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 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 7% of the program costs in childhood. Thus, the information of children's insurance can nudge parents to invest, resulting in greater parental utility and lower social costs of insurance.

Key words: Parental investments, Social insurance, Nudges, 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 children. Yet, 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 examines these questions exploiting the roll-out of the Children's Health Insurance Program (CHIP) in the US. CHIP doubled the share of children eligible for public insurance, but did not expand insurance for pregnant mothers or children in utero. As such, CHIP is unlikely to impact the birth outcomes of children. Nonetheless, birth outcomes may improve if the information of insurance increased parents' private investments in utero. In this paper, I examine birth weight and in-utero investments in the roll-out of CHIP to understand parental responses to children's insurance.

I have three main findings from the analysis. First, pregnant mothers exposed to the roll-out increased private investments in utero, improving birth weight for children with in-utero exposure to CHIP. Second, the investments were consistent with reductions in the present bias of mothers. Due to the benefits on birth weight, investments increased mother utility similar to expansions of her own insurance. Third, in the long run, investments further increased college enrollment, predicting higher tax payments that could offset 7.2% of the program cost in childhood.

To estimate the investment responses, I exploit the roll-out of CHIP as an exogenous shock on mothers' exposure to children's insurance. The roll-out increased the income limit of children's insurance across states. Mothers in states with higher income limits can expect greater insurance probability for their children. Within states, insurance probability increased more for mothers with earlier exposure to CHIP in pregnancy. To capture the variations, I construct insurance 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. I then exploit the within-state variation across exposure timing to estimate the investments responses to the roll-out.

I find that exposure to the roll-out increased mothers' in-utero investments, 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, reducing the probability of low birth weight by 3.6%. The investments were fully concentrated among single pregnant mothers exposed to CHIP since the first trimester. By contrast, investments increased little among married mothers whose children had low predicted eligibility for CHIP.

To understand mechanisms, I examine whether the exposure increased mothers' uptake of own insurance and safety net benefits, and hence increased her resources in pregnancy. Using data from the Survey of Income and Program Participation, I show that the exposure did not affect mothers' insurance coverage, cash transfer incomes, or borrowing from future incomes. Moreover, mothers investing more in utero also had the highest uptake of CHIP for their newborns, but these mothers did not indicate higher expected education for children. This suggests that the investments were not motivated by the long-run effects of investments on child outcomes.

After ruling out mothers' insurance, incomes, and the long-run effects of investments as mechanisms, I explore two behavioral mechanisms whereby the exposure may have adjusted mothers' perception of investments. First, the exposure may have increased mothers' altruism for the child. Second, the opportunity to enroll the child in the program may have shifted mothers' inter-temporal weights towards future utilities, 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. The exposure could increase investments by increasing mothers' altruism for the child. Across trimesters, because present-biased mothers tend to delay investments and end up investing less in the child, a behavioral effect reducing the present bias could increase investments and further shift investments to early trimesters of pregnancy. Matching investments across mothers' exposure to CHIP, I find that the exposure reduced present bias by 14.3% in the roll-out, with little effect on altruism.

Based on the model estimates, I examine the welfare impacts of the exposure focusing on mothers' valuation of the exposure. Mothers value the exposure because it reduces behavioral biases and results in better outcomes for children. Despite investment costs, the exposure increased mother utility by $0.31 due to the benefits on birth weight. Relative to the program spending on the information outreach, mothers value the exposure at 76% of the spending, which is comparable to her valuation of own insurance from Medicaid (Hendren and Sprung-Keyser, 2020). For children's insurance, this result suggests that the information of insurance can improve child outcomes and hence increase parental utility as effectively as expansions of parents' own insurance.

In the long run, investments increased college enrollment by 8.2% for children of single mothers. This effect could reduce the social costs of insurance by increasing earnings and tax payments in adulthood. However, because mothers did not internalize the long-run effects of investments, the fiscal externality was under-stated in mothers' valuation of the exposure. To quantify the externality, I predict the life-cycle earning benefit for children based on the effects on college enrollment. The earning benefit results in higher tax payments which offset 7.2% of the program cost in childhood. Thus, parental investments can have large impacts on the fiscal cost of insurance by improving the long-run outcomes of children.

These findings suggest that the information of children's insurance can powerfully nudge parental investments in children. The investments improved child outcomes before the program investments, and predict lower social costs of insurance through the long-run effects on education. Investigations into the mechanism of investments reveal that the information reduced parents' present bias and increased parental utility due to the benefits on children. Thus, information outreach nudging parents to invest not only improves child outcomes, but ultimately improves parents' own utility and the cost-effectiveness of insurance.

This paper contributes to several strands of literature. First, although numerous studies have estimated the 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 children. Specifically, it uncovers how the information of insurance impacts parental preferences and investments, and estimates the resulting benefits on children and the insurance program. The role of information for investments is consistent with findings from early-childhood interventions (Heckman and Mosso, 2014), where improving parenting skills with information and preference change can have larger impacts on child outcomes than simple transfer policies.

