effects of insurance. This paper examines in-utero investments in the roll-out of insurance to isolate parental responses from program investments in the child. Hence, it contributes to the literature on children's insurance by establishing parental investments as a critical pathway to the benefits to children. Therefore, effective designs of children's insurance should encourage positive investment responses from parents. The role of parental investments has received similar attention in the literature on early-childhood interventions (Heckman and Mosso, 2014), where programs improving parenting skills through information and preference change are shown to have larger impacts on child outcomes than simple transfer programs.

This paper also contributes to a growing literature that evaluates the welfare of social insurance programs through the lens of beneficiaries' valuation of the insurance (Finkelstein and Hendren 2020; Finkelstein *et al.* 2019a; Finkelstein *et al.* 2019b). Here, I quantify mother's valuation of her exposure to CHIP by first estimating the behavioral effects of exposure implied by her investment responses. In doing so, I also contribute to the literature on structural behavioral models, especially the models of dynamic inconsistencies and self-control (Laibson 1997; O'Donoghue and Rabin 1999; DellaVigna and Malmendier 2006; Duflo *et al.* 2011; Sadoff *et al.* 2020), with new evidence from parental investments.

Finally, this paper contributes to the literature applying behavioral insights to the design of social policies. To combat present bias, for instance, policymakers may consider taxes and subsidies to help individuals internalize their biases (Herrnstein *et al.* 1993; Gruber and Köszegi 2001; O'Donoghue and Rabin 2006). Alternatively, informational nudges (Thaler and Sunstein, 2009) can achieve behavioral changes by adjusting the behavioral biases. In the roll-out of CHIP, the information of children's insurance reduced mother's present bias. The behavioral effect then increased mother's utility as effectively as subsidized expansions of her own insurance.

The rest of the paper proceeds as follows. I introduce the Children's Health Insurance Program in Section 2, motivate the investment responses to CHIP exposure in Section 3, and describe the data in Section 4. Section 5 presents empirical evidence on the investment responses and explores mechanisms. Section 6 estimates the long-run effects on education outcomes. Section 7 estimates the behavioral effects and evaluates welfare using a structural model of in-utero investments. Section 8 concludes.

2 Children's Health Insurance Program

The Children's Health Insurance Program, or CHIP, was created by the Balanced Budget Act (BBA) of 1997 under a new Title XXI of the Social Security Act. Title XXI offered states the option to enroll children ineligible for Medicaid either through an expansion of the existing Medicaid program or through a separate insurance program for children. States opting for either type of expansion were eligible for federal funding totaling $40 billion in the first ten years of Title XXI (FY1998-FY2007). States could only use the funding to expand insurance for children (age 0 to 18), not for adult parents.

Nearly all states expanded insurance for children between 1997 and 2000.[1] Table 1 lists

[1]The only exception is Tennessee, where the Medicaid program disenrolled a large number of enrollees

the timing of CHIP onset by states, along with changes in the income limit of insurance for different age groups of children.[2] Of the 50 states that expanded insurance for children, 11 states also expanded insurance for adult parents using state funding.[3] I focus on the 39 states expanding insurance exclusively for children to understand the parental responses to social insurance for children.

Overall, the roll-out of CHIP increased the income limit of Medicaid/CHIP by 80% of the federal poverty level (henceforth FPL) across states. The expansion significantly increased the *expected* insurance eligibility for children. Figure 1 shows the share of children eligible for Medicaid/CHIP based on the income limits of insurance known at the time of pregnancy.[4] Around 15% of children born in Jan. 1997 were eligible for Medicaid/CHIP in childhood. Eligibility increased for cohorts exposed to the roll-out in 1997-2000. By Dec. 2000, all states (except Tennessee) had expanded insurance for children. The expansion doubled the share of children eligible for Medicaid/CHIP to 30% in the Dec-2000 cohort. On average, the Dec-2000 cohort can expect 5.7 (= 30% $\cdot$ 19) years of childhood eligible for public insurance.

3 Conceptual Framework

To conceptualize the investment responses, I consider a two-period model where parental investments occur in utero ($t = 0$) and in childhood ($t = 1$). In each period, parents receive an exogenous income Y_t, and divide the income between own consumption c_t – which generates utility $u(c_t)$ – and costly investment v_t in the child. In-utero investments affect the child's health status at birth. Children born with lower health, such as those with disability and special health service needs, require larger medical expenses in childhood. CHIP lowers the medical expenses for parents investing in a less healthy child. I analyze

in 2002. Before the disenrollment, individuals with income up to 400% FPL were eligible for the state's Medicaid program.

[2] I collect the income limit and the program onset date of Medicaid/CHIP from program fact sheets available at https://www.medicaid.gov/CHIP. For instance, the fact sheet for the state of New York is available at https://www.medicaid.gov/sites/default/files/CHIP/Downloads/NY/NYCurrentFactsheet.pdf. I track subsequent expansions from 2001 to 2013 combining the program fact sheets and the Trends of CHIP/Medicaid Eligibility charts published by the Kaiser Family Foundation available at https://www.kff.org/medicaid/state-indicator/medicaidchip-upper-income-eligibility-limits-for-children/?currentTimeframe=0&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D.

[3] States expanding insurance for children as well as adult members of the family are marked with an asterisk in the "infant" column in Table 1.

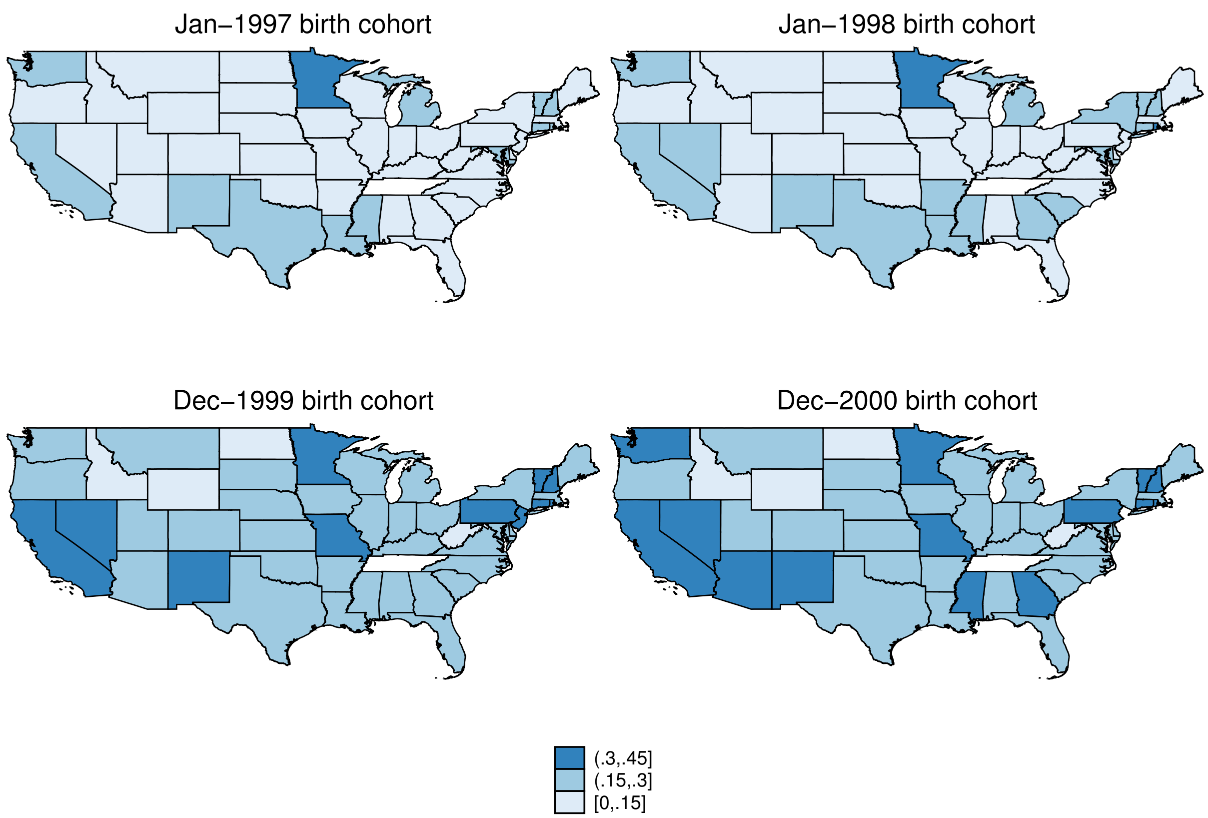
[4] I use income limits summarized in Table 1 and follow the standard "simulated eligibility" approach pioneered by Currie and Gruber (1996a) and Currie and Gruber (1996b) to calculate the probability. I show details of the calculation in Appendix A.

Table 1: CHIP onset and the income limit for children's insurance

State	Program Onset	Income Limits (% FPL)		
		infant	age 1-5	age 6-18
Alabama	Oct-98	133-200	133-200	100-200
Alaska*	Mar-99	133-200	133-200	100-200
Arizona	Nov-98	140-150	133-150	100-150
Arkansas	Sep-97	133-200	133-200	100-200
California	Jul-98	200-250	133-200	100-200
Colorado	May-98	133-185	133-185	100-185
Connecticut	Jun-98	185-300	185-300	185-300
Delaware	Feb-99	185-200	133-200	100-200
District of Columbia*	Oct-98	185-200	133-200	100-200
Florida	Apr-98	185-200	133-200	100-200
Georgia*	Jan-99	185-200	133-200	100-200
Hawaii	Jul-00	185-200	133-200	100-200
Idaho	Oct-97	133-160	133-160	100-160
Illinois*	Jan-98	133-200	133-133	100-133
Indiana	Oct-97	150-150	133-150	100-150
Iowa	Jul-98	185-185	133-133	100-133
Kansas	Jan-99	150-200	133-200	100-200
Kentucky	Jul-98	185-185	133-150	100-150
Louisiana	Nov-98	133-133	133-133	100-133
Maine	Aug-98	185-185	133-185	125-185
Maryland*	Jul-98	185-200	185-200	185-200
Massachusetts*	Oct-97	185-200	133-150	100-150
Michigan	Sep-98	185-200	150-200	150-200
Minnesota	Oct-98	275-280	275-275	275-275
Mississippi	Jan-99	185-185	133-133	100-133
Missouri	Jul-98	185-300	133-300	100-300
Montana	Jan-99	133-150	133-150	100-150
Nebraska*	Sep-98	150-185	133-185	100-185
Nevada	Oct-98	133-200	133-200	100-200
New Hampshire	Jan-99	300-300	185-300	185-300
New Jersey	Mar-98	185-200	133-200	100-200
New Mexico	Mar-99	185-235	185-235	185-235
New York	Jan-99	185-192	133-192	100-192
North Carolina	Oct-98	185-200	133-200	100-200
North Dakota	Oct-99	133-140	133-140	100-140
Ohio*	Jan-98	133-150	133-150	100-150
Oklahoma*	Dec-97	150-185	133-185	100-185
Oregon*	Jul-98	133-170	133-170	100-170
Pennsylvania	Jun-98	185-235	133-235	100-235
Rhode Island	May-97	250-250	250-250	100-250
South Carolina	Oct-97	185-185	133-150	100-150
South Dakota	Jul-98	133-133	133-133	100-133
Tennessee	–	–	–	–
Texas	May-00	185-200	133-200	100-200
Utah	Aug-98	133-200	133-200	100-200
Vermont	Oct-98	225-300	225-300	225-300
Virginia	Nov-98	133-185	133-185	100-185
Washington	Jan-00	200-250	200-250	200-250
West Virginia	Nov-00	150-200	133-200	100-200
Wisconsin*	Jul-99	185-185	185-185	100-185
Wyoming	Nov-99	133-133	133-133	100-133

Notes: States marked with an asterisk * expanded insurance for children as well as adult members of the family. I show increases in the income limit for infants (age 0), small children (age 1-5), and older children (age 6+) in each state. Footnote 2 in the main text details the sources of the information.

Figure 1: Share of children eligible for Medicaid/CHIP, 1997-2000



Notes: The map shows the share of children eligible for Medicaid/CHIP for birth cohorts between Jan. 1997 and Dec. 2000, based on the income limits of insurance (Table 1) known at the time of pregnancy. Appendix A details the calculation.

the effect of this insurance on investments in childhood and in utero below.

3.1 Childhood Investments

Let superscript $h = 0, 1$ denote the child's health status at birth, with $h = 1$ indicating a healthy child. A less healthy child incurs out-of-pocket medical expenses $OOPC$ in childhood. The medical expenses limit non-health investments v_1^h which are inputs to the child's education outcome $s(v_1^h)$. Given health status h, parents choose investment v_1^h to maximize the following utility

$$U_1^h(v_1^h) = u\left(c_1^h\right) + \Gamma(s(v_1^h)) + \delta\, V^h(s(v_1^h)), \tag{1}$$

where $c_1^h = Y_1 - v_1^h - OOPC \cdot 1\{h = 0\}$ is consumption after health and non-health investments, and $\Gamma(\cdot)$ is parents' utility from the child's education $s(v_1^h)$. $V^h(s(v_1^h))$ is the utility from the child's adult outcomes given education $s(v_1^h)$ and health h. δ is the discount factor.

Due to the medical expenses $OOPC$, non-health investment is smaller in the less healthy child.[5] By reducing the medical expenses, CHIP increases v_1^0 and narrows the education gap $\Delta\Gamma = \Gamma(s(v_1^1)) - \Gamma(s(v_1^0))$ by child health. The reduction in the education gap results in smaller gaps in adult outcomes $\Delta V = V^1(s(v_1^1)) - V^0(s(v_1^0))$ and in consumption $\Delta u = u(c_1^1) - u(c_1^0)$ by child health.

3.2 In-Utero Investments

In $t = 0$, parents choose in-utero investments to maximize the sum of utility in utero and in childhood as follows

$$U_0(v_0) = u(c_0) + w(v_0) + \delta\,\rho(v_0)\,\tilde{U}_1^1 + \delta\,(1 - \rho(v_0))\,\tilde{U}_1^0, \tag{2}$$

where $c_0 = Y_0 - v_0$ is consumption after investments, and $w(v_0)$ is the utility from the child's birth weight. $\rho(v_0)$ is the probability of giving birth to a healthy child, which increases with in-utero investment v_0 at decreasing rates: $\rho' > 0$ and $\rho'' < 0$. $\tilde{U}_1^h = \text{argmax}_{v_1^h}\, U_1^h(v_1^h)$ is the maximized utility in $t = 1$ given health h.

Optimal in-utero investment satisfies the following first-order condition

$$\delta\,\rho'(v_0)\,\Delta\tilde{U}_1 + w'(v_0) = u'(c_0). \tag{3}$$

The first term $\delta\,\rho'(v_0)\,\Delta\tilde{U}_1 = \delta\,\rho'(v_0)\,(\Delta u + \Delta\Gamma + \delta\,\Delta V)$ is the marginal benefit of invest-

[5] I show proofs in Appendix B.

ment on the future utility of parents. This benefit is larger if the utility gap by child health, $\Delta u + \Delta\Gamma + \delta\Delta V$, is greater in childhood. $w'(v_0)$ is the marginal benefit of the utility from birth weight. Optimal investment balances the marginal benefits with the marginal cost $u'(c_0)$.

CHIP affects the trade-off by lowering the benefit of in-utero investment on future utility. Because CHIP reduces the utility gap by child health, it lowers the marginal benefit $\delta\rho'(v_0)\Delta\tilde{U}_1$ in equation 3. This implies that parents have less incentive to invest in utero in child health. Because CHIP did not affect the cost of in-utero investments but decreased the marginal benefits, equation 3 predicts smaller in-utero investments in response to CHIP.

3.3 Investment Crowd-In

Equation 3 is consistent with the standard prediction that public insurance can "crowd-out" private investments. However, empirical evidence from the roll-out overwhelmingly shows an increase in in-utero investments. The crowd-in response suggests the existence of additional mechanisms that increase the marginal benefit of investments instead of decreasing it.[6] Here, I consider two behavioral mechanisms in which the exposure to the roll-out may have adjusted parents' perception of investment benefits. First, the exposure may have increased parents' utility weight on child outcomes relative to own consumption, increasing the altruism of parents. Second, the exposure may have shifted inter-temporal weights towards utility in future periods, decreasing the present bias of parents.

Altruism. I model altruism as the weight on child outcomes in parents' utility. Exposure to the roll-out could increase altruism by raising parents' awareness of the child's well-being. In equation 3, increasing the child's weight to $\alpha > 1$ revises the first-order condition as follows

$$\delta\rho'(v_0)\Delta\tilde{U}_1(\alpha) + \alpha\, w'(v_0) = u'(c_0), \tag{4}$$

where the utility gap $\tilde{U}_1(\alpha) = \Delta u + \alpha(\Delta\Gamma + \delta\,\Delta V)$ now depends on the gap in child outcomes $\Delta\Gamma + \delta\Delta V$ multiplied by the altruism parameter α. Higher altruism thus increases parents' perceived benefit of investments. When parents care sufficiently more about child outcomes, the perceived benefit could increase despite smaller gaps in $\Delta\Gamma + \delta\Delta V$, resulting in a crowd-in of in-utero investments.

Present Bias. The exposure could further affect investments through the inter-temporal

[6] I focus on marginal effects assuming that the income and the resources of pregnant mothers did not increase in the roll-out. I show empirical support for the assumption in Section 5.5.

preferences of parents. Because in-utero investments have immediate costs but delayed benefits on children, parents who are overly sensitive to their immediate utility tend to under-invest in utero. By shifting inter-temporal weights towards future utility, the exposure could reduce parents' parent bias and increase investments in utero. More generally, present bias has been shown to affect health investments such as smoking (Gruber and Köszegi, 2001), preventive care (Fang and Wang, 2015), and food choice (Sadoff *et al.*, 2020). Here, I illustrate the implications for parental investments using the $\beta-\delta$ representation of present bias (Laibson, 1997).

Present bias affects in-utero investments according to the following condition

$$\beta\,\delta\,\rho'(v_0)\,\Delta\tilde{U}_1(\alpha,\beta) + \alpha\,w'(v_0) = u'(c_0). \tag{5}$$

Compared to equation 4, present-biased parents value the future benefits of investments less due to the bias term $\beta < 1$, and invest less in utero. Exposure to the roll-out could shift parents' inter-temporal weights towards future benefits for children, resulting in less present bias (higher β) and greater tolerance of investments in utero.

In equation 5, increasing either α or β predicts greater in-utero investment v_0. However, the behavioral effects have different implications for the timing of investments across trimesters within pregnancy. Because present bias generates cost avoidance in each trimester, a behavioral effect lowering present bias could further shift in-utero investments towards early stages of pregnancy. I exploit this distinction to interpret the empirical results in Section 5 and in the structural model in Section 7.

4 Data

I use the universe of birth certificate records in the US to study the investment responses to the roll-out of CHIP. The birth certificate shows the child's birth weight, mother's demographics, and in-utero investments such as pre-natal visits and smoking. I focus on the 39 states that expanded insurance exclusively for children during the roll-out, and focus on mothers between age 21 and 40 at the time of delivery. I therefore exclude teen pregnancies and pregnancies above age 40 from the analysis.[7]

Table 2 summarizes insurance eligibility, in-utero investments, and birth weight for children born in 1997-2001. The average income limit of Medicaid/CHIP is 175% FPL over this period. While exposed to the same income limits, children of single mothers

[7] 17% of the births in 1997-2001 were given by women below age 20. I exclude this group because states can extend maternity coverage for CHIP enrollees up to age 20. 82% of the births were given by women between age 21-40, and the remaining 1% were by women above age 40.

are twice as likely to be eligible (44% compared to 23% on average) based on predicted eligibility. Single mothers are less likely to start pre-natal care in the first trimester, more likely to delay care till the third trimester, and have higher rates of smoking in pregnancy. Birth weight is lower by 100 grams for children of single mothers.

Table 2: Summary statistics, children born in 1997-2001

	All Mothers		Single Mothers	
	Observations	Mean	Observations	Mean
Medicaid/CHIP				
income limit (100% FPL)	12,094,302	1.75	2,978,094	1.74
eligibility	12,094,302	0.23	2,978,094	0.44
care started in 1st trimester (%)	12,117,214	84.99	2,966,116	72.67
care started in 3rd trimester (%)	12,117,214	5.44	2,966,116	11.29
# doctor visits	12,000,696	11.72	2,929,395	10.79
$\geq$ 5 cigarettes daily (%)	9,727,610	8.13	2,365,340	15.49
$\geq$ 15 cigarettes daily (%)	9,727,610	2.96	2,365,340	5.55
birth weight (grams)	12,407,979	3339.43	3,067,358	3234.10
low birth weight (% <2,500 grams)	12,407,979	7.10	3,067,358	9.64

Notes: Table summarizes insurance eligibility, in-utero investments, and birth weight for cohorts born between Jan. 1997 and Dec. 2001 in the 39 states expanding insurance exclusively for children during the roll-out of CHIP. I predict children's eligibility for Medicaid/CHIP based on the income limits of insurance known at the time of pregnancy. Appendix A details the calculation.

5 In-utero Investments

5.1 Empirical Strategies

To estimate the investment responses, I exploit the roll-out of CHIP as an exogenous shock on mother's exposure to children's insurance. The roll-out increased the income limit of children's insurance across states. Within states, mothers exposed to CHIP early in the pregnancy had greater duration of exposure to the expansion. I measure the exposure to children's insurance using the income limit of Medicaid/CHIP, and measure in-utero exposure using the average income limit in pregnancy. Specifically, for mothers starting pregnancy in year-month t and in state s, I construct in-utero exposure $eliginc_{ts}$ as follows

$$eliginc_{ts} = \begin{cases} inc_s^{pre} & \text{if } j \leq -10, \\ \frac{|j|}{9} \cdot inc_s^{pre} + \left(1 - \frac{|j|}{9}\right) \cdot inc_s^{post} & \text{if } -9 \leq j \leq -1, \\ inc_s^{post} & \text{if } j \geq 0, \end{cases} \tag{6}$$

where $j = t - T_s$ compares the pregnancy onset time t and the CHIP onset time T_s (both in year-month) in state s. inc_s^{pre} and inc_s^{post} are the income limits of children's insurance before and after CHIP, respectively.[8]

Intuitively, equation 6 states that in-utero exposure to the roll-out is a simple weighted average of income limits inc_s^{pre} and inc_s^{post}, where the weights equal the share of pregnancy exposed to each limit. For instance, mothers gaining exposure to CHIP in month $|j|$ of the pregnancy have weight $\frac{|j|}{9}$ associated with the pre-CHIP limit inc_s^{pre}. Mothers starting pregnancy more than 9 months before CHIP ($j \leq -10$) are exposed only to inc_s^{pre}, and mothers starting pregnancy after CHIP ($j \geq 0$) are fully exposed to the CHIP limit inc_s^{post}. Thus, in-utero exposure increases within states for mothers with earlier exposure and hence greater duration of exposure to CHIP. In the empirical analysis, I exploit the variation across exposure timing focusing on mothers starting pregnancy between 16 months before and 4 months after CHIP ($-16 \leq j \leq 4$).

I estimate parental responses to children's insurance using the following specification

$$y_{itc} = \beta_1 \cdot eliginc_{ts(c)} \cdot single + \beta_2 \cdot eliginc_{ts(c)} + \beta_c \cdot single + \alpha_c + \tau_t + \alpha_{s(c)} \cdot \tau_{y(t)} + \epsilon_{itc}, \quad (7)$$

where y_{itc} is the investment of mother i starting pregnancy in time t. $eliginc_{ts(c)}$ is her in-utero exposure to children's insurance. I include county fixed effects α_c and control for time-varying factors by state-year in $\alpha_{s(c)} \cdot \tau_{y(t)}$. Because children of single mothers are twice as likely to be eligible for insurance (Table 2), I examine whether investments differ by single motherhood indicated by $single$. Based on the eligibility differences, we should expect larger responses from single mothers captured in β_1 than from married mothers captured in β_2. This difference allows me to further control for time-varying factors by state-year-month in the following specification

$$y_{itc} = \beta \cdot eliginc_{ts(c)} \cdot single + \beta_c \cdot single + \alpha_c + \tau_t + \alpha_{s(c)} \cdot \tau_t + \epsilon_{itc}, \quad (8)$$

where $\alpha_{s(c)} \cdot \tau_t$ absorbs the main effect of exposure $eliginc_{ts(c)}$ and fully controls for unobserved differences across states and over time. β estimates the investment responses of single mothers.

Both equation 7 and 8 control for differences by single motherhood in local areas (counties) with $\beta_c \cdot single$. Within counties and mother groups, I exploit the variation in exposure timing across cohorts to estimate the investment responses. The empirical strategy requires that mothers do not selectively enter pregnancy or single motherhood in

[8] Using the program language, I refer to income limits in 100% federal poverty levels (FPL). For instance, an income limit of "200% FPL" in the CHIP program implies that $inc_s^{post} = 2$.

response to CHIP, and that confounding policy changes across states do not explain the investments. I rule out responses in fertility and single motherhood in Appendix Table I1, and fully control for time-varying factors across states in equation 8. I illustrate the identifying variation showing sharp changes in investments across exposure timing in the event study. I then incorporate additional heterogeneity across mother groups using simulated eligibility in Section 5.4, finding similar results for single mothers.

5.2 Birth Weight

I first examine the effect of in-utero exposure on the child's birth weight. The roll-out is unlikely to impact the birth weight of children because CHIP did not expand insurance for pregnant mothers. An increase in the birth weight, however, indicates the existence of private investment responses to the roll-out. In Table 3, I estimate the effect on birth weight using equation 7 and 8.

Exposure to the roll-out significantly increased the child's birth weight. In column 1, gaining a 100% FPL exposure increased birth weight by 10.6 grams, or by 0.32% above the mean. In column 3, the exposure decreased the probability of low birth weight (<2,500 grams) by 0.32 percentage points, or by 4.5% below the mean. Both effects are fully concentrated among children of single mothers. Moreover, replacing the main effect of *eliginc* with a full set of state-year-month fixed effects in column 2 and 4 yields very similar results for children of single mothers. These estimates imply that the roll-out of CHIP, which expanded income limits from 122% FPL to 202% FPL in 1997-2000, increased birth weight by $10.6 \cdot 80\% = 8.5$ grams, and decreased low birth weight by $4.5\% \cdot 80\% = 3.6\%$ for children of single mothers.

To illustrate the identifying variation, I estimate the following event study specification

$$y_{itc} = \sum_{\substack{j=-16 \\ j\neq -10}}^{4} \beta_j \cdot eliginc_{ts(c)} \cdot single \cdot 1\{t - T_{s(c)} = j\} + \gamma \cdot eliginc_{ts(c)} + \beta_c \cdot single + \alpha_c + \tau_t + \alpha_{s(c)} \cdot \tau_{y(t)} + \epsilon_{itc}, \tag{9}$$

where I expand the term $\beta_1 \cdot eliginc_{ts(c)} \cdot single$ in equation 7 by the timing of exposure indexed by j, and estimate separate effects across cohorts with β_j. I normalize the effect on children conceived 10 months before CHIP to zero ($\beta_{-10} = 0$). These children and earlier cohorts ($j \leq -10$) were born before the CHIP onset, and hence were not exposed to CHIP in utero. In-utero exposure then increased with j for later cohorts.

Panel (a) of Figure 2 plots estimates of β_j for birth weight. Birth weight did not increase

Table 3: Effects of exposure on birth weight

	(1)	(2)	(3)	(4)
	Birth weight (grams)		Low birth weight (%)	
$eliginc \cdot single$	10.66***	10.61***	-0.32***	-0.32***
	(2.51)	(2.51)	(0.10)	(0.10)
$eliginc$	-1.76		0.005	
	(4.09)		(0.14)	
y mean	3342.57		7.08%	
R^2	0.02	0.02	0.01	0.01
N	4,315,394		4,315,394	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
Notes: Table shows the effect of in-utero exposure on birth weight (grams) and low birth weight (<2,500 grams). I estimate separate effects for single and married mothers using equation 7 in column 1 and 3, and estimate effects on single mothers using equation 8 in column 2 and 4. Robust standard errors clustered at the level of states in the parenthesis.

for children never exposed to CHIP in utero ($j \leq -10$). For children exposed to CHIP in the second and third trimester ($-9 \leq j \leq -4$), the exposure had no significant impact on birth weight. Exposure significantly increased birth weight for children exposed to CHIP in the first trimester ($-3 \leq j \leq -1$) and those fully exposed to CHIP in utero ($j \geq 0$). Among these children, gaining a 100% FPL exposure increased birth weight by 4.1 grams, and decreased low birth weight by 1.6% (Appendix Table I2).[9] The overall effect on birth weight was concentrated among children of single mothers exposed to CHIP since the first trimester.

5.3 In-Utero Investments

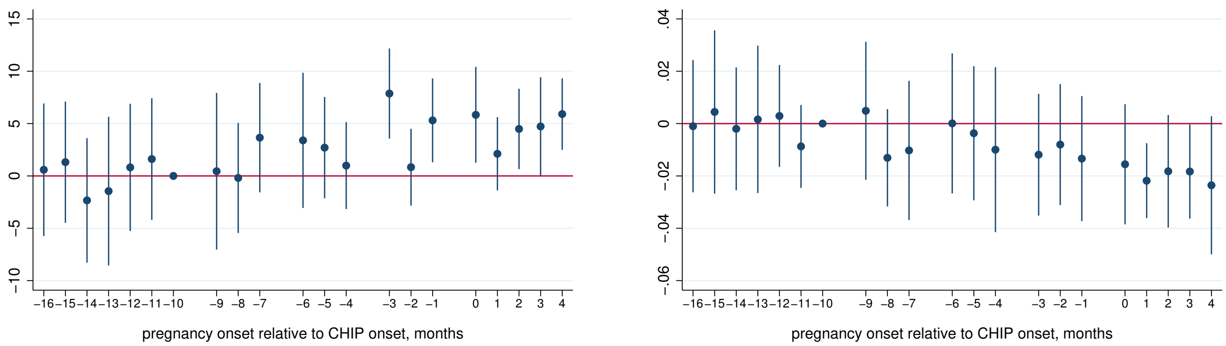
The effect on birth weight suggests that exposure to the roll-out may have increased mother's private investments in the child. To detect the investment responses, I examine mother's pre-natal visits and smoking in pregnancy, and estimate the effects of exposure on the *timing* and the *level* of investments using equation 7 and 8. I find that exposure to the roll-out increased mother's early onset of pre-natal visits, reduced the delay in pre-natal visits, and reduced smoking in pregnancy.

Investment Timing. I examine responses in the timely onset of pre-natal visits in Table 4. Pre-natal care begins when the pregnant woman has the first pregnancy-related doctor

[9]To succinctly summarize the results across cohorts, I group children by the trimester of exposure and estimate effects for six exposure groups in Appendix Table I2.

Figure 2: Effects of exposure on birth weight and pre-natal care onset, event study

(a) Birth Weight (grams) (b) Month Care Started



Notes: Figure plots the effect of in-utero exposure on birth weight in panel (a) and on the onset month of pre-natal visits in panel (b), for cohorts with different timing of exposure to CHIP. Mothers starting pregnancy more than 10 months before CHIP were not exposed to CHIP in pregnancy. In-utero exposure then increased for later cohorts. 95% confidence intervals are based on robust standard errors clustered by states.

visit. The Guidelines for Perinatal Care (Freeman and Poland, 1992) recommends that pregnant women have one doctor visit per month in the first two trimesters, and have four visits per month towards the end of pregnancy. Nonetheless, around 15% of mothers delay the onset of care till the second or third trimester, and 5% start care in the third trimester. In Table 4, gaining a 100% FPL exposure decreased late care onset past the first trimester by 1.1 percentage points, or by 7% below the mean, and decreased very late onset in the third trimester by 14%. The exposure reduced the time to the first pre-natal visit by 0.05 months. These responses were fully concentrated among single mothers.

Panel (b) of Figure 2 plots the event study estimates for the timing of care onset from equation 9. The month of care onset did not decrease for mothers not exposed to CHIP in pregnancy, and decreased by a small and insignificant amount for mothers exposed to CHIP in the first trimester. The overall effect on the timing of care onset was concentrated among single mothers with full exposure to CHIP ($j \geq 0$). For these mothers, gaining a 100% FPL exposure reduced late care onset by 2.5%, and reduced very late onset in the third trimester by 5.5% (Appendix Table I3).

Investment Levels. I next examine if improvements in the early onset of visits led to a greater number of visits by the end of pregnancy. In Table 5, gaining a 100% FPL exposure increased pre-natal care by 0.09 visits. This effect is small in magnitude. Compared to

Table 4: Effects of exposure on the timing of pre-natal visits

	(1)	(2)	(3)	(4)	(5)	(6)
	Month care started		Late onset (%) (2nd/3rd trimester)		Very late onset (%) (3rd trimester)	
eliginc · *single*	-0.046***	-0.046***	-1.09***	-1.10***	-0.75***	-0.75***
	(0.014)	(0.014)	(0.26)	(0.27)	(0.25)	(0.25)
eliginc	0.018		0.33		0.29	
	(0.015)		(0.32)		(0.17)	
y mean	2.45		15.08%		5.48%	
R^2	0.08	0.08	0.06	0.06	0.04	0.04
N	4,200,326		4,200,326		4,200,326	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table shows the effect of in-utero exposure on the month of care onset in column 1-2, late care onset past the first trimester in column 3-4, and very late onset in the third trimester in column 5-6. I estimate separate effects for single and married mothers using equation 7 in odd-numbered columns, and estimate effects on single mothers using equation 8 in even-numbered columns. Robust standard errors clustered at the level of states in the parenthesis.

the sample average of 11.7 visits in pregnancy, the exposure increased pre-natal visits by less than 1%. Results by the timing of exposure in Appendix Table I4 show a similar null effect on the number of visits, including for mothers with full exposure to CHIP ($j \geq 0$). Among these mothers, the number of pre-natal visits did not increase significantly with exposure despite earlier onset of pre-natal visits.

Table 5: Effects of exposure on the number of pre-natal visits and smoking

	(1)	(2)	(3)	(4)	(5)	(6)
	# Pre-natal visits		Smoking (%) (≥5 cigarettes daily)		Heavy smoking (%) (≥15 cigarettes daily)	
eliginc · *single*	0.091**	0.089*	-0.45**	-0.46**	-0.38***	-0.39***
	(0.045)	(0.045)	(0.18)	(0.18)	(0.13)	(0.13)
eliginc	-0.050		-0.073		0.058	
	(0.041)		(0.16)		(0.13)	
y mean	11.74		8.41%		3.12%	
R^2	0.07	0.07	0.06	0.06	0.03	0.03
N	4,157,327		3,331,203		3,331,203	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table shows the effect of in-utero exposure on the number of pre-natal visits and smoking intensity. I estimate separate effects for single and married mothers using equation 7 in odd-numbered columns, and estimate effects on single mothers using equation 8 in even-numbered columns. Robust standard errors clustered at the level of states in the parenthesis.

The birth certificate also indicates the number of cigarettes consumed daily by the pregnant mother. Because the consumption is recalled as an average in pregnancy, the duration of the recall adds noises to the data and potentially attenuates the smoking responses. To limit the attenuation bias, I focus on the intensive margin and examine smoking more than 5 and 15 cigarettes daily in column 3-6 of Table 5. Gaining a 100% FPL exposure reduced smoking more than 5 cigarettes daily by 5%, and reduced smoking more than 15 cigarettes daily by 13%. These effects were similarly concentrated among single mothers exposed to CHIP since the first trimester (Appendix Table I4).

5.4 Heterogeneity

Effects by States. In addition to examining investment responses by the timing of exposure, I further explore heterogeneity across states using the following specification

$$\begin{aligned} y_{itc} = &\sum_k \beta_k \cdot eliginc_{ts(c)} \cdot single \cdot 1\{s = k\} + \gamma \cdot eliginc_{ts(c)} \\ &+ \beta_c \cdot single + \alpha_c + \tau_t + \alpha_{s(c)} \cdot \tau_{y(t)} + \epsilon_{itc}, \end{aligned} \tag{10}$$

where β_k estimates the effect of CHIP exposure in state k.[10] I plot estimates of β_k by the size of expansion across states in Appendix Figure J1. Exposure had the largest impact on birth weight among small expansion states increasing income limits by less than 70% FPL.[11] The expanded income limit (162% FPL) remained 40% FPL below the national average. In these states, a 100% FPL expansion would increase birth weight by 16 grams, or by 50% above the average effect across states. The reduction in smoking is also larger in the small expansion states.[12] By comparison, the majority of states (65% of births) expanded income limits by 75%-90% FPL, and the effects on birth weight and investments in this range are comparable to the average effects across states.[13] Finally, a handful of states (10% of births) expanded income limits by more than 100% FPL.[14] The effects on

[10]The state-specific effects can also be estimated from the state-level regression

$$y^k_{it} = \beta^k_1 \cdot eliginc^k_t \cdot single^k_i + \beta^k_2 \cdot single^k_i + \tau^k_t + \epsilon^k_{it}, \tag{11}$$

where $eliginc^k_t$ differs in state k by the timing of exposure across cohort t. In practice, equation 10 and equation 11 give very similar estimates by states. I plot estimates of β_k from equation 10.

[11]Around 25% of all births occurred in the small expansion states. The largest expansion state in this group is Maine, where income limit increased by 55% FPL. States such as Louisiana, South Dakota, Wyoming, Iowa, and Mississippi expanded income limits by only 22.58% FPL. I do not estimate state-specific effects for Minnesota where the income limit increased by a minimal 0.26% FPL in the roll-out.

[12]I examine smoking intensity by half packs (10s) of cigarettes daily. Specifically, I use integer 0, 1, and 2 to indicate non-smokers (<5 cigarettes daily), light smokers (≥5 and <15 cigarettes daily), and heavy smokers (≥15 cigarettes daily), respectively, so that intensity increases by half packs (10s) of cigarettes daily.

[13]This range includes states with the largest number of births such as California, Texas, New York, and Florida. In these populous states, birth weight increased by 13.6 grams per 100% FPL exposure, or by 30% above the average effect across states.

[14]These states are Rhode Island, Connecticut, New Hampshire, Pennsylvania, and Missouri.

birth weight and investments tend to be smaller in the largest expansion states.

Simulated Exposure. Complementing the main analysis, I incorporate additional heterogeneity in mother's exposure to children's insurance using the simulated eligibility strategy (Currie and Gruber 1996a; Currie and Gruber 1996b). Specifically, I apply the income limit of Medicaid/CHIP to calculate the probability of being eligible for insurance for a fixed sample of children. Because children of low-income mothers are more likely to be eligible, I calculate the probability by mother demographics – across race, education, and marital status – to simulate mother's exposure to children's insurance.[15] I then estimate investment responses to simulated exposure $eligCHIP$ in the following specification

$$y_{its} = \beta \cdot eligCHIP_{d(i)ts} + \alpha_s \cdot \gamma_d + \alpha_s \cdot \tau_t + \epsilon_{its}, \tag{12}$$

where exposure $eligCHIP_{d(i)ts}$ differs across state s, cohort t, and mother demographics d.

By construction, exposure $eligCHIP_{d(i)ts}$ is larger for mother demographics with greater predicted eligibility for CHIP, for cohorts exposed to CHIP earlier in pregnancy, and in states expanding insurance to higher income limits. I control for time-varying factors across states with $\alpha_s \cdot \tau_t$, and control for unobserved differences across states and mother demographics with $\alpha_s \cdot \gamma_d$. Within states and mother demographics, I exploit eligibility differences by the timing of exposure across cohorts to estimate the investment responses.

I find similar effects on birth weight and investments using the simulated exposure in Appendix Table I5. Increasing exposure by 10 percentage point eligibility increases birth weight by 3.2 grams, and the effect is concentrated among children of single mothers. For these children, the roll-out increased eligibility from 0.33 to 0.50, increasing birth weight by 8.1 grams. This effect is comparable to the 8.5 gram increase implied by estimates from equation 8 in Table 3.[16] Similarly, investment responses to eligibility increases are comparable to the effects of expanded income limits for single mothers,[17] supporting the results from equation 8.

[15] I show details of the simulation in Appendix A. Simulated exposure differs sharply by the marital status of mothers. Specifically, the roll-out of CHIP increased simulated exposure to 50% for single mothers, and to 16% for married mothers.