This paper also contributes to a growing literature that evaluates the welfare of insurance programs based on beneficiaries' valuation of the insurance (Finkelstein and Hendren 2020; Finkelstein *et al.* 2019a; Finkelstein *et al.* 2019b). Here, I quantify mothers' valuation of the exposure by first estimating the behavioral effects of the exposure implied by the investment responses. In so doing, I also contribute to the literature on structural behavioral models, especially 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 adds to the literature on the application of 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). Absent financial incentives, informational nudges (Thaler and Sunstein, 2009) can induce behavioral changes by adjusting the behavioral biases. In the roll-out of CHIP, I find that the informational nudge increased utility as effectively as subsidized expansions of mothers' 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. 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 the Title XXI of the Social Security Act. Title XXI allowed states to expand public insurance for children either through an existing Medicaid program or through a separate program for children. States opting for either type of expansion were eligible for a total of $40 billion federal funding 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 the timing of CHIP onset across states, along with changes in the income limit of insurance for children in different age groups.[2] Of the 50 states that expanded insurance

[1] The only exception is Tennessee, where the Medicaid program disenrolled a large number of enrollees 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 collect information on subsequent expansions in 2001-2019 based on the 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.

for children, 11 states also expanded insurance for adults using state funding.[3] I focus on the 39 states expanding insurance exclusively for children to estimate the parental responses to children's insurance.

During the roll-out, the income limit of Medicaid/CHIP increased by 80% of the federal poverty level (henceforth FPL) across states. The expansion significantly increased the insurance eligibility for children. Figure 1 shows the share of children predicted to be eligible for Medicaid/CHIP based on income limits known at the time of pregnancy.[4] Before the roll-out, around 15% of the children born in Jan. 1997 were eligible for Medicaid/CHIP in childhood. The roll-out in 1997-2000 doubled the share of eligible children to 30% across states. By Dec. 2000, all states (except Tennessee) had expanded insurance for children, and on average, children could expect 5.7 (= 30% · 19) years of childhood eligible for public insurance.

3 Conceptual Framework

To conceptualize the parental responses to the expansion, I consider a two-period model where 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. Less healthy children require additional health services in childhood, and the out-of-pocket cost is lower if the child is eligible for public insurance. I analyze how the insurance eligibility could impact 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

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

[3] States expanding insurance for children as well as adult members of the family are marked with an asterisk beside the state name in 1.

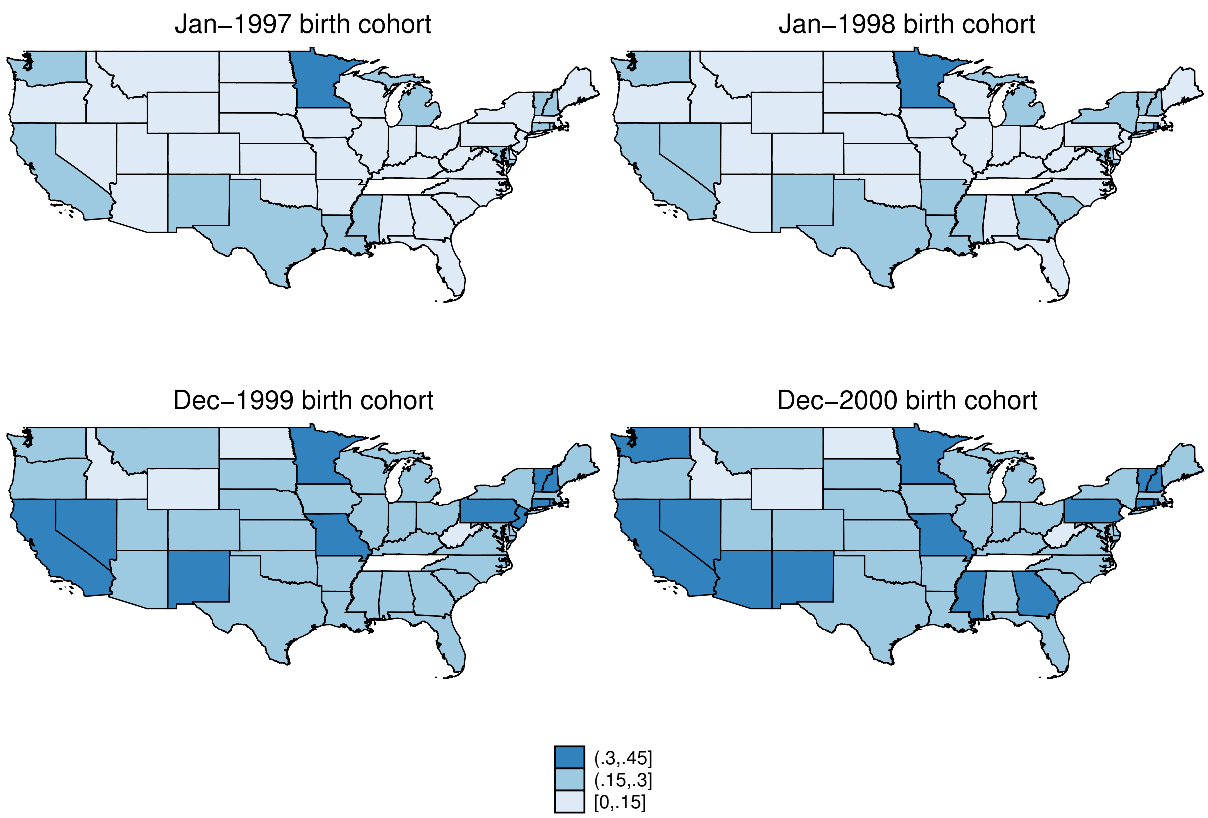
[4] I calculate the probability of being eligible for Medicaid/CHIP applying the income limits in Table 1 to a reference population in the 2000 census, following the "simulated eligibility" approach pioneered by Currie and Gruber (1996a) and Currie and Gruber (1996b). I show details of the calculation 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 the onset timing and increases in the income limit for infants (age 0), small children (age 1-5), and older children (age 6+) in each state. Footnote 2 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. For each cohort, I predict the probability of being eligible for Medicaid/CHIP based on the income limits of insurance (Table 1) known in pregnancy. Appendix A details the calculation.

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, which may vary by education $s(v_1^h)$ and health h. δ is the discount factor.

Because the medical expenses decrease parents' resources, non-health investments are smaller in the less healthy child.[5] Gaining eligibility for Medicaid/CHIP reduces the out-of-pocket expenses, allowing parents to invest more in the less healthy child. The investments reduce the education gap $\Delta\Gamma = \Gamma(s(v_1^1)) - \Gamma(s(v_1^0))$ by child health, and further reduce the gaps in adult outcomes $\Delta V = V^1(s(v_1^1)) - V^0(s(v_1^0))$ and 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 investment v_0 to maximize the utility in utero and in childhood

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

where $c_0 = Y_0 - v_0$ is consumption, 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 $\rho'' < 0$. $\tilde{U}_1^h$ is the maximized utility in childhood given health h.[6]

Optimal investment in utero 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 on future utilities. 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 on the utility from birth weight. Optimal investment balances the marginal benefits with the marginal cost $u'(c_0)$.

The roll-out of CHIP affects the trade-off by reducing the benefits of investments on future utilities. Because the expansion 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 investment costs in utero but reduced the marginal benefits, equation 3 predicts smaller in-utero investments in

[5] I show detailed proofs in Appendix B.

[6] I assume for simplicity that parents know their future income Y_1 and hence the insurance eligibility of children. In practice, parents may predict incomes and children's insurance probability based on program rules known in pregnancy. In general, insurance probability increases with higher income limits of insurance.

response to CHIP.

3.3 Investment Crowd-In

Contrary to the prediction in equation 3, empirical evidence in Section 5 shows substantial increases in mothers' in-utero investments in the roll-out. The crowd-in suggests the existence of additional mechanisms that increased the benefit of investments instead of decreasing it.[7] To explain the crowd-in, I motivate two behavioral mechanisms whereby the exposure to the roll-out may have adjusted parents' preferences and hence the perception of investment benefits.

Altruism. The exposure may increase investments by raising parents' altruism for children. I model the behavioral effect as an increase in the utility weight on child outcomes. In equation 3, increasing the utility 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 $\Delta\Gamma + \delta\Delta V$ adjusted by the utility weight α. Larger utility weight thus increases parents' perceived benefit of investments. When parents care sufficiently more about child outcomes, the perceived benefit could increase despite smaller gaps in $\Delta\Gamma + \delta\Delta V$, leading to a crowd-in of investments.

Present Bias. The exposure could also increase investments by adjusting parents' inter-temporal preferences. Because investments have immediate costs but delayed benefits, parents who are overly sensitive to their immediate utilities tend to under-invest in utero. By shifting inter-temporal weights towards future utilities, the roll-out of insurance could reduce parent bias and increase investments in utero.[8] In the $\beta-\delta$ representation (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 over-discount the future benefits of investments with $\beta < 1$, and under-invest in utero. The opportunity to enroll the child in CHIP may shift parents' inter-temporal weights towards future utilities, resulting in more

[7] I focus on changes in the 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.

[8] 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).

forward thinking and less present bias in pregnancy.

While an increase in either α or β predicts greater investments in equation 5, the behavioral effects have different implications for the timing of investments across trimesters. Because present bias generates cost avoidance in each trimester, a reduction in present bias could further shift investments towards early stages of pregnancy. I exploit this distinction in the investment timing to interpret the empirical findings in Section 5.

4 Data

I estimate the investment responses using the universe of birth certificates in the US. The certificates indicate the child's birth weight, time and location of the birth, as well as mother demographics and investments such as pre-natal visits and smoking. I restrict the sample to the 39 states that expanded insurance exclusively for children. Because states can provide maternity benefits to CHIP enrollees up to age 20, I exclude teen pregnancies and focus on mothers between age 21 and 40 at the time of delivery.[9]

Table 2 summarizes insurance eligibility, investments, and birth weight for children born in 1997-2000. While exposed to the same income limits (163% FPL over this period), children of single mothers were twice as likely to be eligible (41% compared to 21% on average) for Medicaid/CHIP. I exploit the eligibility difference in addition to the exposure timing across cohorts in the empirical analysis. Single mothers tend to have later onset of pre-natal visits and smoke more in pregnancy. Birth weight was lower by 100 grams for children of single mothers.