[16] Specifically, simulated exposure implies a birth weight gain of $(0.50 - 0.33) \times 47.5 = 8.1$ grams. The roll-out expanded income limits by 80% FPL, implying an increase in birth weight by $10.6 \times 80\% = 8.5$ grams applying estimates from equation 8 in Table 3.

[17] Specifically, increases in simulated exposure imply a 0.9 percentage point reduction in late care onset and a 0.2 percentage point reduction in heavy smoking for single mothers in the roll-out. These effects are comparable to the 0.9 percentage point reduction in late care onset and the 0.3 percentage point reduction in heavy smoking implied by estimates from equation 8.

5.5 Mechanism

The empirical results show compelling evidence of investment crowd-in following the roll-out of CHIP. To understand mechanisms, I first examine whether the exposure to children's insurance increased mother's uptake of own insurance and safety net benefits. I also examine whether mothers increased in-utero investments to improve the long-run outcomes of children. I find little support for these mechanisms. I then discuss how behavioral effects on mother's altruism and present bias may explain the investment responses.

Budget Constraint. I examine mother's insurance and income in pregnancy using the Survey of Income and Program Participation (SIPP). I find no evidence that the exposure to children's insurance increased mother's uptake of own insurance in pregnancy (Appendix Table I6). I also find no evidence that the exposure increased mother's cash transfer incomes or health spending in pregnancy (Appendix Table I7). Similarly, I find no evidence that mothers borrowed more from future incomes to invest more in pregnancy (Appendix Table I8). These results are inconsistent with a resource-based mechanism where the exposure increased in-utero investments by relaxing mother's budget constraint in pregnancy.

Long-Run Effects. Investments could also increase if mothers internalized the long-run effects of investments on child outcomes. In this case, mothers investing more during the roll-out should expect better outcomes for their children later in life. I test this implication examining mother's decision to enroll the child in CHIP and her expectation of the child's education attainment in Appendix Table I9. Mothers exposed to CHIP since the first trimester, in addition to investing more in utero, also had substantially higher uptake of CHIP for their newborns, but despite their investments, these mothers did not indicate higher expected education for the child. These results are inconsistent with a mechanism motivated by the long-run effects of investments on child outcomes.

Altruism. I next examine the two behavioral mechanisms that I examine empirically in the structural analysis. Exposure to the roll-out may increase mother's altruism for the child by increasing her awareness of the child's well-being. The behavioral effect increases mother's utility from investments, and may result in a greater number of pre-natal visits and less smoking in pregnancy. Empirically, however, the exposure significantly shifted the timing of pre-natal visits towards early trimesters but had smaller and weaker effects on the number of visits by the end of pregnancy. I hence consider additional mechanisms that may better explain the timing and the number of investments in pregnancy.

Present Bias. To explain responses in the investment timing, I explore behavioral effects of the exposure on the time preferences of mothers. Specifically, exposure to the roll-out may have shifted mother's intertemporal weights towards utility in future periods, reducing mother's sensitivity to the immediate costs of investments. The reduction in present bias predicts less delay in investments and more self-control over additive consumption such as smoking, consistent with earlier onset of visits and reduced smoking in pregnancy. I formally investigate the behavioral mechanisms using a dynamic model of in-utero investments in Section 7, where I exploit the investment responses to quantify the behavioral effects of the exposure.

6 Education Outcomes

I next examine the long-run effects of exposure on children's education attainment using the American Community Survey (ACS). I find that children with in-utero exposure to the roll-out have higher college enrollment rates. In high school, they are more likely to attend the grade appropriate for their age. These effects are concentrated among children of single mothers.

6.1 Empirical Strategy

I estimate the effects of in-utero exposure on education using the following specification

$$
\begin{aligned}
y_{ibqt} =& \beta_0 \cdot eliginc_{ibq}^{utero} \cdot single + \beta_1 \cdot eliginc_{ibq}^{utero} + \beta \cdot X_{ibqt} \\
&+ \gamma_b + \psi_q + \tau_t + \gamma_b \cdot \psi_{y(q)} + \gamma_b \cdot \tau_t + \beta_b \cdot single + \epsilon_{ibqt}, \qquad (13)
\end{aligned}
$$

where y_{ibqt} is the education of child i born in year-quarter q and state b surveyed in year t. $eliginc_{ibq}^{utero}$ is the in-utero exposure of child i, constructed as the average income limit of Medicaid/CHIP in the three quarters before birth. $single$ indicates children of single mothers. Since in-utero investments were concentrated among single mothers in the roll-out, the long-run effects on education tend to be larger for children of single mothers (β_0) than for children of married mothers (β_1). In X_{ibqt}, I include childhood exposure $eliginc_{ibqt}^{child}$, constructed as the average income limit between birth and year t, and the child's age.[18]

I control for unobserved differences by single motherhood across states in $\beta_b \cdot single$. Within states and mother groups, I exploit the variation in exposure timing across cohorts

[18] I include separate controls of childhood exposure for children of single and married mothers in X_{ibqt}.

to estimate the long-run effects on education. I use state-year fixed effects to account for state-specific trends in the roll-out and in the long-run follow-up.[19] In the robustness check, I further include *single*-year fixed effects to account for the long-term trends in single motherhood. Exploiting the roll-out, I estimate equation 13 for children conceived 7 quarters before CHIP through 2 quarters after CHIP.[20]

I use two measures of single motherhood based on mother's marital history. The first measure requires that the mother has never married by the time of the survey. Under this measure, the child was born to single mothers who remained single throughout parenthood. The second measure only requires that the mother is unmarried in survey year t. Ex ante, one might expect larger effects of exposure on children raised continuously in single-mother households.

Equation 13 may yield biased estimates on education, if mothers adjusted the probability of single parenthood in response to the exposure. Empirically, I rule out responses in the marital status of mothers in Appendix Table I10, and rule out fertility responses in Appendix Table I1. Thus, differences in the timing of exposure are plausibly exogenous to children of single mothers. I illustrate the identifying variation with event study estimates across exposure timing below.

6.2 Effects on Education

I study the education outcomes of children expected to enter Grade 9 or above in 2010-2018, focusing on their grade-for-age status in high school, high school graduation, and college enrollment using equation 13. I show the results for college enrollment first.

College Enrollment. Table 6 shows the effects on college enrollment. Column 3-4 estimates the preferred specification in equation 13. Gaining a 100% FPL exposure to the roll-out increased college enrollment by 1.71 percentage points for children of single mothers, or by 10.8% above the mean. The effect is about 1 percentage point larger for children of never-married mothers. Controlling for long-term trends in single motherhood in column 5-6 yields similar estimates. Removing year-specific effects for both states and single motherhood in column 1-2 also yields similar estimates for children of single mothers. Thus, the long-run impacts of in-utero exposure on college enrollment are not

[19] Specifically, $\gamma_b \cdot \psi_{y(q)}$ controls for state-specific trends in the roll-out of CHIP, and $\gamma_b \cdot \tau_t$ controls for trends in the long-run follow-up.

[20] These children are born between the second quarter of 1996 and the first quarter of 2002. The average child – born in the fourth quarter of 1998 – expects to enter Grade 1 in 2004-2005 and expects to graduate high school (Grade 12) in 2016-2017. I track their education through high school and into college using ACS 2010-2018. I detail the sample construction in Appendix C.

sensitive to the choice of controls in the specification.

To illustrate the identifying variation, Appendix Figure J2 plots separate effects by exposure timing across cohorts. Children conceived more than 4 quarters before CHIP were not exposed to CHIP in utero, and college enrollment did not increase for these children. The overall effect on college enrollment was concentrated among children exposed to CHIP since the first trimester. For these children, gaining a 100% FPL exposure in utero increased college enrollment by 0.59-0.69 percentage points (Appendix Table I11).

Table 6: Effects of in-utero exposure on college enrollment

	(1)	(2)	(3)	(4)	(5)	(6)
$eliginc^{utero} \cdot single$	2.72***	1.58***	2.91***	1.71***	2.60***	1.86***
	(0.60)	(0.41)	(0.58)	(0.40)	(0.99)	(0.70)
$eliginc^{utero}$	-1.09*	-1.26**	-0.76	-0.94	-0.74	-1.06
	(0.57)	(0.59)	(0.90)	(0.93)	(0.93)	(0.99)
single						
never married	Y		Y		Y	
state-year FE			Y	Y	Y	Y
single-year FE					Y	Y
y mean	15.78%		15.78%		15.78%	
R^2	0.34	0.34	0.35	0.35	0.35	0.35
N	385,065		385,063		385,063	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effect of in-utero exposure on college enrollment. *single* indicates children of single mothers. I estimate effects for children of never married mothers in odd-numbered columns, and for children of single mothers unmarried in the survey year in even-numbered columns. I examine the robustness of results with different controls in the specification. The preferred specification in column 3-4 controls for state-year fixed effects for the roll-out of CHIP and for the long-run follow-up. The full specification in column 5-6 further controls for long-term trends in single motherhood with *single*-year fixed effects. I remove both sets of controls in column 1-2. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parenthesis.

High School. I also examine the effect of in-utero exposure on children's grade progress through high school, focusing on the "grade-for-age" status (whether the child attends the grade appropriate for her age) and high school graduation. Appendix Table I12 shows the estimates. In-utero exposure significantly improved grade-for-age. For children of never-married mothers, gaining a 100% FPL exposure in utero reduced late grade entry by 2.36 percentage points, or by 20% below the mean. For children of single mothers, the exposure reduced late grade entry by 1.56 percentage points.

In-utero exposure further improved high school graduation rates for children of single mothers. Gaining a 100% FPL exposure increased high school graduation by 0.75 percentage points for children of single mothers, or by 2.6% above the mean. The increase in high school graduation is smaller than the effect on college enrollment. This suggests that in-utero exposure increased college enrollment among high school graduates who would not have attended college absent the exposure. Across cohorts, the effects on high school graduation were concentrated among children of never-married mothers gaining full exposure to CHIP in utero (Appendix Table I11).

Effect Magnitude. Focusing on college enrollment, I compare the effect of gaining in-utero exposure to CHIP with the effect of gaining Medicaid insurance to understand the magnitude of the results. Exploiting Medicaid expansions that simultaneously expanded insurance for pregnant mothers and infants, Miller and Wherry (2019) found that a ten percentage point increase in Medicaid eligibility in utero and in the first year of life increased college enrollment by 0.35 percentage points.[21] This effect implies that the roll-out of CHIP would increase college enrollment by 0.60 percentage points.[22] In practice, the exposure to CHIP increased college enrollment by 1.13 percentage points for children of single mothers, and by 0.29 percentage points for children on average.[23] Therefore, in-utero exposure to CHIP increased college enrollment by around half the effect of insurance expansions for pregnant mothers and infants.

6.3 Discussion

Empirical results from Section 5 and 6 show that in-utero exposure to the roll-out of CHIP significantly improved the birth weight and the college enrollment of children. Specifically, the exposure decreased low birth weight by 3.6% and increased college enrollment by 10.8% for children of single mothers. To understand the magnitude of the effect on birth weight, I compare the effect of insurance exposure with the effects of cash transfers to single mothers. For instance, Hoynes *et al.* (2015) estimated that expanding the Earned Income Tax Credit (EITC) by $1,000 reduced low birth weight by 6.5% among single mothers. By comparison, in-utero exposure to the roll-out of CHIP resulted in around half the reduction in low birth weight. Thus, in-utero exposure improved birth weight similar to a $500 expansion of EITC, and in the long run, increased college enrollment by around half the effect of insurance expansions for pregnant mothers and infants.

[21] Similarly, Levine and Schanzenbach (2009) found that CHIP eligibility in the first year of life improved Reading scores in Grade 4, providing one pathway for the longer-term effects on attainment.

[22] Specifically, CHIP increased children's insurance eligibility by 17 percentage points, leading to an increase in college enrollment by $17 * 0.035 = 0.60$ percentage points.

[23] Specifically, CHIP expanded income limits by 80% FPL, increasing college enrollment by $0.8*1.41 = 1.13$ percentage points for children of single mothers, or by $25.46\% * 1.13 = 0.29$ percentage points on average.

7 Behavioral Mechanisms

I next investigate the behavioral mechanisms using a dynamic model of in-utero investments. In the model, mothers choose smoking and pre-natal visits each trimester to invest in the birth weight of the child. Because investments occur over multiple trimesters, mothers may delay investments and end up investing less in the child. The exposure to CHIP shifted the timing and the level of investments, which I exploit to estimate the behavioral effects of the exposure. I then evaluate welfare based on the model estimates.

7.1 Setting

Pre-Natal Visits. Let v_{it} be the number of visits each month chosen by mother i in trimester t, with $t = 1, 2, 3$. I follow the medical guidelines and allow the maximum number of visits each month to increase from one in the first trimester to two visits in the second trimester, and finally to four visits in the third trimester.[24] The maximum number of visits is 21 in the model. Empirically, mothers take an average of 11 visits in pregnancy.

Mother's utility per visit depends on a random coefficient η_i and a taste shock υ_{it}, where η_i captures mother's taste for visits. The taste is drawn from three potential types in the population, and the distribution of η_i across types depends on mother characteristics X_i. To account for investment costs, I subtract out-of-pocket cost c_{it} from the utility, and absorb any non-monetary cost inside type η_i. I calibrate c_{it} by mother age a_i and health shock ξ_{st}.[25] The utility from v_{it} visits in trimester t is given in dollar terms by

$$\vartheta(v_{it}; \upsilon_{it}, \xi_{it}, a_i) = 3\, v_{it} \left[\eta_i + \upsilon_{it} - c_{it}(a_i, \xi_{it}) \right]. \tag{14}$$

Smoking. I discretize mother's smoking decision s_{it} using cut-points at 5 and 15 cigarettes daily. $s_{it} = 0$ for non-smokers with less than 5 cigarettes daily, $s_{it} = 1$ for light smokers with 5 to 15 cigarettes daily, and $s_{it} = 2$ for heavy smokers with over 15 cigarettes daily. Utility from 10 more cigarettes daily is $\zeta_i + \omega_{it}$, where ζ_i is mother's taste (net of costs) for smoking, and ω_{it} is a taste shock. Multiplied by smoking intensity $s_{it} \in \{0, 1, 2\}$, the utility

[24] The higher frequency of visits in the third trimester matches the guideline recommendation of weekly visits for near-term mothers.

[25] I calibrate c_{it} from the Medical Expenditure Panel Survey (MEPS), matching average costs and the mass at zero by age. 86% of the visits incur zero out-of-pocket costs. I detail the calibration in Appendix D. Due to the small amount of costs, I do not model borrowing from future trimesters or periods after childbirth. This is consistent with the empirical evidence that the exposure had little effect on mother's debt, income, or insurance in pregnancy.

from smoking in trimester t is given by

$$\psi(s_{it}\,;\omega_{it}) = s_{it}\,(\zeta_i + \omega_{it})\,. \tag{15}$$

Birth Weight. The child is born at the end of the third trimester. Birth weight b_i depends on mother's pre-natal visits and smoking in pregnancy. I specify a flexible birth weight production function as follows

$$log(b_i) = \phi_i + \phi_1 \cdot V_i + \phi_2 \cdot V_i^2 + \phi_3 \cdot smoke_i + \phi_4 \cdot heavy_i + \Phi(V_i, V_i^2, smoke_i, heavy_i) + \sigma\xi_{i3}\,, \tag{16}$$

where $V_i = 3\sum_{t=1}^{3} v_{it}$ is the total number of visits of mother i. I use the quadratic form to allow for decreasing marginal benefits of visits given by $\phi_1 + 2\phi_2 \cdot V_i$.

$smoke_i$ and $heavy_i$ are binary variables derived from the average smoking intensity $\bar{s}_i = \frac{1}{3}\sum_{t=1}^{3} s_{it}$. I let $smoke_i = 1$ for mothers consuming more than 5 cigarettes daily ($\bar{s}_i \geq 5$), and let $heavy_i = 1$ for heavy smokers consuming more than 15 cigarettes daily ($\bar{s}_i \geq 15$). The effect of smoking is captured by ϕ_3, and the incremental effect of heavy smoking is captured by ϕ_4.

I further include flexible interaction terms between pre-natal visits and smoking in $\Phi(V_i, V_i^2, smoke_i, heavy_i)$. The interactions allow the marginal benefit of visits to vary by smoking intensity. Birth weight also depends on an endowment effect ϕ_i drawn from the type distribution of mother i. Larger ϕ_i values increase the return of investments on birth weight. Finally, health shock ξ_{i3} impacts birth weight through the parameter σ.

Altruism. Mother's utility from the child's birth weight is given by $L(b_i) = \alpha\, b_i^{\theta}$, where θ governs the marginal utility of birth weight, and α is the utility weight on child outcomes. An increase in altruism increases α, resulting in greater utility from birth weight relative to investments $\vartheta(v_{it}\,; \upsilon_{it}, \xi_{it}, a_i)$ and $\psi(s_{it}\,;\omega_{it})$.

Present Bias. I model present bias using the β-δ representation. I fix $\delta = 1$ for quarterly discounting in the long run. In the short run, present-biased mothers choose investments in $t = 3$ to maximize utility

$$U_3\Big(v_{i3}, s_{i3}\,; \varepsilon_{i3}, \mathcal{I}_{i3}\Big) = \vartheta(v_{i3}\,; \upsilon_{i3}, \xi_{i3}, a_i) + \psi(s_{i3}\,;\omega_{i3}) + \beta\,\mathbb{E}\Big[L(b_i)|\mathcal{I}_{i3}, v_{i3}, s_{i3}\Big], \tag{17}$$

where $\varepsilon_{i3} = (\upsilon_{i3}, \xi_{i3}, \omega_{i3})$ is the vector of transitory shocks in $t = 3$. $\mathcal{I}_{i3} = (3\sum_{t=1}^{2} v_{it}, \sum_{t=1}^{2} s_{it}, X_i)$ is the state vector of cumulative investments and mother characteristics X_i. Let (v_{i3}^*, s_{i3}^*)

denote investments in $t = 3$. The long-run utility implied by the investments is

$$\mathcal{U}_3\left(v_{i3}^*, s_{i3}^*; \varepsilon_{i3}, \mathcal{I}_{i3}\right) = \vartheta(v_{i3}^*; v_{i3}, \xi_{i3}, a_i) + \psi(s_{i3}^*; \omega_{i3}) + \mathbb{E}\left[L(b_i)|\mathcal{I}_{i3}, v_{i3}^*, s_{i3}^*\right]. \tag{18}$$

Compared to the long-run utility (equation 18), present-biased mothers under-value the utility from birth weight in equation 17, discounting $\mathbb{E}[L(b_i)|\mathcal{I}_{i3}, v_{i3}, s_{i3}]$ with $\beta < 1$.

In $t = 2$, present-biased mothers discount future utility $\mathcal{U}_3$ with $\beta < 1$, and choose investments to maximize utility

$$U_2(v_{i2}, s_{i2}; \varepsilon_{i2}, \mathcal{I}_{i2}) = \vartheta(v_{i2}; v_{i2}, \xi_{i2}, a_i) + \psi(s_{i2}; \omega_{i2}) + \beta\, \mathbb{E}[\mathcal{U}_3|\mathcal{I}_{i2}, v_{i2}, s_{i2}], \tag{19}$$

where $\mathcal{U}_3$ is the long-run utility implied by investments in $t = 3$ (equation 18). Maximizing equation 19 yields investments (v_{i2}^*, s_{i2}^*) in $t = 2$. Recursively, mothers discount the long-run utility implied by (v_{i2}^*, s_{i2}^*) with $\beta < 1$ to determine investments in $t = 1$.[26] I hence solve for mother i's investments $\left(v_{it}^*, s_{it}^*\right)_{t=3,2,1}$ from equation 17 to 20. I then match the investments with empirical counterparts to estimate the model parameters.

7.2 Estimation

I estimate the model parameters using the method of simulated moments (MSM). To quantify the behavioral effects, I let altruism α and present bias β vary by mother's exposure to CHIP, and match investments across exposure to estimate the effects on preferences. I detail the construction of the exposure measure and the moment conditions identifying the parameters below.

CHIP Exposure. Building on the definition of in-utero exposure $eliginc$ (equation 6), I construct CHIP exposure $\Delta\ell_{js} = eliginc_{js} - inc_s^{pre}$ as the incremental exposure due to the onset of CHIP. Intuitively, $\Delta\ell_{js}$ is larger in states with greater expansion of insurance, and increases within states for mothers gaining earlier exposure to CHIP. Specifically, for mothers starting pregnancy within 9 months before CHIP ($-9 \le j \le -1$), $\Delta\ell_{js} = (1+\frac{j}{9})\cdot\Delta inc_s$ increases with j for mothers with earlier exposure to CHIP, and increases with expansion size $\Delta inc_s = inc_s^{post} - inc_s^{pre}$. Mothers gaining full exposure to CHIP ($j \ge 0$) have $\Delta\ell_{js} = \Delta inc_s$, and mothers never exposed to CHIP in pregnancy ($j \le -10$) have $\Delta\ell_{js} = 0$.

I calculate $\Delta\ell_{js}$ for 324,400 non-college-educated single mothers starting pregnancy

[26] Specifically, investments in $t = 1$ maximize the utility

$$U_1(v_{i1}, s_{i1}; \varepsilon_{i1}, \mathcal{I}_{i1}) = \vartheta(v_{i1}; v_{i1}, \xi_{i1}, a_i) + \psi(s_{i1}; \omega_{i1}) + \beta\, \mathbb{E}[\mathcal{U}_2|\mathcal{I}_{i1}, v_{i1}, s_{i1}], \tag{20}$$

where $\mathcal{U}_2$ is the long-run utility implied by investments in $t = 2$.

within one year before CHIP ($-12 \leq j \leq -1$). These mothers lived in states where the income limit was between 110% and 130% FPL before CHIP, and the expansion increased income limits by 20% to 90% FPL after CHIP. I hence estimate the behavioral effects of CHIP exposure starting from a common baseline exposure level across states.[27] I discretize $\Delta\ell_{js}$ into 5 nodes, corresponding to 0%, 10%, 30%, 50%, and 70% FPL exposure. I assign mothers with $j \leq -10$ to the zero exposure node, and assign mothers with $j \geq -9$ to the nearest positive node to construct CHIP exposure $\Delta\ell_i$ for mother i.

Behavioral Effects. To model the behavioral effects, I allow mother's altruism α_i to differ across CHIP exposure $\Delta\ell_i$ according to the following equation

$$\alpha_i = \alpha_0 + \alpha_1 \Delta\ell_i, \tag{21}$$

where the intercept α_0 is the baseline altruism for mothers unexposed to CHIP ($\Delta\ell_i = 0$). The slope $\alpha_1 = \frac{\alpha_i - \alpha_0}{\Delta\ell_i}$ gives the change in altruism for a unit increase in CHIP exposure. Starting from the baseline altruism α_0, the slope α_1 determines the altruism for mothers with different exposure to CHIP. In practice, I normalize $\alpha_0 = 1$.[28] Similarly, I specify a behavioral equation for present bias

$$\beta_i = \beta_0 + \beta_1 \Delta\ell_i, \tag{22}$$

where β_0 is the baseline present bias for $\Delta\ell_i = 0$, and $\beta_1 = \frac{\beta_i - \beta_0}{\Delta\ell_i}$ is the change in present bias for a unit increase in CHIP exposure. I therefore estimate parameters (α_1, β_0, β_1) to quantify the behavioral effects of CHIP exposure.

Moment Conditions. Based on equation 21 and 22, I quantify the behavioral effects using CHIP exposure as a shifter of mother preferences. Higher altruism from the exposure tends to predict greater investments in the child, whereas a reduction in present bias could further impact the timing of investments in pregnancy. I therefore match investment levels and timing across CHIP exposure to quantify the behavioral effects

1. percent of mothers starting pre-natal visits in the first, second, and the third trimester at each exposure level in $\Delta\ell_i$,

2. number of pre-natal visits at each exposure level in $\Delta\ell_i$,

[27] 91% of single mothers lived in states where the income limit before CHIP was between 110% and 130% FPL. I show details of the sample construction in Appendix E.

[28] This is because mother's utility weight for her own investments is already estimated in the taste types η_i and ζ_i. Different scaling of α_0 does not affect the relative utility weights between the mother and the child.

3. percent of smokers at each exposure level in $\Delta\ell_i$.

To estimate the birth weight production function in equation 16, I construct moment conditions exploiting the exposure levels in $\Delta\ell_i$ as instruments.[29] Specifically, I match the reduced-form relationship between birth weight and $\Delta\ell_i$ in addition to the first-stage relationship between investments and $\Delta\ell_i$. The relative shifts in birth weight and investments across different $\Delta\ell_i$ inform the production of birth weight from investments. I also match the interaction of birth weight and investments in a separate set of moment conditions.

I further include a large number of auxiliary moment conditions to capture additional investment responses and heterogeneity across mothers. Compared to the moment conditions identifying the behavioral effects and the production of birth weight, the auxiliary conditions receive lower weights in the estimation. In total, I employ 272 moment conditions to estimate the model parameters. I detail the full list of moment conditions and the estimation procedure in Appendix F.

Mother Types. I model the distribution of mother types using a multinomial Probit. Given mother characteristics X_i, the multivariate Probit generates the probability distribution of mother i across three potential types in the population. Specifically, the probability of being type $k = 0, 1, 2$ for mother i is as follows

$$P_i^k = P^k\left(X_i\,;\pi^k\right) = \frac{F(\pi^k \cdot X_i)}{\sum_{n=0,1,2} F(\pi^n \cdot X_i)}, \tag{23}$$

where F is the cumulative distribution function of a standard normal. X_i includes mother age, whether the mother had fetal death in previous pregnancies, has any maternal risk factor on the birth certificate, and the smoking rate in the mother's county of residence. I summarize mother characteristics in Appendix E. I illustrate the identification of mother types from mother characteristics with estimation results. As is standard in multinomial Probit, I normalize the coefficients for one of the types (type 1) to zero: $\pi^1 = 0$.

7.3 Results

Behavioral Effects. The top panel of Table 7 estimates the behavioral effects of CHIP exposure. The exposure had little effect on altruism. The estimated slope parameter α_1 is small and indistinguishable from zero. Therefore, the investments are not driven

[29]The production function in equation 16 requires three instruments for three endogenous investments: pre-natal visits V_i and smoking indicators $smoke_i$ and $heavy_i$. I use indicators for the five exposure levels in $\Delta\ell_i$ as instruments in the moment conditions.

by increased altruism for the child. By contrast, CHIP exposure significantly reduced the present bias of mothers. Gaining a 100% FPL exposure increases mother's short-term patience by $\beta_1 = 0.13$. Compared to the baseline patience ($\beta_0 = 0.75$), the roll-out – which expanded income limits by 80% FPL – increased short-term patience to 0.85 ($= 0.75 + 80\% \cdot 0.13$) for mothers fully exposed to CHIP in pregnancy, lowering their present bias by 14.3% ($= 80\% \cdot 0.13/0.75$).

I illustrate the identification of the behavioral effects comparing simulated investments with empirical counterparts in the data. In Figure 3, the share of mothers staring care in the first trimester increased with CHIP exposure (panel a), and the share starting care in the third trimester decreased with exposure (panel b). Simulated investments match these patterns in the data. Despite earlier onset of visits, the number of visits increased only slightly with CHIP exposure (panel c), and smoking decreased with exposure in panel (d). Simulated investments match these patterns in the data. Thus, the early onset of visits and the reduction in smoking are primarily explained by the effect of exposure on present bias.

Mother Types. The middle section of Table 7 summarizes mother's types and the birth weight endowment. Most mothers (53.16%) are type 2 mothers who derive positive utility from pre-natal visits and have a distaste for smoking. Another large share of mothers (37.31%), type 1 mothers, have a significant distaste for smoking. These mothers are the "never-smokers" with a near-zero probability of smoking in pregnancy. Their taste for visits is not statistically different from zero. The remaining share of mothers (9.53%) are type 0 mothers who strongly prefer smoking, almost always smoke in pregnancy, and derive zero utility from visits. Type 0 mothers also have larger birth weight endowment for their children.

To illustrate the identification of mother types, I show in Appendix Figure J3 that simulated investments recover differences by mother characteristics exploited in the multinomial Probit. Specifically, the simulated number of visits matches the difference by mother risk factors in panel (a), and simulated smoking intensity matches the empirical distribution across county smoking rates in panel (b). Birth weight is lower for mothers with fetal death in previous pregnancies, and simulated birth weight matches this difference in the data (Appendix Figure J4).

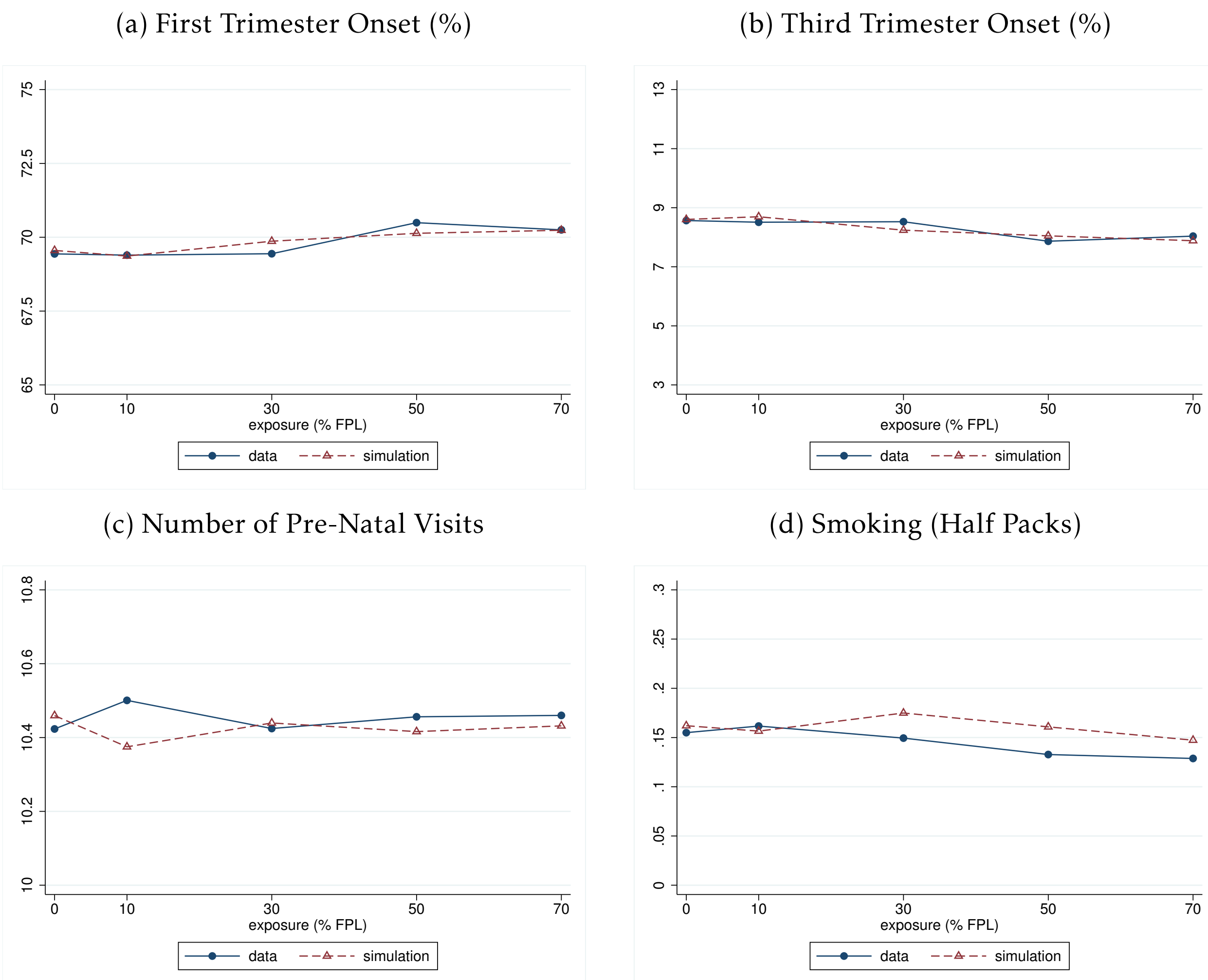
Birth Weight Production. The lower panel of Table 7 estimates the birth weight production function in equation 16. Pre-natal visits significantly increase birth weight, but the marginal effect diminishes with greater numbers of visits. By contrast, smoking has significant detrimental impacts on birth weight. The relative magnitude between the

Table 7: Estimated model parameters

Behavioral Effects			
α_0:	1	α_1:	0.001
	–		(0.006)
β_0:	0.75	β_1:	0.13
	(0.071)		(0.040)
Mother Types	Type 0	Type 1	Type 2
Taste for visits η_i	-0.017	-0.38	3.76
	(0.067)	(0.27)	(0.32)
Taste for cigar. ζ_i	38.77	-947.77	-17.69
	(8.30)	(<0.001)	(1.85)
Endowment ϕ_i	3.56	2.06	2.00
	(0.40)	(0.16)	(0.15)
Share (%)	9.53	37.31	53.16
Birth Weight Production			
V_i	1.54	$V_i \cdot smoke$	0.61
	(0.010)		(0.022)
V_i^2	-0.093	$V_i \cdot heavy$	4.72
	(<0.001)		(3.20)
$smoke$ ($\bar{s}_i \geq 5$)	-10.54	$V_i^2 \cdot smoke$	0.025
	(0.022)		(0.001)
$heavy$ ($\bar{s}_i \geq 15$)	-4.95	$V_i^2 \cdot heavy$	-0.77
	(7.19)		(0.32)
Birth Weight Valuation			
θ:	0.53		
	(0.011)		

Notes: Table shows estimates of the model parameters. The top panel shows estimates of the behavioral effects in equation 21 and 22. The middle panel shows estimates of mother types – in terms of visits, smoking, and the birth weight endowment – as well as the share of each type in the population. The last panel shows estimates of the birth weight production function (equation 16) and mother's marginal utility from birth weight governed by θ. Standard errors of the estimated parameters in the parenthesis.

Figure 3: Investment responses to CHIP exposure, model fit



Notes: Figure compares simulated investments with empirical counterparts for different exposure levels in $\Delta\ell_i$. I focus on the timing of care onset in panel (a) and panel (b), the number of pre-natal visits in panel (c), and smoking intensity in half packs (10 cigarettes) daily in panel (d). I simulate investments for ten million pregnant mothers and plot simulated investments by exposure levels in dotted lines. I plot the empirical counterparts in solid lines.

two suggests that the negative impacts of smoking are comparable to missing 7 pre-natal visits in pregnancy. The interaction terms between visits and smoking further imply that the optimal number of visits is around 9 for non-smoking mothers, and around 15 for smokers.

The endowment ϕ_i impacts birth weight by increasing the return to investments. High-endowment mothers with higher returns to their investments tend to invest more in response to the exposure. To illustrate this point, I simulate investments and birth weight across mother types in Appendix Figure J5. Consistent with higher return to investments, type 0 mothers increased the number of visits by a small amount despite having near-zero tastes for visits (panel b), and significantly reduced smoking (panel c) despite having the strongest taste for smoking, By contrast, investment responses from type 1 and type 2 mothers are very modest. As a result, the overall increase in birth weight is highly concentrated among children of type 0 mothers (panel d).

7.4 Welfare

I next use the model estimates to quantify the welfare impacts of the exposure. The exposure improves welfare because it reduces mother's behavioral biases and results in better outcomes for the child. I reveal mother's valuation of these effects from her investments. I then compare her valuation with the social cost of exposure to inform program effectiveness using the marginal value of public funds (Finkelstein and Hendren, 2020).

Utility. I use mother's long-run utility to evaluate the welfare impacts of investments. Under the welfare metric, optimal investments maximizing the long-run utility generate welfare $\mathcal{U}^*$.[30] By deviating investments away from the long-run optimal, present bias results in a welfare loss $\frac{\mathcal{U}^*-\mathcal{U}^i}{\mathcal{U}^*}$ relative to the long-run utility $\mathcal{U}^*$, where $\mathcal{U}^i$ is welfare in the roll-out ($i = 1$) or in the absence of CHIP ($i = 0$). Compared to the absence of CHIP, exposure to the roll-out reduced present bias and increased welfare by $\frac{\mathcal{U}^1-\mathcal{U}^0}{\mathcal{U}^*}$. I summarize this welfare effect in Table 8.

CHIP exposure increased mother's long-run utility by 0.063%. Across mother types,

[30]Formally, given investment profile $I = (v_t, s_t)_{t=1,2,3}$, the long-run utility is given by

$$\mathcal{U}(I) = \mathbb{E}\left[\sum_{t=1}^{3} \vartheta(v_t; \varepsilon_t, \mathcal{I}_t) + \sum_{t=1}^{3} \psi(s_t; \varepsilon_t, \mathcal{I}_t) + L\left(b^i; \varepsilon_3, \mathcal{I}_3\right)\right], \tag{24}$$

which sums over utility in each trimester applying the long-run discount factor $\delta = 1$. Optimal investments I^* maximizing equation 24 give the long-run utility $\mathcal{U}^* = \mathcal{U}(I^*)$.

this effect is mainly concentrated among type 0 mothers, where long-run utility increased by 0.20%. To understand how investments contribute to the welfare effect, I calculate mother's valuation of investments M^i and of the child's birth weight C^i.[31] Investments have larger costs on utility for type 0 and type 1 mothers, but the benefits on birth weight more than offset the costs for all mother types. On net, the exposure increased utility the most for type 0 mothers, where investments have the largest benefits on birth weight.

Table 8: Welfare effects of CHIP exposure

	All	Type 0	Type 1	Type 2
$\frac{\mathcal{U}^1-\mathcal{U}^0}{\mathcal{U}^*}$ (%)	0.063	0.20	0.066	0.037
	(<0.001)	(0.001)	(<0.001)	(<0.001)
$\frac{C^1-C^0}{\mathcal{U}^*}$ (%)	0.12	0.35	0.21	0.012
	(<0.001)	(0.001)	(<0.001)	(<0.001)
$\frac{M^1-M^0}{\mathcal{U}^*}$ (%)	-0.057	-0.15	-0.15	0.025
	(<0.001)	(0.001)	(<0.001)	(<0.001)
Share (%)	100	9.53	37.31	53.16

Notes: Table summarizes the welfare effect of CHIP exposure relative to the long-run utility $\mathcal{U}^*$. I calculate mother's valuation of the child's birth weight C^i and of investments M^i, where superscript i indicates utility in the roll-out ($i = 1$) and in the absence of CHIP ($i = 0$). I then summarize welfare separately for birth weight and investments using the equation $\frac{\mathcal{U}^1-\mathcal{U}^0}{\mathcal{U}^*} = \frac{C^1-C^0}{\mathcal{U}^*} + \frac{M^1-M^0}{\mathcal{U}^*}$. Standard errors of the welfare effects from ten million simulated individuals in the parenthesis.

MVPF. Since I measure utility in dollars, the utility difference $\mathcal{U}_i^1 - \mathcal{U}_i^0$ is also mother's willingness to pay (WTP) for the exposure. Specifically, mother i is willing to pay up to the utility difference for the exposure compared to receiving zero exposure to CHIP. Formally, I calculate the WTP as

$$WTP_i = \frac{\mathcal{U}_i^1 - \mathcal{U}_i^0}{\Delta \ell_i} = \frac{C_i^1 - C_i^0}{\Delta \ell_i} + \frac{M_i^1 - M_i^0}{\Delta \ell_i}, \tag{25}$$

where I normalize the utility difference $\mathcal{U}_i^1 - \mathcal{U}_i^0$ by the exposure $\Delta \ell_i$ to calculate the WTP for a 100% FPL exposure to CHIP. I similarly calculate the WTP for birth weight $\frac{C_i^1 - C_i^0}{\Delta \ell_i}$ and for investments $\frac{M_i^1 - M_i^0}{\Delta \ell_i}$.