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 mothers' exposure to children's insurance. The roll-out increased the income limit of insurance across states. Mothers in states with higher income limits can expect greater insurance probability for children. Within states, insurance probability increased more for pregnant mothers gaining earlier exposure and hence greater duration of exposure to CHIP. I summarize the variations using the average income limit in pregnancy. Specifically, for mothers starting pregnancy in year-month t and state s, I construct in-utero exposure

[9] Teen pregnancies accounted for 17% of the births in 1997-2000, and pregnancies above age 40 accounted for 1%. 82% of the births in 1997-2000 were given by women between age 21-40.

Table 2: Summary statistics, children born in 1997-2000

	All Mothers		Single Mothers	
	Observations	Mean	Observations	Mean
Medicaid/CHIP				
Income limit (100% FPL)	9,878,786	1.63	2,418,021	1.62
Predicted eligibility	9,730,233	0.21	2,365,890	0.41
Care started in 1st trimester (%)	9,633,393	84.93	2,332,309	72.36
Care started in 3rd trimester (%)	9,622,393	5.46	2,332,309	11.44
# Doctor visits	9,539,497	11.73	2,303,023	10.78
≥ 5 cigarettes daily (%)	7,661,813	8.37	1,845,508	15.89
≥ 15 cigarettes daily (%)	7,661,813	3.10	1,845,508	5.80
Birth weight (grams)	9,872,895	3,342.30	2,416,286	3,234.47
Low birth weight (% <2,500 grams)	9,872,895	7.07	2,416,286	9.69

Notes: Table summarizes insurance eligibility, in-utero investments, and birth weight for children born between Jan. 1997 and Dec. 2000 in the 39 states expanding insurance exclusively for children over this period. I predict children's eligibility for Medicaid/CHIP based on the income limits of insurance known in pregnancy. Appendix A provides details of the prediction.

$eliginc_{ts}$ 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.[10]

Intuitively, equation 6 states that in-utero exposure is a simple weighted average of income limits inc_s^{pre} and inc_s^{post}, with the weights equal to 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}, whereas mothers starting pregnancy after CHIP ($j \geq 0$) are fully exposed to the CHIP limit inc_s^{post}. Therefore, in-utero exposure increases within states for mothers with earlier exposure and hence greater duration of exposure to CHIP. I exploit the variation across exposure timing in the empirical analysis, focusing on mothers starting pregnancy 16 months before through 4 months after CHIP ($-16 \leq j \leq 4$).

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

I estimate investment 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 control for county fixed effects α_c and time-varying factors by state-year in $\alpha_{s(c)} \cdot \tau_{y(t)}$. Because predicted eligibility is twice as large for children of single mothers (Table 2), I examine investment differences by single motherhood indicated by $single$. In particular, one might expect larger responses from single mothers captured in β_1 than from married mothers in β_2. In a robustness analysis, I 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 across 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 the roll-out did not affect mothers' fertility choice or marital status, 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 further examine investments across simulated eligibility by mother demographics in Section 5.4, finding similar results for single mothers.

5.2 Birth Weight

Before examining investment responses, I first examine whether birth weight improved with insurance exposure in utero. Because CHIP did not expand insurance for pregnant mothers, an increase in birth weight indicates the existence of private investment responses in the roll-out. Table 3 shows the results on birth weight applying equation 7 and 8.

Exposure to the roll-out significantly increased birth weight for children of single mothers. Gaining a 100% FPL exposure increased birth weight by 10.6 grams in column 1, and decreased the probability of low birth weight (<2,500 grams) by 0.32 percentage points in column 3, or by 4.5% below the mean. In both cases, exposure had little impact on birth weight for children of married mothers. In column 2 and 4, replacing the main effect of exposure with a full set of state-year-month fixed effects yields very similar results for children of single mothers. Based on these estimates, the roll-out of CHIP in 1997-2000, which expanded the income limit of insurance from 122% FPL to 202% FPL, increased birth weight by $10.6 \cdot 80\% = 8.5$ grams, and decreased the probability of low birth weight by $4.5\% \cdot 80\% = 3.6\%$ for children of single mothers.

Table 3: Effects of insurance 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 insurance exposure on birth weight (grams) and the percentage of children with low birth weight (<2,500 grams). I estimate separate effects by single motherhood applying equation 7 in column 1 and 3, and focus on children of single mothers applying equation 8 in column 2 and 4. Robust standard errors clustered at the level of states in the parentheses.

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

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

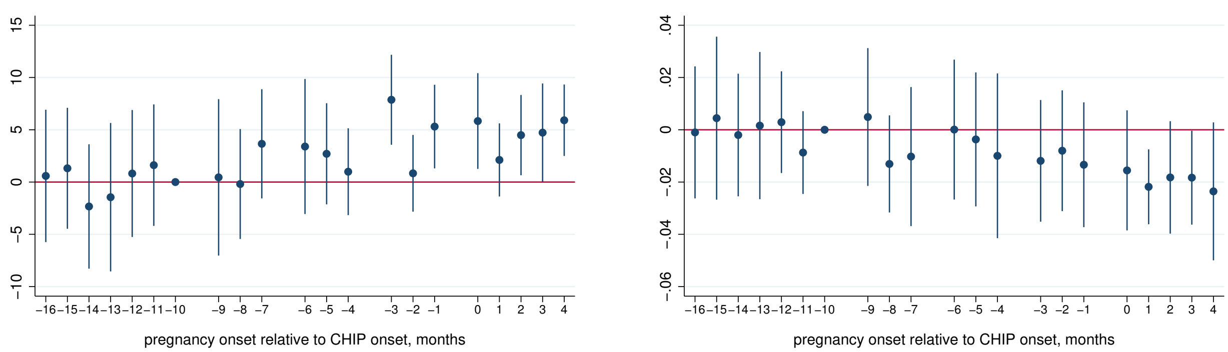
where I expand the term $\beta_1 \cdot eliginc_{ts(c)} \cdot single$ in equation 7 by the exposure timing j, and estimate separate effects across cohorts with β_j. I normalize the estimate on children conceived 10 months before CHIP to zero ($\beta_{-10} = 0$). These children and earlier cohorts ($j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