I compare mother's WTP with the social cost of the exposure to construct the marginal

[31] Specifically, mother utility $\mathcal{U}^i = C^i + M^i$ is the sum of utility from birth weight and investments. I therefore decompose the welfare effect $\frac{\mathcal{U}^1-\mathcal{U}^0}{\mathcal{U}^*}$ by the effect on birth weight $\frac{C^1-C^0}{C^*}$ and on investments $\frac{M^1-M^0}{M^*}$ in Table 8.

value of public funds (MVPF) for the exposure (Finkelstein and Hendren 2020; Hendren and Sprung-Keyser 2020). I measure the social cost using the spending on program outreach during the roll-out. Since the goal of the outreach was to introduce the program to the public (Williams and Rosenbach, 2007), I assume an even distribution of outreach spending across households. This gives a cost of exposure $\Delta G = \$0.42$ per household.[32]

Relative to costs, the MVPF for CHIP exposure is as follows

$$MVPF = \varphi \frac{WTP}{\Delta G} = \varphi \frac{WTP^C}{\Delta G} + \varphi \frac{WTP^M}{\Delta G}, \tag{26}$$

where $WTP = \frac{1}{N}\sum_i WTP_i \Delta inc_{s(i)}$. Because CHIP exposure is larger in states expanding insurance to higher income limits, I scale WTP_i by the size of expansion $\Delta inc_{s(i)} = inc_{s(i)}^{post} - inc_{s(i)}^{pre}$ to calculate the average WTP in the roll-out. To the extent that society may value the transfer to pregnant mothers more than the dollar costs, I allow for higher welfare weight $\varphi > 1$ for pregnant mothers.

I summarize the MVPF in Table 9. Mothers are willing to pay \$0.49 for the benefit of the exposure on birth weight, which more than offsets the program spending on outreach (\$0.41). Net of investment costs, mothers are willing to pay \$0.31 for the exposure, and hence the exposure is valued at $\frac{\$0.31}{\$0.41} = 76\%$ of the spending. To understand magnitudes, I ask how mothers value the exposure relative to expansions of own insurance. For instance, recent Medicaid expansions in Oregon and Massachusetts suggest that low-income adults value their own insurance between 55% and 116% of the program spending (Finkelstein *et al.* 2019a; Finkelstein *et al.* 2019b). By comparison, the MVPF of CHIP exposure falls in the middle range of these estimates.[33] Therefore, given the same amount of program spending, mothers value the exposure to children's insurance as much as expansions of own insurance.

For the insurance program, this result suggests that the information of insurance can effectively "nudge" investments by reducing the behavioral biases of parents. Parents value the nudge because they value the benefits of investments on children. Thus, in addition to improving child outcomes, outreach efforts encouraging parental investments also improve parental utility as effectively as expansions of parents' own insurance.

7.5 Fiscal Externality

Because MVPF is based on mother's WTP for the exposure, social benefits not internalized by her investments are not captured in the welfare metric. One such benefit is the fiscal

[32] I detail the calculation of outreach costs and examine robustness in Appendix G.

[33] See Appendix Table D.I of Hendren and Sprung-Keyser (2020) for a summary of these estimates.

Table 9: MVPF of CHIP exposure

	WTP	WTP^C	WTP^M	$MVPF$
$\varphi = 1$	0.31	0.49	-0.18	0.76
	(0.001)	(0.002)	(0.001)	(0.002)
$\varphi = 2$	0.62	0.98	-0.36	1.51
	(0.002)	(0.003)	(0.003)	(0.005)
$\varphi = 3$	0.93	1.47	-0.54	2.27
	(0.003)	(0.005)	(0.004)	(0.007)

Notes: Table summarizes the marginal value of public funds (MVPF) for CHIP exposure. To calculate the MVPF, I normalize mother's WTP by the cost of the exposure (\$0.41) measured by the spending on program outreach. I calculate separate WTP for birth weight WTP^C and for investments WTP^M, and summarize the MVPF varying mother's welfare weight φ in the table. Standard errors from ten million simulated individuals in the parenthesis.

impact on program costs, which may operate through the long-run effects of investments on education, earnings, and tax payments. In the roll-out of CHIP, since mothers investing more in utero did not expect higher education for the child, the increase in college enrollment and the potential impacts on program costs are not internalized in mother's WTP for the exposure. Here, I quantify the fiscal externality predicting future tax payments from college enrollment.

Specifically, the roll-out of CHIP increased college enrollment by $80\% \cdot 1.71 = 1.37$ percentage points for children of single mothers (Table 6). Assuming that college students induced by the exposure attend college for two years, and assuming an 11.3% return on earnings for each year of college enrollment (Zimmerman, 2014), I calculate that exposure to the roll-out can increase earnings by $2 \cdot 11.3\% \cdot 0.0137 = 0.31\%$ for children of single mothers. Discounted to year 1997, the life-cycle earning benefit amounts to \$1,101.11 per child of single mother under a 2% annual discount rate.

Assuming that the earning benefit is subject to a 18.9% marginal tax rate (Hendren and Sprung-Keyser, 2020), exposure to the roll-out increases tax payments by $18.9\% \cdot \$1,101.11 = \$208.11$ per child of single mother, or by $\frac{\$208.11}{\$2,483.10} = 8.4\%$ of the initial program cost in childhood. Hence, parental responses to the roll-out could lower the net cost of the program by 8.4% in the long run. I examine robustness in Appendix H. Fiscal externality increases to 15.4% of the cost when students enroll in college for 4 years, and drops to 6.0% assuming a 2-year enrollment and a 3% annual discount rate. Compared to the fiscal externality of *program* investments in children, parental investments in the roll-out could further lower the program cost by over 6% over the long term.[34]

8 Discussion and Conclusion

Social policies for children increasingly harness parental investments to augment the policy impacts on children. In K-12 and pre-school, for instance, parent-school partnerships and family-based interventions lower the informational and behavioral frictions facing parents, thus improving their investments and their children's educational outcomes.[35] To effectively engage parents, policymakers need to understand how parents invest in the child and how responses to policies might impact investments and child outcomes. In the context of social insurance, I bring evidence to bear on these questions exploiting the roll-out of the Children's Health Insurance Program (CHIP) in the US.

I find that pregnant mothers exposed to the roll-out of CHIP increased private investments in utero. Specifically, the exposure increased mother's early onset of pre-natal visits and reduced smoking in pregnancy. These investments are consistent with reduced present bias of mothers, and increased birth weight for children with in-utero exposure to CHIP. Due to the benefits to children, mothers value the exposure as much as expansions of her own insurance. This result suggests that mothers highly value child outcomes, but may suffer from behavioral biases that limit their investments in the child.

The behavioral mechanism has several implications for policies. First, parents may exhibit present bias in their investments due to unawareness of future investment opportunities for the child. Informing parents of program eligibility through outreach and reminders can foster forward thinking and increase investments, with potentially larger effects on more present-biased parents (Mayer *et al.*, 2019). Second, effective engagement strategies can feature low-cost, light-touch interventions that nudge investments without providing significant financial incentives to individuals (Goldin *et al.*, 2021). In the roll-out of CHIP, the informational nudge increased parental investments, and improved parental utility as effectively as subsidized expansions of parents' own insurance.

Finally, combating the behavioral biases also generates social benefits that lower the fiscal cost of insurance. This is because fetal and early-life environments have persistent

[34]Focusing on children born in the early 1980s, Brown *et al.* (2020) estimates that each childhood year of insurance eligibility increased tax payments in age 19-28 by $178 in 2000 dollars. Exposure to the roll-out of CHIP predicts an increase in tax payments between $12 and $32 by age 28, further reducing the net cost of the program by 6.7% to 18.0% in the long run.

[35]See Bergman (2019) for a survey of parental engagements in K-12, and see Brooks-Gunn *et al.* (2000) for a survey in pre-school.

impacts on later-life outcomes (Almond and Currie 2011; Almond *et al.* 2018), resulting in large social externalities from parental investments. In the roll-out of CHIP, for instance, parental investments could lower the social cost of insurance by 8.4% through the long-run impacts on education, earnings, and tax payments. These private and social benefits of investments motivate outreach efforts engaging parents in children's insurance programs.

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Appendix

A Insurance Eligibility

I simulate children's insurance eligibility using the sample of all women between age 21 and 40 in the 2000 decennial census. In state s and time t, child i in age band b is eligible for Medicaid/CHIP if the family income $finc_i$ is below the income limit inc^b_{st}. I parameterize the income limit in terms of the share of children eligible for insurance as follows

$$eligCHIP^b_{st} = \frac{1}{N}\sum_i 1\{finc_i \leq inc^b_{st}\}, \tag{A1}$$

where $N = 1,948,731$ is the number of women in age 21-40 in the 2000 census. That is, I assume that each woman in the sample had a child in age band b, and calculate the share of women whose children would be eligible for Medicaid/CHIP given the income limit inc^b_{st}. Thus, $eligCHIP^b_{st}$ captures insurance eligibility in a fixed population of mothers and their incomes. Differences in $eligCHIP^b_{st}$ are due to exogenous variation in program rules that shifted income limits across state, time, and age.

I calculate $eligCHIP^b_{st}$ for three age bands: infants (age 0), small children (age 1-5), and older children (6+). Changes in the income limits across states by age bands are listed in Table 1. I average out age groups to calculate simulated eligibility $eligCHIP_{st}$ in childhood:

$$eligCHIP_{st} = \frac{1}{19} eligCHIP^0_{st} + \frac{5}{19} eligCHIP^{1-5}_{st} + \frac{13}{19} eligCHIP^{6+}_{st}, \tag{A2}$$

where instead of using b in the superscript, I make explicit the ages in the age band.

The income limits imply that children from low-income families are more likely to qualify for Medicaid/CHIP. To explicitly account for the eligibility differences by incomes, I calculate separate eligibility for mother demographic groups that differ by marital status, race, and education. Specifically, eligibility for children in age b and group g is given by

$$eligCHIP^b_{gst} = \frac{1}{N_g}\sum_{i\in\mathcal{G}} 1\{finc_i \leq inc^b_{st}\}, \tag{A3}$$

where $\mathcal{G}$ is the collection of children in demographic group g. $eligCHIP^b_{gst}$ is the share of children in age b and group g who would be eligible for Medicaid/CHIP in a fixed population of mothers and incomes. Within group g, differences in eligibility $eligCHIP^b_{gst}$ are due to exogenous variation in income limits across state, time, and age.

I then average out ages to calculate simulated eligibility $eligCHIP_{gst}$ in childhood

$$eligCHIP_{gst} = \frac{1}{19} eligCHIP^0_{gst} + \frac{5}{19} eligCHIP^{1-5}_{gst} + \frac{13}{19} eligCHIP^{6+}_{gst}. \tag{A4}$$

Note that $eligCHIP_{gst}$ is specific to income limits known in time t. To calculate in-utero exposure, I use the average eligibility in a 9-month pregnancy

$$eligCHIP_{g(i)st} = \frac{1}{9}\sum_{\tau=0}^{8} eligCHIP_{gs\tau}, \tag{A5}$$

where $eligCHIP_{gs\tau}$ is eligibility in month τ of the pregnancy, and $eligCHIP_{g(i)st}$ gives the in-utero exposure for mothers starting pregnancy in time t. I plot $eligCHIP_{g(i)st}$ across states and cohorts during the roll-out in Figure 1, and use it as the simulated exposure to children's insurance in Section 5.4. Eligibility increased substantially from 0.15 to 0.30 between 1997 and 2000 (or from 2.85 eligible years to 5.70), and increased much more for children of single mothers from 0.33 to 0.50 over the same period.

In most of the empirical analyses, I simply use the income limit of Medicaid/CHIP as the exposure measure (without calculating the implied share of children eligible), and use the average income limit in a 9-month pregnancy as mother's in-utero exposure to children's insurance. Specifically, in-utero exposure is given by

$$eliginc_{st} = \frac{1}{9}\sum_{\tau=0}^{8} inc_{s\tau}, \tag{A6}$$

where $inc_{s\tau} = \frac{1}{19}inc^{0}_{s\tau} + \frac{5}{19}inc^{1-5}_{s\tau} + \frac{13}{19}inc^{6+}_{s\tau}$ is the income limit known in state s and month τ of pregnancy. $eliginc_{st}$ gives the in-utero exposure for mothers starting pregnancy in time t in state s.

B Detailed Proofs

I solve parents' investment problem starting from the childhood stage in $t = 1$. Given child health $h = 0, 1$, parents choose non-health investment v_1^h to maximize the utility

$$U_1^h(v_1^h) = u\left(Y_1 - v_1^h - OOPC \cdot 1\{h = 0\}\right) + \Gamma(s(v_1^h)) + \delta V^h(s(v_1^h)), \tag{B1}$$

where $u(Y_1 - v_1^h - OOPC \cdot 1\{h = 0\})$ is the utility from consumption after investing v_1^h. A less healthy child ($h = 0$) incurs medical expenses $OOPC$. Non-health investments improve education $s(v_1^h)$ and adult outcomes summarized in $V^h(s(v_1^h))$. Optimal investments v_1^{h*} satisfy the first order condition

$$u'(c_1^{h*}) = \Gamma' s'(v_1^{h*}) + \delta V' s'(v_1^{h*}), \tag{B2}$$

where $c_1^{h*} = Y_1 - v_1^{h*} - OOPC \cdot 1\{h = 0\}$ is the optimal consumption given child health h.

Equation B2 states that optimal investment v_1^{h*} balances the marginal cost of investment $u'(c_1^{h*})$ with the marginal benefit on the child's education and adult outcomes $\Gamma' s'(v_1^{h*}) + \delta V' s'(v_1^{h*})$. When CHIP reduces $OOPC$, a decrease in v_1^{h*} would lower the marginal cost on the left hand side but increase the marginal benefit on the right hand side assuming concavity for Γ, s, and V. Therefore, v_1^{h*} must increase when CHIP reduces $OOPC$. Since $OOPC = 0$ for the healthy child, non-health investment is larger in the healthy child. This implies that the marginal benefit of investment is larger for the less healthy child, and from equation B2, so is the marginal cost of investment. Therefore, total investment is larger in the less healthy child, but non-health investment is smaller due to the medical expenses $OOPC$.

Let $\tilde{U}_1^h = U_1^h(v_1^{h*})$ denote the maximized utility in childhood given optimal investments v_1^{h*}. In the fetal stage ($t = 0$), parents choose in-utero investment v_0 to maximize utility

$$U_0(v_0) = u(c_0) + w(v_0) + \delta \rho(v_0) \tilde{U}_1^1 + \delta (1 - \rho(v_0)) \tilde{U}_1^0, \tag{B3}$$

where consumption $c_0 = Y_0 - v_0$, and $w(v_0)$ is parents' utility from birth weight as a function of in-utero investment v_0. Larger v_0 also increases the probability of giving birth to a healthy child, and the probability $\rho(v_0)$ is concave in v_0. Optimal in-utero investment v_0^* satisfies

$$\delta \rho'(v_0^*) \Delta \tilde{U}_1 + w'(v_0^*) = u'(c_0^*), \tag{B4}$$

where $\Delta \tilde{U}_1 = u(c_1^*) - u(c_0^*) + \Gamma(s(v_1^{1*})) - \Gamma(s(v_1^{0*})) + \delta V^1(s(v_1^{1*})) - \delta V^0(s(v_1^{0*})) = \Delta u + \Delta\Gamma + \delta\Delta V$ is parents' utility gap in own consumption (Δu), child's education ($\Delta\Gamma$) and adult outcomes (ΔV). Because reducing $OOPC$ increases non-health investment in the less healthy child, CHIP narrows the gap in child outcomes $\Delta\Gamma + \Delta V$ by child health. From equation B2, the investment lowers the marginal benefit on the right hand side, implying higher consumption levels for parents of the less healthy child. Therefore, consumption gap Δu also decreases after CHIP. As a result, CHIP reduces the overall utility gap $\Delta \tilde{U}_1 = \Delta u + \Delta\Gamma + \delta\Delta V$, and hence reduces marginal benefit $\delta \rho'(v_0^*) \Delta \tilde{U}_1$ in equation B4. In response, v_0 decreases after CHIP.

Altruism. I model altruism as the weight on child outcomes in parents' utility. Suppose that exposure to the roll-out increases the utility weight on child outcomes to $\alpha > 1$. Optimal investments in $t = 1$ now solve

$$u'(c_1^{h*})/\alpha = \Gamma' s'(v_1^{h*}) + \delta V' s'(v_1^{h*}), \tag{B5}$$

and in-utero investment v_0 solves

$$\delta \rho'(v_0^*) \Delta \tilde{U}_1(\alpha) + \alpha w'(v_0^*) = u'(c_0^*), \tag{B6}$$

where the utility gap $\Delta \tilde{U}_1(\alpha) = \Delta u + \alpha(\Delta\Gamma + \delta\Delta V)$ places weight α on the gap in child outcomes.

When CHIP increases altruism α in addition to lowering $OOPC$, non-health investments increase for both health types in equation B5. The additional investments lower consumption c_1^{1*} for parents of the healthy child. For parents of a less healthy child, because $OOPC$ also decreases after CHIP, the change in consumption is ambiguous. In the case that parental consumption is a normal good, decreasing $OOPC$ increases consumption c_1^{0*}. This would imply that the consumption gap Δu narrows after CHIP. However, $\Delta\Gamma + \delta\Delta V$ depends on the size of investment responses and the marginal effects of investments $(\Gamma' s' + \delta V' s')$ by child health. These quantities are indeterminate from equation B5. In general, altruism could increase parents' perception of investment benefits by increasing their valuation of child outcomes in the utility gap $\Delta \tilde{U}_1(\alpha) = \Delta u + \alpha(\Delta\Gamma + \delta\Delta V)$,[36] potentially increasing in-utero investments based on equation B6.

Present Bias. I model present bias using the $\beta - \delta$ representation in Laibson (1997). Present-biased parents discount future utility to the current period by an additional factor $\beta < 1$. When investments have delayed payoffs, present bias generates over-sensitivity to immediate costs and predicts under-investments in the short run. Specifically, investments of present-biased parents satisfy the following condition in childhood

$$u'(c_1^{h*})/\alpha = \Gamma' s'(v_1^{h*}) + \beta \delta V' s'(v_1^{h*}), \tag{B7}$$

and the following condition in utero

$$\beta \delta \rho'(v_0^*) \Delta \tilde{U}_1(\alpha, \beta) + \alpha w'(v_0^*) = u'(c_0^*), \tag{B8}$$

where utility gap $\Delta \tilde{U}_1(\alpha, \beta) = \Delta u + \alpha(\Delta\Gamma + \delta\Delta V)$ depends on investments v_1^{h*} under present bias β and altruism α.

When CHIP increases α and β in addition to lowering $OOPC$, non-health investments increase even more for both health types. However, the effect on consumption is am-

[36] For illustration, consider the special case where $u(c) = \log(c)$, and $\Gamma(s(v)) + \delta V(s(v)) = (1 + \delta k)\log(v)$, where k captures the return of education on adult outcomes. It is easy to solve that $\Delta u + \alpha(\Delta\Gamma + \delta\Delta V) = (1 + \alpha + \alpha\delta k)\log\left(\frac{Y_1}{Y_1 - OOPC}\right)$, which may increase with $\alpha > 1$ from the exposure to CHIP.

biguous for parents of a less healthy child, and the gap in child outcomes may change depending on the investment responses and the marginal effects of investments by child health. In general, the behavioral effects allow parents' perception of investment benefit $\beta\,\delta\,\rho'(v_0^*)\,\Delta\tilde{U}_1(\alpha,\beta)$ to increase with β and α from the exposure,[37] potentially increasing in-utero investments based on equation B8.

[37] Continuing the example in footnote 36, allowing for present bias, perceived investment benefit $\beta\,\delta\,\rho'(v_0^*)\,\Delta\tilde{U}_1(\alpha,\beta) = \rho'(v_0^*)\,\beta\delta(1+\alpha+\alpha\,\beta\,\delta\,k)\log\left(\frac{Y_1}{Y_1 - OOPC}\right)$ could increase due to larger β and α from the exposure.

C Education Outcomes

Sample Construction. To exploit the roll-out of CHIP, I restrict the sample to children conceived 7 quarters before till 2 quarters after CHIP in the American Community Survey (ACS). I further restrict the sample to children who are age-ready for high school (Grade 9) or above to focus on education outcomes in high school and in college. Because the oldest cohort – those conceived 7 quarters before CHIP – are born in the second quarter of 1996, the earliest time for the children to be age-ready for Grade 9 is 2010-2011. I therefore use the 2010-2018 waves of ACS to examine the education outcomes. During this period, the average child in the sample – born in the fourth quarter of 1998 – expects to enter Grade 1 in 2004-2005, and expects to complete high school (Grade 12) in 2016-2017. Appendix Table C1 summarizes the estimation sample.

Table C1: Sample summary, education outcomes ($N = 385,063$)

	mean	s.e.		mean	s.e.
grade-for-age (%)	88.21	0.052	child age	16.89	0.003
graduate high school (%)	28.79	0.073	birth year	1998.36	0.002
enroll in college (%)	15.78	0.059	survey year (t)	2015.25	0.003
mother never married (%)	8.64	0.045	$eliginc^{utero}$ (100% FPL)	1.58	0.001
mother unmarried in t (%)	25.46	0.070	$eliginc^{child}$ (100% FPL)	2.33	0.001

Notes: Table summarizes the estimation sample for education outcomes. I construct the sample from children conceived 7 quarters before till 2 quarters after CHIP, who are expected to attend high school or above in 2010-2018 waves of the American Community Survey (ACS). I determine the expected grade given child age based on the school entry age, and identify the child's mother using the family interrelationships variables developed by Ruggles *et al.* (2020). Based on mother's marital status, I define single motherhood requiring that the mother has never married, or is unmarried in survey year t.

Variable Definition. I determine the child's grade-for-age status – whether the child attends the grade level expected of her age – based on the school entry age in the state. Specifically, children turning five before the cut-off month in the year can attend kindergarten in the same year, and those turning five after the cut-off attend in the next year. Since ACS provides the quarter of birth rather than the month, I assume that children born in the same quarter as the cut-off are born after the cut-off month, and hence adopt the more generous criterion in determining grade-for-age.[38] For children expected to have finished Grade 12, grade-for-age indicates whether the child has obtained a regular high school diploma or is enrolled in college. I also examine high school graduation and college enrollment as distinct outcomes after Grade 12.

I identify mothers of school-age children in the ACS using the family interrelationships variables developed by Ruggles *et al.* (2020). Based on mother's marital status, I define single motherhood requiring that the mother has never married, or is unmarried in survey year t. 8.64% of children live in households where the mother has never married, and 25.46% live in households where the mother is unmarried in year t.

[38] Similar definition is adopted in Kearney and Levine (2019). Following Deming and Dynarski (2008), I code school entry cut-offs for CHIP cohorts based on Appendix Table 1 of Bedard and Dhuey (2007).

D Calibration of Out-Of-Pocket Costs

I calibrate the out-of-pocket cost of pre-natal visits from the Medical Expenditure Panel Survey (MEPS) "Event Files." The Event Files contain information on the visits to physicians, hospitals and other health facilities by household members in a calendar year. For each visit, the Event Files record the reason for seeking medical care, the insurance coverage of the medical costs, and payments made by the individual and by the provider. From these records, I identify pregnant mothers as hospital patients whose reason of the visit was "to give birth to a child."

For pregnant mothers, I identify pre-natal visits as those related to a pregnancy condition taken in a 9-month period prior to the birth event. I look up pregnancy-related conditions from the Clinical Classification Codes provided by MEPS. The visit should take place in an office setting where the mother consulted directly with a medical doctor. Appendix Table D1 summarizes the out-of-pocket cost per visit for low-educated single mothers who had a birth event in 1997-2001.

Table D1: Out-of-pocket costs (OOPC) per pre-natal visit, MEPS

	(1) $OOPC$	(2) $OOPC > 0$	(3) $OOPC(> 0)$
age	0.80	0.10***	-15.32
	(1.05)	(0.024)	(9.79)
age^2	-0.011	-0.002***	0.25
	(0.018)	(< 0.001)	(0.16)
constant	-9.69	-1.41***	249.04
	(15.02)	(0.33)	(144.72)
y mean	3.42	0.14	24.26
N	1,750	1,750	251

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table predicts the out-of-pocket cost (OOPC) per pre-natal visit using a quadratic function of age. Column 1 predicts the average cost per visit. Column 2 predicts the probability of incurring a positive out-of-pocket cost. Column 3 predicts the average cost conditional on incurring a positive cost. Sample includes pre-natal visits by non-college educated single mothers who had a birth event in a hospital between 1997 and 2001 in MEPS. All dollars adjusted to the 2000 level by the CPI-Urban price index.

86% of the pre-natal visits had zero out-of-pocket costs (y mean in column 2). The probability of zero costs varied significantly with age. To approximate the empirical distribution, I model the out-of-pocket cost as following a two-node distribution over zero cost and a positive amount depending on the mother's age. The mass at zero is determined by the regression coefficients in column 2. The level of the positive cost is determined by the regression coefficients in column 3. Although I predict out-of-pocket costs using a quadratic function of mother age, I discretize mother age into four 5-year age groups, and calibrate the cost per visit as follows

$$c_{it}(a_i, \xi_{it}) = \sum_{g=0}^{3} 1\{\xi_{it} \geq F^{-1}(1-z_g)\} \cdot 1\{20 + 5g \leq a_i \leq 25 + 5g\} \cdot \\ \left[249.04 - 15.32 \cdot (22.5 + 5g) + 0.25 \cdot (22.5 + 5g)^2\right], \tag{D1}$$

where $g = 0, 1, 2, 3$ indexes age groups 21-25, ..., 36-40. z_g is probability of positive out-of-pocket costs for group g. In the model, positive out-of-pocket costs occur when the health shock ξ_{it} is greater than $F^{-1}(1-z_g)$, where F is the cumulative distribution function of a standard normal.[39] Larger health shocks increase the probability of paying positive out-of-pocket costs. I use the median age in each age group and the regression coefficients in column 3 of Appendix Table D1 to calibrate the positive cost level.

[39] Empirically, $z_0 = 0.105$, $z_1 = 0.128$, $z_2 = 0.295$, $z_3 = 0.369$.

E Structural Sample

E.1 Sample Definition

The structural model examines the investment responses of non-college-educated single mothers whose pregnancy onset was within one year prior to the CHIP onset. Compared to the analysis in Section 5, the structural model examines a more homogeneous group of single mothers (those without college education) and uses a shorter event window around CHIP. In particular, mothers starting pregnancy more than one year before CHIP and those starting pregnancy after CHIP are not included in the structural analysis.

I further restrict the sample to states with homogeneous income limits before CHIP, and exclude states with very small or very large expansions of income limits after CHIP. Specifically, states increasing income limits by less than 20% FPL (MN) and by over 90% FPL (CT, MO, NH, PA, RI) are excluded.[40] These states account for 10% of the births by low-educated single mothers. Moreover, 5 states (MN, MI, NM, VT, WA) expanded insurance above 130% FPL prior to CHIP, and the remaining states (91% of the births by low-educated single mothers) have pre-CHIP income limits between 110% -130% FPL. I focus on the latter set of states and estimate the behavioral effects starting from a homogeneous exposure level (110%-130% FPL) prior to CHIP. In equation 21 and 22, the intercept (α_0, β_0) corresponds to the altruism and present bias at this exposure level.

The final sample further excludes a small fraction of mothers giving birth before the 7th month of pregnancy, and those with missing birth weight or the onset time of pre-natal visits. I exclude these mothers because the structural model assumes that the child is born in the third trimester, relies on the timing of visits to estimate time preferences, and examines birth weight as the main outcome of pregnancy. The final sample includes 324,400 low-educated single mothers. I summarize the sample in Table E1.

Table E1: Summary statistics, structural estimation sample

	Endogenous Variables			Mother Characteristics	
	mean	s.e.		mean	s.e.
log birth weight	8.07	0.20	$\Delta\ell_i$ (% FPL)	24.79	24.07
care onset in			age group	0.69	0.90
first trimester (%)	69.68	45.96	prior fetal death (%)	28.01	44.90
second trimester (%)	21.94	41.39	any risk factor (%)	28.76	45.26
third trimester (%)	8.37	27.70	county smoking (%)	30.51	16.11
# pre-natal visits	10.46	4.27	trimester of exposure	1.51	1.11
$\geq$ 5 cigar. daily (%)	10.88	31.14	missing smoking (%)	30.26	45.94

Notes: Table summarizes the sample of non-college educated single mothers in the structural analysis. The left panel summarizes birth weight and investments to be matched with predictions from the model. The right panel summarizes mother characteristics and CHIP exposure $\Delta\ell_i$. The last two variables – the trimester of exposure and the percent of mothers missing records of smoking – are exploited in the construction of moment conditions. Because not all states ask mothers about smoking in pregnancy (affecting 30% of the estimation sample), I treat "missing" as a distinct level of smoking and calculate the share of smokers including all mothers in the denominator.

[40] I do not examine investments at exposure above 90% FPL due to the small number of states (5) in this range. Instead, each exposure node (between 0% FPL and 70% FPL) includes at least 20 states in the structural analysis.

E.2 Mother Characteristics

The right panel of Table E1 summarizes mother characteristics exploited in the structural analysis. Mother's age group and CHIP exposure $\Delta\ell_i$ enter as state variables in the dynamic model. Mother's age (grouped into 5-year age bands between age 21 and 40) affects out-of-pocket costs and hence the utility from pre-natal visits ϑ. $\Delta\ell_i$ shifts altruism and present bias through equation 21 and 22. The next three characteristics – whether mother has fetal death in previous pregnancies, has any pregnancy risk factor, and the population smoking rate in her county of residence – determine the distribution of taste types η_i and ζ_i and the endowment type ϕ_i according to equation 23. Mother had fetal death in previous pregnancies if the live birth order of the child is less than the total birth order. Risk factor is an indicator set to 1 if the mother has at least one comorbidity indicated on the birth certificate. To construct the county smoking rate, I first calculate monthly smoking rates for non-college-educated women (both pregnant and non-pregnant) in each county from the Behavioral Risk Factor Surveillance System (BRFSS). I then use the average smoking rate in the fifth quarter prior to CHIP (or three months before the start of the estimation sample) to compute the county smoking rate.

The last two characteristics, the trimester of exposure and the share of mothers with missing records of smoking, are exploited in the construction of moment conditions. I group mothers by the trimester of exposure in some of the moment conditions to focus on the timing variation in the exposure. Because not all states ask mothers about their smoking during pregnancy (affecting 30% of the estimation sample), I treat "missing" as a distinct level of smoking, and calculate the share of smokers including all mothers in the denominator in the moment conditions.

F Moment Conditions and Estimation

Moment Conditions. I construct moment conditions to estimate three key equations in the structural model: the behavioral effects in equation 21 and 22, and the birth weight production in equation 16. To identify the behavioral effects, I exploit responses in the timing and the level of investments across exposure levels in $\Delta\ell_i$. I identify the birth weight production function using exposure levels in $\Delta\ell_i$ as instruments. Therefore, the model parameters can be estimated from the following set of moment conditions

1. 4×5 moments on the percent of mothers starting pre-natal visits in the first, second, and third trimester, and the percent without pre-natal visits, by exposure $\Delta\ell_i$,

2. 5 moments on the number of pre-natal visits, by exposure $\Delta\ell_i$,

3. 5 moments on the percent of mothers smoking more than 5 cigarettes daily, by exposure $\Delta\ell_i$,

4. 6×3 moments on log birth weight interacted with indicators of 6 levels of pre-natal visits and 3 levels of smoking,

5. 5 moments on log birth weight, by exposure $\Delta\ell_i$,

In addition, I include the following set of auxiliary moment conditions to capture additional investments and heterogeneity by mother age. These moment conditions are less weighted in the estimation.

6. 4×4 moments on the percent of mothers starting pre-natal visits in the first, second, and third trimester, and the percent without pre-natal visits, by cohort j,

7. 16×5 moments on the percent of mothers starting pre-natal visits in a given trimester and taking a given number of visits by the end of pregnancy, by exposure $\Delta\ell_i$,

8. 2×5 moments on the percent of mothers who are non-smokers (<5 cigarettes daily) or heavy smokers (≥15 cigarettes daily), by exposure $\Delta\ell_i$,

9. 4×5 moments on the percent of mothers with very low or very high number of visits (≤6 or ≥15) who also smoke less than 5 or over 15 cigarettes daily, by exposure $\Delta\ell_i$,

10. $3 \times 6 \times 3$ moments on the probability of birth weight falling below 2,500 grams and below two terciles (3,062 grams and 3,450 grams), interacted with 6 levels of pre-natal visits and 3 levels of smoking,

11. 3×5 moments on the probability of birth weight falling below 2500 grams and below two terciles (3,062 grams and 3,450 grams), by exposure $\Delta\ell_i$,

12. 6×4 moments on the number of pre-natal visits, by mother age a_i.

In total, I employ 272 moment conditions to estimate the model parameters.

Simulated Moment Conditions. Moment conditions that vary by exposure $\Delta\ell_i$ take the following form

$$\mathbb{E}\left[d_i^l | \Delta\ell_i = k\right] - D^l(\Theta; k) = 0, \tag{F1}$$

where d_i^l is the outcome of interest in moment condition l for individual i, and Θ is the model parameters. The outcome implied by the model for exposure k is $D^l(\Theta; k)$, obtained by simulating optimal investments given Θ. At true parameter values, simulated outcomes $D^l(\Theta; k)$ should match the sample counterpart $\mathbb{E}\left[d_i^l | \Delta\ell_i = k\right]$.

Following French and Jones (2011), I transform the conditional expectation in equation F1 into an unconditional expectation as follows

$$\mathbb{E}\left[\left(d_i^l - D^l(\Theta; k)\right) \cdot 1\{\Delta\ell_i = k\}\right] = 0, \tag{F2}$$

and the sample counterpart is given by

$$m^l = \frac{1}{N}\sum_i \left(d_i^l - D^l(\Theta; k)\right) \cdot 1\{\Delta\ell_i = k\}, \tag{F3}$$

where m^l is the moment residual given model parameter Θ.

I similarly construct the moment residuals for investments by mother age groups and for the birth weight production function.[41] Stacking up, $m = \left(m^l\right)$, $l = 0, ..., 271$ is a vector of moment residuals with the variance-covariance matrix $\mathbf{S}$.

Estimation. The method of simulated moment (MSM) searches for parameter values that best match the simulated outcomes $D^l(\Theta)$ with the sample counterparts. The estimated parameter $\hat{\Theta}$ minimizes moment residuals m according to the following objective function

$$\hat{\Theta} = argmin_{\Theta}\, m(\Theta)' \mathbf{W}\, m(\Theta), \tag{F5}$$

where $\mathbf{W}$ is the weighting matrix. I choose a diagonal weighting matrix where the weights are inverse to the variance of moment residuals and are larger for the main identifying moments.[42] The estimate $\hat{\Theta}$ is asymptotically normal: $\sqrt{I}\left(\hat{\Theta} - \Theta_0\right) \sim N(0, \mathbf{V})$, and the

[41] In particular, moment conditions for log birth weight interacted with visits and smoking inputs are the follows

$$m^l = \frac{1}{N}\sum_i \left[\log(b_i) \cdot 1\{V_i = p\} \cdot 1\{\bar{s}_i \geq q\} - D^l(\Theta)\right], \tag{F4}$$

where $p = 3, 6, ..., 18$, and $q = 5, 15$.

[42] Specifically, diagonal element $w_{ll} = \gamma_l \left[\frac{1}{N}\sum_i (d_i^l - D^l)^2 \cdot 1\{\Delta\ell_i = k\}\right]^{-1}$ for condition l in equation F3, where D^l is the sample statistic. I increase γ_l so that the 53 main moment conditions receive the largest weights in the estimation.

variance-covariance matrix $\mathbf{V}$ equals

$$\mathbf{V} = (1+r)(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}\mathbf{D}'\mathbf{W}\mathbf{S}\mathbf{W}\mathbf{D}(\mathbf{D}'\mathbf{W}\mathbf{D})^{-1}, \tag{F6}$$

where $\mathbf{D} = \frac{\partial m}{\partial \Theta'}\Big|_{\Theta_0}$ is the Jacobian of moment residuals at the true parameter, and r is the ratio of observed to simulated number of individuals.

I simulate investments for 10 million pregnant mothers drawn from the data. For each mother, I draw a vector of standard normal shocks, and transform the z-draws into taste and health shocks based on model parameters Θ. I then solve for optimal investments given state $\mathcal{I}_{it} = (3\sum_{\tau=1}^{t-1} v_{i\tau}, \sum_{\tau=1}^{t-1} s_{i\tau}, X_i)$, from equation 17 to 20. I use the decision rules to generate simulated profiles $D^l(\Theta)$, and calculate the fit with sample counterparts according to equation F5. The algorithm tries different parameter values to find the best fitting parameters $\hat{\Theta}$.

G Calculation of MVPF

Outreach Spending. I determine outreach spending in the roll-out of CHIP based on program reports in 2000. According to the Balanced Budget Act of 1997, the total budget of CHIP is capped at the federal level by the "allotment," and states' share of the total budget is determined from an allotment formula. States can spend no more than 10% of the budget on "program administration, outreach, and additional health assistance and initiatives related to the program."[43] In 2000, the federal allotment for CHIP is \$4.3 billion, and actual spending on outreach constitutes a small share of the administrative costs subject to the 10% cap. For instance, only 6% of the administrative costs are spent on outreach in Pennsylvania, and 14% in California.[44] Assuming that 10% of the administrative costs are outreach costs, total outreach spending is $\$4.3\,\text{billion} \cdot 10\% \cdot 10\% = \$43$ million in 2000. Since the goal of the outreach is to inform the public of the program (Williams and Rosenbach, 2007), I assume an even distribution of the spending across the population. I therefore divide the total spending by the number of US households (105 million) in 2000, and calculate the cost of exposure ΔG to be $\frac{\$43\,\text{million}}{105\,\text{million}} = \$0.41$ per household.[45]

Robustness. I calculate alternative MVPFs where I increase the outreach spending by a factor of $1 + \varpi$, where ϖ captures the additional administrative costs resulting from the outreach. For instance, outreach efforts may increase application to the program and the costs of processing the application. For states expanding insurance through the Medicaid program, information about CHIP may increase the uptake of Medicaid insurance among parents, hence increasing the overall administrative burden of insurance programs. I allow for these potential effects by setting $\varpi = 0.5$, the upper bound of the marginal cost of public funds commonly applied in the literature. Appendix Table G1 calculates the MVPF of CHIP exposure using the adjusted cost ($\Delta G = \$0.62$ per household). The main findings for welfare remain unchanged under alternative cost calculations.

[43] A detailed list of items subject to the 10% cap is available in the attachment of a letter from the Health Care Financing Administration, available at https://www.medicaid.gov/sites/default/files/Federal-Policy-Guidance/downloads/SMD120897b.pdf.

[44] A report prepared by the United States General Accounting Office (GAO) summarizes outreach spending based on state responses to a 2000 survey. The report is available at https://www.gao.gov/new.items/he00086.pdf.

[45] Historical households tables are published by the Census Bureau at https://www.census.gov/data/tables/time-series/demo/families/households.html.

Table G1: MVPF of CHIP exposure, $\Delta G = \$0.62$

	WTP	WTP^M	WTP^C	$MVPF$
$\varphi = 1$	0.29	0.43	-0.13	0.46
	(0.003)	(0.005)	(0.004)	(0.004)
$\varphi = 2$	0.59	0.85	-0.27	0.94
	(0.005)	(0.010)	(0.007)	(0.009)
$\varphi = 3$	0.88	1.28	-0.40	1.40
	(0.008)	(0.015)	(0.011)	(0.013)

Notes: Table summarizes the marginal value of public funds (MVPF) for CHIP exposure, applying an alternative cost of exposure $\Delta G = \$0.62$. The new cost measure accounts for potential increases in administrative costs as a result of program outreach, adjusting the original outreach spending by a marginal cost of public funds of 50%. Standard errors from ten million simulated individuals in the parenthesis.

H Fiscal Externality

I calculate the fiscal externality of CHIP exposure in three steps. First, I calculate the cost of initial program investments based on spending in the first 19 years of the program (FY1998-FY2016). Next, I predict the life-cycle increases in earnings based on the effect of CHIP exposure on college enrollment. Finally, I calculate the increase in tax payments and compare it with the initial program costs to quantify the fiscal externality of CHIP exposure. I detail the calculations below.

Program Costs. Because the total spending of CHIP is capped at the federal level by the allotment, I divide the allotment by the number of children (age 0-18) to calculate the cost of program investment per child in a given year. I accumulate the investment costs through the childhood years of the 1998 birth cohort (which overlap with the first 19 years of CHIP since the 1998 fiscal year), and discount the cumulative cost to the year before birth (1997) using a 2% annual discount rate. Appendix Table H1 lists the annual CHIP allotment (in 2000 dollars), number of children each year, and the cost per child discounted to 1997. In total, CHIP invested $\$1,354.42$ per child in the first 19 years of the program.