Figure 2 plots estimates of β_j for birth weight in panel (a). Insurance exposure did not increase birth weight for children never exposed to CHIP in utero ($j \leq -10$), or for children exposed to CHIP in the second and third trimester ($-9 \leq j \leq -4$). By contrast, exposure significantly increased birth weight for children exposed to CHIP in the first trimester ($-3 \le j \le -1$) and those fully exposed to CHIP in utero ($j \ge 0$). Among these children, gaining a 100% FPL exposure to CHIP increased birth weight by 4.1 grams and decreased low birth weight by 1.6% (Appendix Table I2).[11] Therefore, the increase in birth weight was concentrated among children of single mothers exposed to CHIP since the first trimester in utero.

Figure 2: Effects of insurance exposure on birth weight and care onset, event study

(a) Birth Weight (grams)

(b) Month Care Started



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

5.3 In-Utero Investments

The increase in birth weight suggests that exposure to the roll-out may have increased mothers' private investments in utero. To detect the investments, I examine mothers' pre-natal visits and smoking, and show responses in the timing and the level of investments using equation 7 and 8. I find that exposure resulted in earlier onset of visits and reduced smoking in pregnancy.

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

[11] To succinctly summarize the results, I group children by the trimester of exposure and show estimates across six exposure groups in Appendix Table I2. The estimates indicate the effect of CHIP exposure on birth outcomes, where the reference group ($-12 \le j \le -10$) had zero exposure to CHIP in utero.

The Guidelines for Perinatal Care (Freeman and Poland, 1992) recommends monthly doctor visits in the first two trimesters and weekly visits in the final month of pregnancy. Nonetheless, in Table 2, 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. Insurance exposure did not affect the onset of care for mothers never exposed to CHIP in pregnancy, and decreased the time to the first visit by an insignificant amount for mothers exposed to CHIP in the first trimester. The overall increase in the early onset of care was concentrated among single mothers with full exposure to CHIP ($j \geq 0$). For these mothers, gaining a 100% FPL exposure to CHIP reduced late care onset by 2.5%, and reduced very late onset in the third trimester by 5.5% (Appendix Table I3).

Table 4: Effects of insurance exposure on the timing of care onset

	(1)	(2)	(3)	(4)	(5)	(6)
	Month Care Started		Late Onset (%) (2nd/3rd trimester)		Very Late Onset (%) (3rd trimester)	
$eliginc \cdot single$	-0.05***	-0.05***	-1.09***	-1.10***	-0.75***	-0.75***
	(0.01)	(0.01)	(0.26)	(0.27)	(0.25)	(0.25)
$eliginc$	0.02		0.33		0.29	
	(0.02)		(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 effects of insurance 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 by single motherhood using equation 7 in odd-numbered columns, and focus on the investments of single mothers using equation 8 in even-numbered columns. Robust standard errors clustered at the level of states in the parentheses.

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 led to an additional 0.09 visit in pregnancy. This effect is small in magnitude. Compared to the sample average of 11.7 visits, the exposure increased pre-natal visits by less than 1%. Results across exposure timing in Appendix Table I4 show a similar null effect on the number of visits, including for mothers with full exposure to CHIP. Among these mothers, despite earlier onset of visits, the number of visits did not increase significantly with exposure.

Table 5: Effects of insurance 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	0.09**	0.09*	-0.45**	-0.46**	-0.38***	-0.39***
	(0.05)	(0.05)	(0.18)	(0.18)	(0.13)	(0.13)
eliginc	-0.05		-0.07		0.06	
	(0.04)		(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 effects of insurance exposure on the number of pre-natal visits and smoking in pregnancy. I estimate separate effects by single motherhood using equation 7 in odd-numbered columns, and focus on the investments of single mothers using equation 8 in even-numbered columns. Robust standard errors clustered at the level of states in the parentheses.

The birth certificate also indicates the number of cigarettes consumed daily in pregnancy. Because the consumption recall is subject to measurement errors which may attenuate the smoking responses, I focus on the intensive margin and examine responses across 5 and 15 cigarettes daily in column 3-6 of Table 5. Gaining a 100% FPL exposure reduced smoking over 5 cigarettes daily by 5%, and reduced heavy smoking above 15 cigarettes by 13%. These effects were similarly concentrated among single mothers exposed to CHIP since the first trimester in pregnancy (Appendix Table I4).