I then adjust the average cost to derive the cost per child of single mothers. In the National Health Interview Survey (NHIS), the uptake of CHIP is 30% in 1998-2016, and among single mothers, 55% enrolled their children in CHIP. The implied cost per enrolled child is $\frac{\$1,354,42}{30\%} = \$4,514.73$. Among single mothers, CHIP invested an average of $\$4,514.73 \cdot 55\% = \$2,483.10$ per child of single mothers.

Earning Benefits. I predict the increase in earnings from the effect of CHIP exposure on college enrollment. For children of single mothers, the roll-out of CHIP increased college enrollment by $80\% \cdot 1.71 = 1.37$ percentage points (Table 6). Following Hendren and Sprung-Keyser (2020), I assume that students induced by the exposure to attend college remain in college for two years. Applying an 11.3% return on earnings for each year of college enrollment (Zimmerman, 2014), I calculate that CHIP exposure can increase earnings by $2 \cdot 11.3\% \cdot 0.0137 = 0.31\%$ for children of single mothers.

I then apply the 0.31% effect to the life-cycle earning profile for children of single mothers. I construct the profile from average labor incomes in age 19-64 in the 2014-2018 American Community Survey (ACS).[46] I adjust the earning profile of an average individual to match earnings for children of single mothers using estimates from Lopoo and DeLeire (2014).[47] Because the 0.31% effect on earnings is relative to children without college education, I calculate earnings for the latter group using the college enrollment rate among children of single mothers.[48] Consistent with Zimmerman (2014), I assume that

[46] I assume a 0.5% wage growth rate to predict the earning profiles for children in adulthood. Results are very similar using static wages observed in 2014-2018.

[47] Specifically, Lopoo and DeLeire (2014) finds that children of single parents have lower adult incomes by 27% compared to children of continuously married parents, or by 21% compared to the population average.

[48] College enrollment is 45% among children of single mothers in the ACS. Assuming that students attend college for two years, the implied earning loss for children without college education is $9.09\% = 1 - \frac{1}{45\% \cdot (1+2 \cdot 11.3\%)+55\%}$ below the population average.

Table H1: Cost of program investments, by year

FY	Allotment (billions)	# Children (millions)	Cost per child (discounted to 1997)
1998	4.56	75.37	62.59
1999	4.45	75.89	59.42
2000	4.30	76.42	55.90
2001	4.21	76.74	53.36
2002	3.07	76.95	38.08
2003	3.01	77.16	36.47
2004	2.92	77.37	34.59
2005	3.52	77.58	40.72
2006	3.43	77.90	38.72
2007	4.15	78.11	45.86
2008	4.02	78.22	43.39
2009	8.52	78.22	90.25
2010	9.93	78.22	103.03
2011	10.36	78.01	105.62
2012	11.31	77.79	113.29
2013	12.93	77.69	127.19
2014	13.99	77.69	134.78
2015	8.25	77.71	77.91
2016	10.07	77.69	93.25
Total	126.99	1,470.72	1,354.42

Notes: Table calculates the cost of program investments per child in FY1998-FY2016. Each year, the total spending of CHIP is capped by an allotment determined by the federal government. I divide the allotment by the number of children to determine the cost of investment per child, and discount the cost to year 1997 using a 2% annual discount rate. I adjust all dollars to 2000 levels using CPI-U. I obtain CHIP allotments from the Federal Register, and obtain the number of children each year from the Federal Interagency Forum on Child and Family Statistics, available at https://www.childstats.gov/americaschildren/tables/pop1.asp.

the return of college education on earnings begins from age 23 onward, and enrollment lowers annual earnings in age 19-22 by 12.80%.[49] Discounted to 1997, the life-cycle earning benefit amounts to $\$1,101.11$ per child of single mothers.

Tax Payments. Following Hendren and Sprung-Keyser (2020), I assume that the earning benefits are subject to a marginal tax rate of 18.9%.[50] The implied increase in tax payment, $18.9\% \cdot \$1,101.11 = \$208.11$, amounts to $\frac{\$208.11}{\$2,483.10} = 8.38\%$ of the program costs in childhood. This suggests that the government can expect to recoup 8.4% of the program investments from parental responses to the roll-out.

Confidence Intervals and Robustness. I construct confidence intervals for the fiscal externality to account for uncertainties in the estimated effects on college enrollment and earnings. Specifically, I bootstrap the effect on college enrollment based on the estimate ($\hat{\beta} = 1.37\%$, s.e.=0.32%) in Table 6, and bootstrap the effect on earnings based on the estimate ($\hat{\beta} = 11.3\%$, s.e.=3.83%) in Zimmerman (2014).

Appendix Table H2 compares fiscal externality under different assumptions and shows the empirical 95% confidence intervals from 1,000 bootstrap draws in the square brackets. Under a 3% annual discount rate and a 2-year enrollment in college, fiscal externality of CHIP exposure amounts to 6.0% of the program cost in childhood. The government can rule out a fiscal externality less than 1% or above 15% at the 95% confidence level. Lower discount rate at 2% increases fiscal externality to 8.4% of the cost, and increases it to 15.4% if students attend college for 4 years. In these cases, the more optimistic forecast of the fiscal externality can exceed 20% of the program cost. The preferred estimate (8.4% assuming a 2% discount rate and a 2-year enrollment in college) is in the lower range of estimates shown in Table H2.

[49] Specifically, Zimmerman (2014) finds lower earnings among college attendees in the 4 years after high school. Scaled by the first-stage effect on the years of college, each additional year of college lowers annual earnings in age 19-22 by 12.08%.

[50] The tax rate is based on CBO estimates of tax-and-transfer rates, which include state and federal individual income taxes, SNAP benefits, and subsidies on health insurance benefits. The CBO estimates are available at `https://www.cbo.gov/sites/default/files/114th-congress-2015-2016/reports/50923-marginaltaxrates.pdf`. Hendren and Sprung-Keyser (2020) deducts federal payroll taxes (13.9%) from the estimates and adds a small adjustment for state individual income taxes (2.6%). This is consistent with the view that payroll taxes are partly returned to workers as benefits and do not strictly increase government revenues. Ultimately, I apply the adjusted tax-and-benefit rates reported in Table G.I of Hendren and Sprung-Keyser (2020) for the calculation.

Table H2: Fiscal externality in percent of program costs, robustness

	$r = 3\%$	$r = 2\%$
2-year enrollment	6.02% [1.05%, 14.99%]	8.38% [1.49%, 20.81%]
4-year enrollment	11.02% [1.92%, 27.45%]	15.35% [2.72%, 38.10%]

Notes: Table calculates the fiscal externality of CHIP exposure in percent of program costs in childhood, varying the annual discount rate r and the duration of college enrollment. To account for the uncertainty in the estimated effects on college enrollment and earnings, I follow Hendren and Sprung-Keyser (2020) and bootstrap 1,000 draws from the asymptotic distribution of the estimates. I calculate the implied fiscal externality for each draw, and show the empirical 95% confidence interval in the square brackets.

I Additional Tables

Table I1: Effect of exposure on fertility and single motherhood

	(1) Fertility (%)	(2) Single mothers (%)
exposure in		
4-7 months of age	0	-0.16
	(0.005)	(0.17)
1-3 months of age	0	0
	–	–
3rd trimester	-0.001	0.12
	(0.005)	(0.22)
2nd trimester	0.008	0.16
	(0.009)	(0.30)
1st trimester	0.005	0.34
	(0.009)	(0.27)
0-4 months pre-utero	0.005	0.15
	(0.009)	(0.31)
y mean	0.66%	24.21%
R^2	0.92	0.97
N	808	808

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table shows the effect of in-utero exposure on fertility rates and the share of single mothers among pregnant mothers. To calculate fertility rates, I combine the birth certificate records, which contain the universe of live births, with the fetal death records to arrive at the full count of mothers giving birth in each year-month. I use the gestation estimates in these records to infer the pregnancy onset time, and construct the fertility rate for women between age 21 and 40 by state-year-month. I calculate the share of pregnant mothers who are single based on her marital status at the time of delivery. I group mothers by the trimester of exposure to CHIP, and estimate separate effects across six exposure groups in the table. Robust standard errors clustered at the level of states in the parenthesis.

Table I2: Effects of exposure on birth weight

	(1) Birth weight (grams)	(2) Low birth weight (%)
single · *eliginc* · exposure in		
4-7 months of age	-1.31	0.05
	(1.66)	(0.09)
1-3 months of age	0	0
	–	–
3rd trimester	0.70	0.02
	(1.70)	(0.07)
2nd trimester	1.66	-0.01
	(1.71)	(0.07)
1st trimester	4.07***	-0.12*
	(1.03)	(0.07)
0-4 months pre-utero	4.12***	-0.11**
	(1.09)	(0.05)
y mean	3342.57	7.08%
R^2	0.02	0.01
N	4,315,394	4,315,394

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
Notes: Table estimates the effect of in-utero exposure on birth weight (grams) and low birth weight (<2,500 grams). I group children by the trimester of exposure and estimate effects for six exposure groups. Robust standard errors clustered at the level of states in the parenthesis.

Table I3: Effects of exposure on the timing of pre-natal visits

	(1) Month care started	(2) Late onset (%) (2nd/3rd trimester)	(3) Very late onset (%) (3rd trimester)
single · *eliginc* · exposure in			
4-7 months of age	0.002	0.10	-0.021
	(0.010)	(0.23)	(0.18)
1-3 months of age	0	0	0
	–	–	–
3rd trimester	-0.006	0.034	-0.10
	(0.009)	(0.24)	(0.10)
2nd trimester	-0.004	-0.10	-0.13
	(0.012)	(0.23)	(0.18)
1st trimester	-0.010	-0.25	-0.27
	(0.010)	(0.19)	(0.17)
0-4 months pre-utero	-0.019**	-0.38**	-0.30**
	(0.008)	(0.16)	(0.13)
y mean	2.45	15.08%	5.48%
R^2	0.08	0.06	0.04
N	4,200,326	4,200,326	4,200,326

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
Notes: Table estimates the effects of in-utero exposure on the timing of pre-natal visits, focusing on the month of pre-natal care onset in column 1, late care onset past the first trimester in column 2, and very late onset in the third trimester in column 3. I group mothers by the trimester of exposure and estimate effects across six exposure groups. Effects on mothers whose children are already 1-3 months old at the onset of CHIP are normalized to zero. Robust standard errors clustered at the level of states in the parenthesis.

Table I4: Effects of exposure on the number of pre-natal visits and smoking

	(1)	(2)	(3)
	# Pre-natal visits	Smoking (%) (≥5 cigarettes daily)	Heavy smoking (%) (≥15 cigarettes daily)
single · *eliginc* · exposure in			
4-7 months of age	-0.014	0.12	0
	(0.016)	(0.15)	(0.073)
1-3 months of age	0	0	0
	–	–	–
3rd trimester	0.006	0.12	0.029
	(0.022)	(0.14)	(0.086)
2nd trimester	-0.003	-0.012	-0.092
	(0.024)	(0.10)	(0.064)
1st trimester	0.022	-0.11	-0.16**
	(0.021)	(0.097)	(0.071)
0-4 months pre-utero	0.035	-0.20**	-0.19***
	(0.022)	(0.082)	(0.062)
y mean	11.74	8.41%	3.12%
R^2	0.07	0.07	0.03
N	4,157,327	3,331,203	3,331,203

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effect of CHIP exposure on the number of pre-natal visits and smoking intensity. I group mothers by the trimester of exposure and estimate effects across six exposure groups. Robust standard errors clustered at the level of states in the parenthesis.

Table I5: Effects of simulated exposure on birth weight and investments

	(1)	(2)	(3)	(4)	(5)	(6)
	Birth weight (grams)		Late onset (%) (2nd/3rd trimester)		Heavy smoking (%) (≥ 15 cigar. daily)	
eligCHIP	32.09***	13.08	-0.048***	-0.027	-0.029***	-0.023***
	(11.63)	(12.84)	(0.018)	(0.018)	(0.008)	(0.006)
eligCHIP · *single*		47.51***		-0.054***		-0.014**
		(11.01)		(0.013)		(0.006)
y mean	3343.95		14.94%		3.13%	
R^2	0.03	0.03	0.08	0.08	0.05	0.05
N	4,246,535		4,142,279		3,279,807	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effects of simulated exposure on birth weight (column 1-2), late care onset (column 3-4), and smoking (column 5-6). I simulate CHIP exposure based on the predicted eligibility for children applying income limits of Medicaid/CHIP known at the time of pregnancy. I show details of the simulation in Appendix A. I estimate separate effects by mother's marital status in even-numbered columns. Robust standard errors clustered at the level of states in the parenthesis.

Table I6: Effects of exposure on mother's insurance

	(1)	(2)	(3)	(4)	(5)	(6)
	Any insurance (%)		Primary insurance from Medicaid (%)		Primary insurance from employer (%)	
$eliginc \cdot treat \cdot post$	-1.72	-10.93	-1.13	-11.38	-3.87	-8.48
	(2.42)	(6.96)	(1.85)	(7.90)	(4.53)	(7.06)
$eliginc \cdot treat$	5.87	29.38	3.63	35.09	4.54	19.22
	(8.59)	(17.68)	(5.45)	(21.44)	(10.52)	(20.76)
$eliginc$	-1.82	-1.62	0.039	-0.038	-3.14	-3.26
	(1.29)	(1.23)	(0.050)	(0.49)	(1.92)	(1.94)
$treat$						
pregnant	Y	Y	Y	Y	Y	Y
single		Y		Y		Y
y mean	80.20%	80.20%	4.87%	4.87%	41.80%	41.80%
R^2	0.03	0.03	0.02	0.03	0.02	0.02
N	34,915	34,853	34,421	34,360	34,421	34,360

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effect of CHIP exposure on mother's insurance status, using data from the Behavioral Risk Factor Surveillance System (BRFSS). I restrict the analysis to women in age 21-40 surveyed between 8 months before and 8 months after the onset of CHIP. I show results from the following difference-in-differences specification

$$y_{its} = \beta_0 \cdot eliginc_{st} \cdot treat \cdot post + \beta_1 \cdot eliginc_{st} \cdot treat + \beta_2 \cdot eliginc_{st} + \beta_s \cdot treat + \alpha_s + \tau_t + \alpha_s \cdot \tau_t + \epsilon_{its},$$

where $eliginc$ is the income limit of children's insurance in state s and year-month t. Specifically, $eliginc_{st} = inc_s^{pre}$ before the onset of CHIP, and $eliginc_{st} = inc_s^{post}$ after the onset. $treat$ indicates pregnant mothers in odd-numbered columns, and indicates single pregnant mothers in even-numbered columns. The specification controls for differences by mother groups across states ($\beta_s \cdot treat$), and differences across states over time ($\alpha_s \cdot \tau_t$). β_0 estimates the effect on (single) pregnant mothers for each 100% FPL exposure to the CHIP insurance. BRFSS sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parenthesis.

Table I7: Effects of exposure on cash benefits and health spending

	(1)	(2)	(3)	(4)
	Means-tested cash transfer ($)		Out-of-pocket health spending (thousands $)	
$eliginc \cdot treat \cdot post$	-5.58	58.86	0.056	0.34
	(16.18)	(90.74)	(0.85)	(0.36)
$eliginc \cdot treat$	33.64	-185.74	-2.75	-0.29
	(42.07)	(216.04)	(1.91)	(1.25)
$eliginc$	5.47	6.02	0.36**	0.36**
	(5.42)	(5.42)	(0.16)	(0.16)
$treat$				
pregnant	Y	Y	Y	Y
single		Y		Y
y mean	46.81	46.82	444.37	444.37
R^2	0.02	0.02	0.02	0.02
N	33,808	33,803	11,963	11,963

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effect of CHIP exposure on monthly cash benefits from means-tested programs (column 1-2) and out-of-pocket health spending in the past 12 months (column 3-4), using data from the Survey of Income and Program Participation (SIPP). I restrict the analysis to women in age 21-40 surveyed between 8 months before and 8 months after the onset of CHIP. I show results from the following difference-in-differences specification

$$y_{its} = \beta_0 \cdot eliginc_{st} \cdot treat \cdot post + \beta_1 \cdot eliginc_{st} \cdot treat + \beta_2 \cdot eliginc_{st} + \beta_s \cdot treat + \alpha_s + \tau_t + \alpha_s \cdot \tau_t + \epsilon_{its},$$

where $eliginc$ is the income limit of children's insurance in state s and year-month t. Specifically, $eliginc_{st} = inc_s^{pre}$ before the onset of CHIP, and $eliginc_{st} = inc_s^{post}$ after the onset. $treat$ indicates pregnant mothers in odd-numbered columns, and indicates single pregnant mothers in even-numbered columns. The specification controls for differences by mother groups across states ($\beta_s \cdot treat$), and differences across states over time ($\alpha_s \cdot \tau_t$). β_0 estimates the effects on (single) pregnant mothers for each 100% FPL exposure to the CHIP insurance.

Means-tested cash benefits are asked in the main survey for each month in a 4-month recall. I use benefit amounts reported for the most recent month (the fourth month). Out-of-pocket health spending includes payments made in the household towards the mother's healthcare utilization in the past 12 months, which include health insurance premiums net of reimbursements from third parties. Dollar amounts are in the 2000 levels with CPI-U. SIPP sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parenthesis.

Table I8: Effects of exposure on personal debts

	(1)	(2)	(3)	(4)
	Credit card + store bill debt ($)		Personal debt (thousands $)	
$eliginc \cdot treat \cdot post$	-9.64	-5.93	2.00	-0.58
	(8.81)	(13.81)	(2.41)	(1.45)
$eliginc \cdot treat$	26.92	19.61	-3.68	1.79
	(18.64)	(25.90)	(5.33)	(2.93)
$eliginc$	3.02	2.81	-0.15	-0.17
	(2.63)	(2.57)	(0.48)	(0.47)
treat				
pregnant	Y	Y	Y	Y
single		Y		Y
y mean	1,986.98	1,987.73	4.00	4.00
R^2	0.01	0.01	0.01	0.01
N	12,214	12,209	12,219	12,219

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effect of CHIP exposure on credit card and store bill debts in column 1-2, and total personal debt further including loans and other debts in column 3-4, using data from the Survey of Income and Program Participation (SIPP). I restrict the analysis to women in age 21-40 surveyed between 8 months before and 8 months after the onset of CHIP. I show results from the following difference-in-differences specification

$$y_{its} = \beta_0 \cdot eliginc_{st} \cdot treat \cdot post + \beta_1 \cdot eliginc_{st} \cdot treat + \beta_2 \cdot eliginc_{st} + \beta_s \cdot treat + \alpha_s + \tau_t + \alpha_s \cdot \tau_t + \epsilon_{its},$$

where $eliginc$ is the income limit of children's insurance in state s and year-month t. Specifically, $eliginc_{st} = inc_s^{pre}$ before the onset of CHIP, and $eliginc_{st} = inc_s^{post}$ after the onset. $treat$ indicates pregnant mothers in odd-numbered columns, and indicates single pregnant mothers in even-numbered columns. The specification controls for differences by mother groups across states ($\beta_s \cdot treat$), and differences across states over time ($\alpha_s \cdot \tau_t$). β_0 estimates the effects on (single) pregnant mothers for each 100% FPL exposure to the CHIP insurance.

Table I9: Effects of exposure on program uptake and education expectation

	(1)	(2)	(3)	(4)
		Expected Education		
	Medicaid/CHIP (%)	College degree (%)	Graduate school (%)	Attainment (1-5 scale)
single · *eliginc* · exposure in				
4-7 months of age	1.97	-4.26	7.55	12.35
	(12.71)	(7.93)	(11.41)	(23.98)
1-3 months of age	0	0	0	0
	–	–	–	–
3rd trimester	19.66	-0.63	-0.85	-0.89
	(14.15)	(2.69)	(2.10)	(4.86)
2nd trimester	13.61*	2.58	-2.64	4.53
	(7.64)	(2.01)	(3.51)	(6.55)
1st trimester	47.69***	3.77	-0.68	5.71
	(15.68)	(2.52)	(3.82)	(6.95)
0-4 months pre-utero	36.96**	-2.68	-0.75	-5.08
	(14.26)	(4.96)	(4.59)	(11.93)
y mean	19.41%	86.15%	26.93%	4.06
R^2	0.28	0.12	0.05	0.11
N	1,542	1019	1019	1019

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effect of in-utero exposure on program uptake in column 1, and mother's expected education for the child in column 2-4, using data from the Survey of Income and Program Participation (SIPP). In SIPP, respondents are asked about their enrollment in public insurance programs for each month in a 4-month recall. I focus on enrollment in the most recent month (the fourth month), and examine the child's enrollment in Medicaid/CHIP in the first year of the child's life (age 0) in column 1. Outcomes in column 2-4 are mother's stated expectation of the child's education attainment. The expectation is asked for all children in SIPP households in wave 6 (the middle wave) and wave 12 (the final wave) of the 1996-2000 survey panel, which spans the roll-out of CHIP. In column 4, education attainment is coded on a 1-5 scale, with the integers corresponding to no degree (less than high school), high school, some college, college degree, and graduate school, respectively. SIPP sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parenthesis.

Table I10: Effects of exposure on mother's marital status

	(1) Never married (%)	(2) Unmarried in t (%)
$eliginc^{utero}$	0.62	0.99
	(0.72)	(0.81)
$eliginc^{child}$	0.99	0.33
	(0.87)	(1.22)
y mean	8.64%	25.46%
R^2	0.01	0.01
N	385,063	385,063

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table estimates the effects of exposure on mother's marital status. Column 1 examines the share of single mothers who have never married. Column 2 examines the share of single mothers unmarried in survey year t. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parenthesis.

Table I11: Effects of exposure on high school graduation and college enrollment

	(1)	(2)	(3)	(4)
	Graduate high school (%)		Enroll in college (%)	
$eliginc^{utero} \cdot single \cdot$ exposure in				
7-12 months of age	-0.54	-0.14	-0.81	-0.31
	(0.87)	(0.46)	(0.92)	(0.56)
1-6 months of age	0	0	0	0
	–	–	–	–
second - third trimester	0.39	-0.11	0.18	0.32
	(0.49)	(0.28)	(0.73)	(0.49)
first trimester in and pre utero	0.47	0.12	0.86**	0.59**
	(0.29)	(0.20)	(0.41)	(0.25)
4-9 months pre utero	0.59**	0.29	1.14**	0.69**
	(0.29)	(0.18)	(0.45)	(0.29)
single				
never married	Y		Y	
y mean	28.79%		15.78%	
R^2	0.64	0.64	0.35	0.35
N	385,063		385,063	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table shows the effects of in-utero exposure on high school graduation (column 1-2) and college enrollment (column 3-4), based on the specification in equation 13. I estimate effects for children of never married mothers in odd-numbered columns, and for children of single mothers unmarried in the survey year in even-numbered columns. I group children by the timing of exposure and show separate effects for six exposure groups. Regressions are weighted by ACS sampling weights. Robust standard errors clustered at the level of states in the parenthesis.

Table I12: Effects of exposure on grade progression in high school

	(1)	(2)	(3)	(4)
	Grade-for-age (%)		Graduate HS (%)	
$eliginc^{utero} \cdot single$	2.36***	1.56***	1.71**	0.75**
	(0.61)	(0.51)	(0.68)	(0.37)
$eliginc^{utero}$	0.028	-0.16	-0.75	-0.80
	(1.01)	(0.99)	(0.66)	(0.69)
single				
never married	Y		Y	
y mean	88.21%		28.79%	
R^2	0.095	0.095	0.64	0.64
N	385,063		385,063	

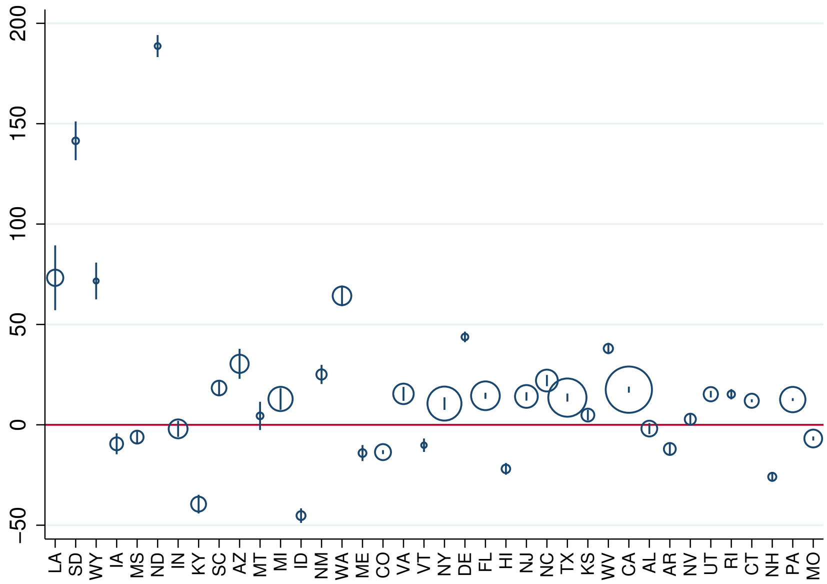
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

Notes: Table shows the effects of in-utero exposure on the grade-for-age status (whether the child attends the grade expected of her age) in column 1-2, and on high school graduation in column 3-4. *single* indicates children of single mothers. I estimate effects for children of never married mothers in odd-numbered columns, and for children of single mothers unmarried in the survey year in even-numbered columns. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parenthesis.

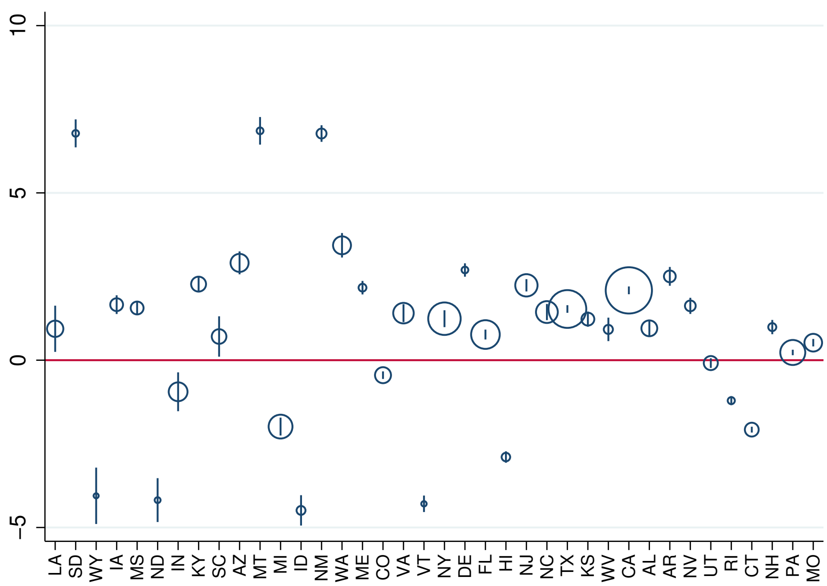
J Additional Figures

Figure J1: Effects of exposure across states

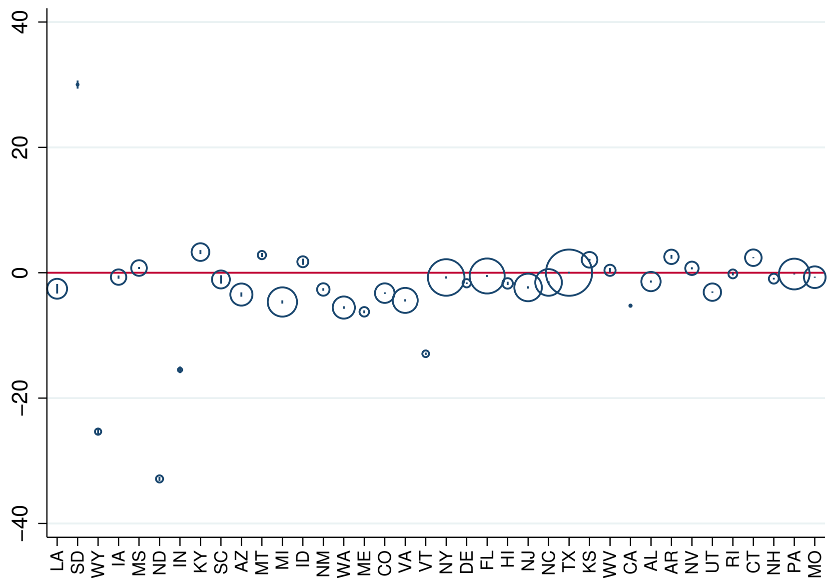
(a) Birth Weight (grams)



(b) First Trimester Care (%)

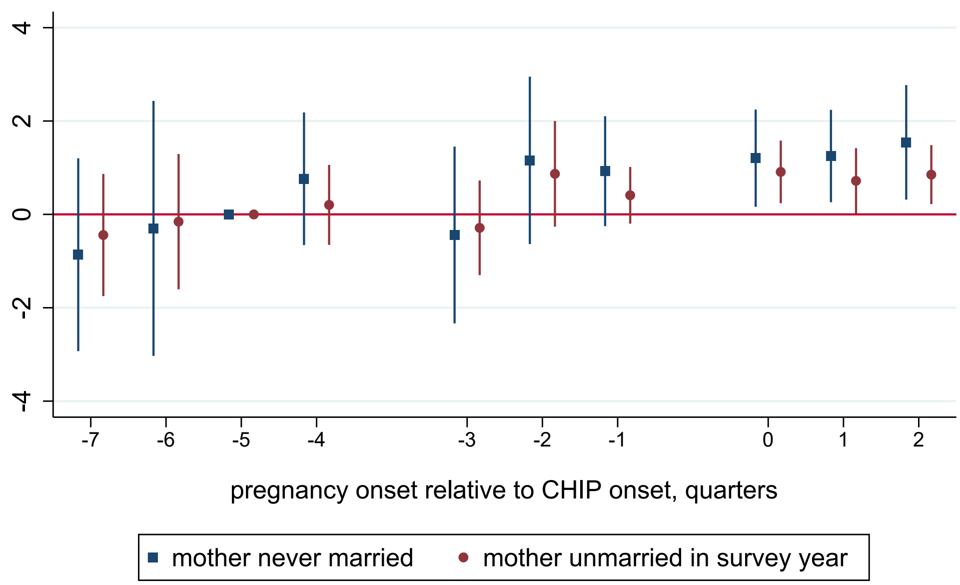


(c) Smoking Intensity (half packs)



Notes: Figure plots state-specific effects of exposure on birth weight in panel (a), first trimester care in panel (b), and smoking intensity in panel (c). Smoking intensity is measured in half packs (10s) of cigarettes daily. I rank states by the size of expansion from small to large on the horizontal axis. On average, states expanded income limits by 80% FPL. Small expansion states from Louisiana (LA) to Maine (ME) expanded income limits between 22.5% FPL and 54.8% FPL. States beginning with Rhode Island (RI) expanded income limits by over 100% FPL. I do not estimate state-specific effects for Minnesota (MN) where the income limit increased by a minimal 0.26% FPL. I indicate the sample size in each state with the circle around the estimates. 95% confidence intervals are based on robust standard errors clustered at the level of states.

Figure J2: Effects of in-utero exposure on college enrollment (%), event study

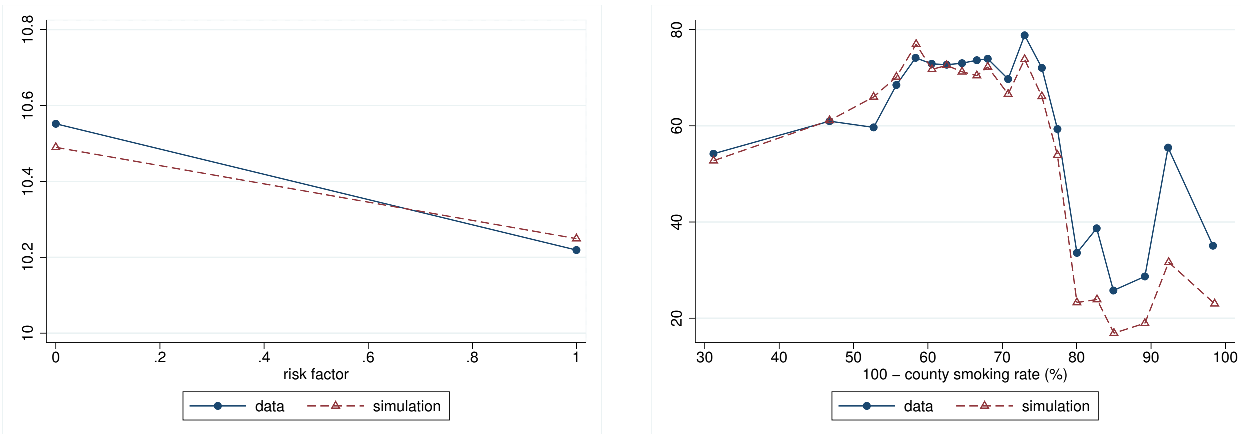


Notes: Figure plots the effect of in-utero exposure on college enrollment by the timing of exposure across cohorts, separately for children of never-married mothers and for children of mothers unmarried in the survey year. The horizontal axis compares the pregnancy onset quarter with the CHIP onset quarter. Children conceived more than 4 quarters before CHIP were not exposed to CHIP in utero. 95% confidence intervals are based on robust standard errors clustered by states.

Figure J3: Simulated investments by mother characteristics

(a) Number of Pre-Natal Visits, by Risk Factor

(b) Non-Smokers (%), by County Smoking Rate

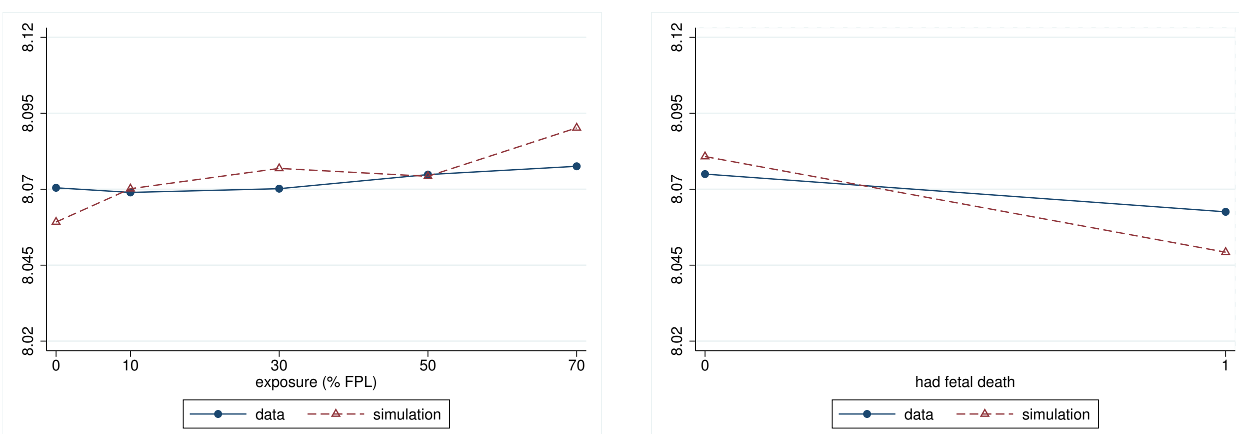


Notes: Figure compares simulated investments with empirical counterparts across mother characteristics that are predictors of mother types. Panel (a) plots pre-natal visits by the presence of mother risk factors. Panel (b) plots smoking status across the distribution of county smoking rates. I construct county smoking rates using the share of smokers among non-college-educated women (pregnant and non-pregnant) in each county in the Behavioral Risk Factor Surveillance System (BRFSS). I simulate investments for ten million pregnant mothers and plot the investments in the dotted line. I plot empirical counterparts in the solid line.

Figure J4: Effect of CHIP exposure on birth weight

(a) By Exposure $\Delta\ell_i$

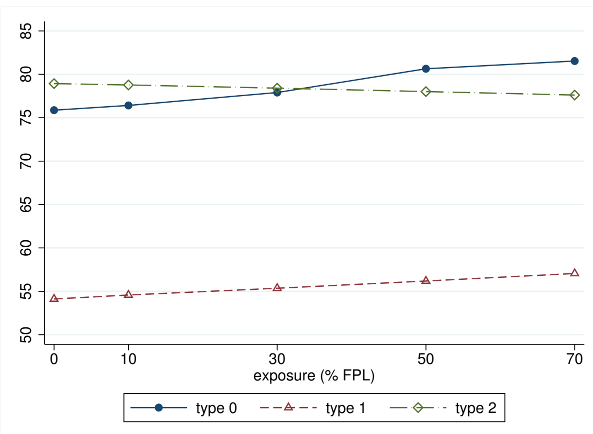
(b) By Fetal Death



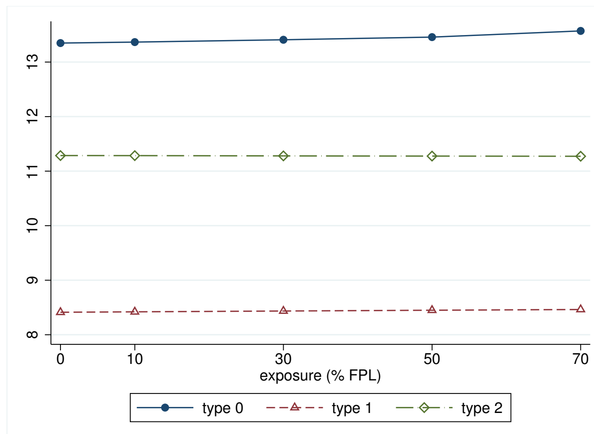
Notes: Figure compares simulated birth weight with empirical counterparts across CHIP exposure $\Delta\ell_i$ in panel (a), and by fetal death in previous pregnancies in panel (b). Mother had fetal death in previous pregnancies if the live birth order of the current birth is smaller than the total birth order. I simulate birth weight for ten million pregnant mothers and plot the simulated birth weight in the dotted line. I plot empirical counterparts in the solid line.

Figure J5: Effect of CHIP exposure on investments and birth weight, by mother types

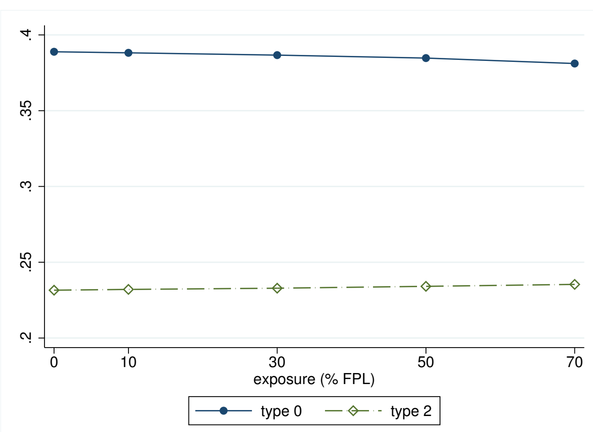
(a) First Trimester Care (%)



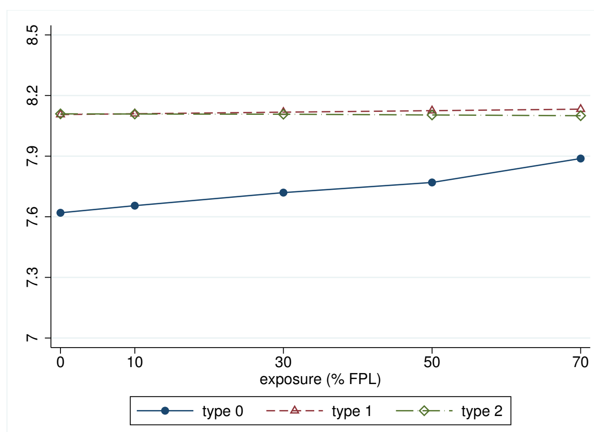
(b) Number of Pre-Natal Visits



(c) Smoking Intensity (Half Packs)



(d) Log Birth Weight



Notes: Figure plots simulated investments and birth weight by CHIP exposure $\Delta\ell_i$ for different mother types. I simulate investments and birth weight at each exposure level in $\Delta\ell_i$ for ten million pregnant mothers, and plot the results by CHIP exposure and mother types. I omit type 1 mothers for smoking intensity in panel (c), since none of the type 1 mothers smoked in the simulation due to significant disutility from smoking.

Appendix References

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