5.4 Heterogeneity

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

$$y_{itc} = \sum_k \beta_k \cdot eliginc^k_{ts(c)} \cdot single + \gamma \cdot eliginc_{ts(c)} + \beta_c \cdot single + \alpha_c + \tau_t + \alpha_{s(c)} \cdot \tau_{y(t)} + \epsilon_{itc}, \quad (10)$$

where β_k estimates the effect of exposure in state k.[12] I plot estimates of β_k in Appendix Figure J1, ranking states by the size of expansion on the horizontal axis. Exposure had the

[12]Specifically, $eliginc^k_{ts(c)} = eliginc_{ts(c)} \cdot 1\{s(c) = k\}$ is insurance exposure interacted with state indicators. The state-specific effects can also be estimated from separate state-level regressions

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

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

largest impact on birth weight in small expansion states increasing income limits by no more than 70% FPL.[13] In these states, the expanded income limit (162% FPL) remained 40% FPL below the national average, and a 100% FPL expansion would increase birth weight by 16 grams, or by 50% above the average effect across states. 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 were comparable to the average effects across states.[14] Finally, a handful of states (10% of births) expanded income limits by more than 100% FPL.[15] The increases in birth weight and investments tend to be smaller in the largest expansion states.

Simulated Exposure. In support of the main analysis, I show similar investment responses using the simulated eligibility strategy (Currie and Gruber 1996a; Currie and Gruber 1996b). Specifically, I calculate the probability of being eligible for Medicaid/CHIP applying the income limit of insurance to 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 mothers' exposure to children's insurance.[16] I then estimate investment responses to simulated exposure $eligCHIP$ in the following specification

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

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 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 $\alpha_s \cdot \tau_{y(t)}$, 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

[13] The small expansion states accounted for 25% of births in the roll-out. The state with the largest expansion in this group was Maine, where the income limit increased by 55% FPL. States such as Louisiana, South Dakota, Wyoming, Iowa, and Mississippi expanded income limits by 22.58% FPL. Minnesota expanded income limits by a minimal 0.26% FPL in the roll-out, essentially maintaining the same income limit (275% FPL) as before. I do not estimate state-specific effects for Minnesota in equation 10.

[14] This range includes some of the most populous states such as California, Texas, New York, and Florida. In these states, birth weight increased by 13.6 grams per 100% FPL expansion, or by 30% above the average effect across states.

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

[16] I show details of the simulation in Appendix A. The roll-out of CHIP increased simulated exposure to 50% for single mothers, and to 22% for married mothers.

Appendix Table I5. Increasing exposure by 10 percentage point eligibility increases birth weight by 2.7 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 8.2 grams. This effect is comparable to the 8.5 gram increase implied by estimates from equation 8 in Table 3.[17] Similarly, investment responses to eligibility increases are comparable to the effects of expanded income limits for single mothers,[18] supporting the results from equation 8.

5.5 Mechanism

The empirical results show compelling evidence that in-utero investments increased in the roll-out of CHIP. To understand mechanisms, I examine whether the exposure increased mothers' uptake of own insurance and safety net benefits using the Survey of Income and Program Participation (SIPP). I also examine whether mothers invested more in utero to improve the long-run outcomes of children. I find little support for these mechanisms. I then discuss how behavioral mechanisms adjusting mothers' altruism and present bias may better explain the investments.

Resource Constraints. I first examine whether the exposure increased investments by increasing mothers' uptake of own insurance and cash benefits. In Appendix Table I6, exposure to children's insurance did not affect mothers' Medicaid coverage or benefits from the Food Stamp and the WIC programs. The exposure also had no impact on mothers' incomes in pregnancy. Moreover, in Appendix Table I7, I find no evidence that mothers borrowed more from future incomes to invest more in utero. Specifically, exposure did not affect mothers' credit card debts, personal loans, or checking and saving account balances. These results are inconsistent with a resource-based mechanism whereby the exposure increased investments by relaxing mothers' 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 also expect better outcomes for children later in life. I test this implication contrasting mothers' decision to enroll the child in CHIP and her expectation of the child's

[17] Specifically, simulated exposure implies a birth weight gain of $(0.50 - 0.33) \times 48.2 = 8.2$ grams. The roll-out expanded income limits by 80% FPL, increasing birth weight by $10.6 \times 80\% = 8.5$ grams based on estimates from equation 8 in Table 3.

[18] 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.

education attainment in Appendix Table I8. Mothers exposed to CHIP since the first trimester, in addition to investing more in utero, also had substantially higher uptake of insurance for their newborns (column 1), but despite their investments, these mothers did not indicate higher expected education for children (column 2-4). This result suggests that investments were not motivated by the long-run effects on child outcomes.

Altruism. The exposure may also increase investments by raising mothers' altruism for the child. This could happen if the roll-out increased mothers' awareness of the child's well-being. The behavioral effect tends to lower the utility cost of investments, which may lead to increased pre-natal visits and less smoking in pregnancy. Empirically, the exposure significantly increased the early onset of visits but had smaller and weaker effects on the total number of visits by the end of pregnancy. The response in the investment timing across trimesters is not fully explained by the behavioral effect on altruism.

Present Bias. To better explain the shifts in the investment timing, I consider behavioral effects of exposure on mothers' inter-temporal preferences. The opportunity to enroll the child in CHIP may have increased mothers' forward thinking and planning, shifting her inter-temporal weights from immediate investment costs to future utilities. The reduction in present bias is consistent with less delay in the investment onset, more self-control over additive consumption such as smoking, and higher program uptake among mothers investing more in utero. I formally investigate the behavioral mechanisms using a dynamic model of in-utero investments in Section 7, where I quantify the effects on altruism and present bias exploiting investment responses in the roll-out.

6 Education Outcomes

I next examine whether investments increased children's education attainment using the American Community Survey (ACS). I find that children exposed to the roll-out in utero were more likely to obtain a high school diploma and enroll in college, and the education gains were concentrated among children of single mothers.

6.1 Empirical Strategy

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

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

where y_{ibqt} is the education attainment of child i conceived in year-quarter q and state s. t is the survey year. $eliginc_{ibq}^{utero}$ is the child's in-utero insurance exposure, calculated as the average income limit of Medicaid/CHIP in the three quarters before birth. $single$ indicates children of single mothers. Because investment responses to the roll-out were concentrated among single mothers, 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). X_{ibqt} includes insurance exposure in childhood, calculated as the average income limit of Medicaid/CHIP between birth and year t, and the child's age.[19]

I control for differences by single motherhood across states with $\beta_b \cdot single$, and control for time-varying factors across states with $\gamma_b \cdot \psi_{y(q)}$. Within states and mother groups, I exploit the variation in the timing of exposure across cohorts to estimate the long-run effects. In a robustness analysis, I further include a full set of state-quarter effects $\gamma_b \cdot \psi_q$ in the following specification

$$y_{ibqt} = \beta \cdot eliginc_{ibq}^{utero} \cdot single + \beta_b \cdot single + \gamma_b + \psi_q + \tau_t + \gamma_b \cdot \psi_q + \theta \cdot X_{ibqt} + \epsilon_{ibqt}, \tag{14}$$

where $\gamma_b \cdot \psi_q$ absorbs the main effect of exposure $eliginc_{ibq}^{utero}$ and flexibly controls for state-specific time trends in the roll-out. β estimates the long-run impacts of exposure on children of single mothers.

Exploiting the roll-out, I estimate equation 13 and 14 for children conceived 7 quarters before through 2 quarters after CHIP. In the sample, the average child was expected to complete high school (Grade 12) by 2016-2017, and children in the earliest cohort were expected to enter high school (Grade 9) in 2010-2011. I hence track children's education attainment from high school to college using 2010-2019 waves of the ACS. Appendix C summarizes the sample in detail.

I consider two measures of single motherhood based on mothers' marital history. The first requires that the mother has never married at the time of the survey. Under this measure, the child was born to a single mother who remained single throughout parenthood. The second measure only requires that the mother was unmarried in survey year t. Ex

[19] I include separate controls of childhood exposure by mother's marital status in X_{ibqt}.

ante, one might expect larger effects in the long run on children raised continuously in single-mother households.

Equation 13 and 14 may yield biased estimates if exposure to children's insurance affected mothers' marital status or fertility choice. Empirically, I rule out responses in the marital status in Appendix Table I9, and rule out fertility responses in Appendix Table I1. Thus, differences in the exposure timing across cohorts are plausibly exogenous to children of single mothers. I illustrate the identifying variation with event study estimates below.

6.2 Effects on Education

College Enrollment. Table 6 shows the effects on college enrollment. Gaining a 100% FPL exposure in utero increased college enrollment by 1.45 percentage points for children of single mothers (column 3), or by 8.2% above the mean. The exposure had larger impacts on children of never-married mothers (column 1), increasing college enrollment by 2.92 percentage points. By contrast, exposure did not increase college enrollment for children of married mothers. Further controlling for state-quarter fixed effects in column 2 and 4 yields similar estimates for children of single mothers. Therefore, consistent with investment responses in utero, the long-run impacts on college enrollment were concentrated among children of single mothers.

To illustrate the identifying variation, I plot event study estimates across exposure timing in Figure 3. Children conceived more than 4 quarters before CHIP were not exposed to CHIP in utero, and college enrollment did not increase for these children (panel a). The overall increase in college enrollment was concentrated among children exposed to CHIP since the first trimester in utero. For these children, gaining a 100% FPL exposure to CHIP increased college enrollment by 0.67 percentage points, and by 1.30 percentage points among children of never-married mothers.

High School. Appendix Table I10 shows the results for high school graduation rates. For children of never-married mothers, gaining a 100% FPL exposure in utero increased high school graduation rates by 1.55 percentage points, or by 4.9% above the mean. The increase in high school graduation is smaller than the effect on college enrollment, suggesting that exposure increased college enrollment among high school graduates who would not have attended college absent the exposure. Across exposure timing, the increase in high school graduation rates was concentrated among children of never-married mothers with full exposure to CHIP in utero (panel b of Figure 3).

Table 6: Effects of insurance exposure on college enrollment (%)

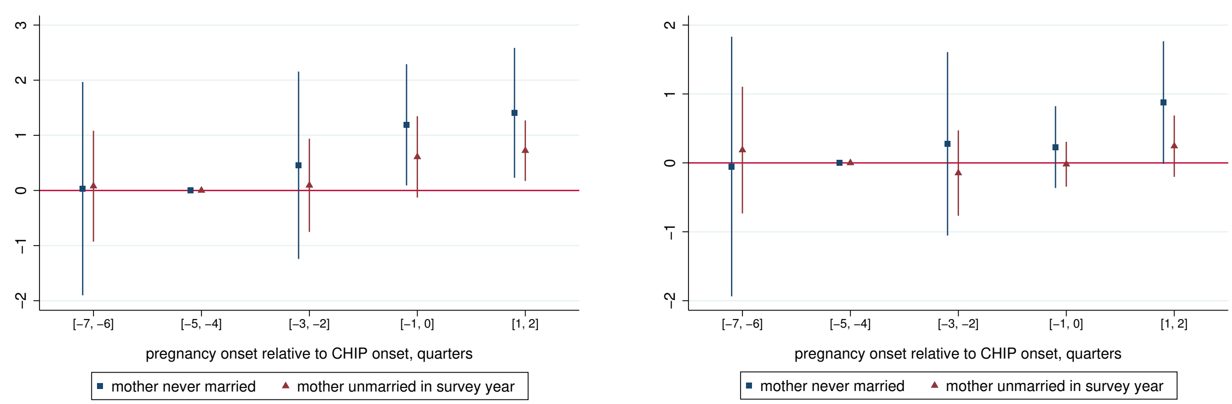
	(1)	(2)	(3)	(4)
$eliginc^{utero} \cdot single$	2.92***	2.87**	1.45**	1.40**
	(1.07)	(1.08)	(0.55)	(0.55)
$eliginc^{utero}$	0.24		0.06	
	(0.90)		(0.92)	
never-married mothers	Y	Y		
y mean	17.73%		17.73%	
R^2	0.36	0.36	0.36	0.36
N	304,367		304,367	

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

Notes: Table estimates the effects of insurance exposure on college enrollment. *single* indicates children of single mothers. Single mothers in column 1-2 have never married, and were unmarried in the survey year in column 3-4. I estimate separate effects by single motherhood using equation 13 in column 1 and 3, and focus on children of single mothers using equation 14 in column 2 and 4. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parentheses.

Figure 3: Effects of insurance exposure on college enrollment and high school graduation rates, event study

(a) College Enrollment (%) (b) High School Graduation (%)



Notes: Figure plots the effects of insurance exposure on college enrollment in panel (a) and on high school graduation rates in panel (b), across cohorts with different timing of exposure to CHIP. Children conceived more than 4 quarters before CHIP were not exposed to CHIP in utero. Exposure increased for later cohorts with earlier exposure to CHIP in utero. 95% confidence intervals are based on robust standard errors clustered at the level of states.

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.[20] This effect implies that the roll-out of CHIP would increase college enrollment by 0.60 percentage points.[21] In practice, the exposure increased college enrollment by 1.13 percentage points for children of single mothers, or by 0.33 percentage points for children on average.[22] 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 increased birth weight and led to higher college enrollment rates in the long run. Specifically, the exposure reduced low birth weight by 3.6% and increased college enrollment rates by 8.2% for children of single mothers. To understand the magnitude of the effect on birth weight, I compare the effect of insurance exposure with that 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, or by twice the effect of in-utero exposure to CHIP. 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.

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 child's birth weight. I examine investment timing across trimesters in addition to

[20]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.

[21]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.

[22]Specifically, CHIP expanded income limits by 80% FPL, increasing college enrollment by $0.8*1.45 = 1.16$ percentage points for children of single mothers, or by $28.28\% * 1.16 = 0.33$ percentage points on average.

total investments in utero to quantify the behavioral effects of exposure. I then evaluate welfare based on the model estimates.

7.1 Setting

Pre-Natal Visits. Let v_{it} be the monthly number of visits chosen by mother i in trimester t, with $t = 1, 2, 3$. Following the medical guidelines, I increase the maximum number of monthly visits from 1 in the first trimester to 2 in the second trimester and finally to 4 in the third trimester.[23] In total, the model allows for 21 visits in pregnancy. In the data (Table 2), mothers took around 11 visits in pregnancy.

Mother i's utility per visit depends on her taste for visits η_i and a taste shock υ_{it}. Taste η_i is a random coefficient distributed across three mother types in the population. I use the random coefficient to capture unobserved heterogeneity in the preferences for investments. To account for investment costs, I calibrate out-of-pocket cost c_{it} based on mother age a_i and a health shock ξ_{st}, and subtract the dollar cost from the utility.[24] I net out non-monetary costs of visits in taste η_i. The utility of taking v_{it} visits each month in trimester t is given in dollar terms as follows

$$\vartheta(v_{it}\,; \upsilon_{it}, \xi_{it}, a_i) = 3\, v_{it}\left[\eta_i + \upsilon_{it} - c_{it}(a_i\,, \xi_{it})\right]. \tag{15}$$

Smoking. I model smoking choice s_{it} using cut-points at 5 and 15 cigarettes daily. Specifically, I set $s_{it} = 0$ if mother i smokes fewer than 5 cigarettes daily, $s_{it} = 1$ if she smokes 5 to 15 cigarettes, or roughly half a pack daily, and $s_{it} = 2$ if she smokes more than 15 cigarettes daily. Each increment of smoking corresponds to around half a pack daily, and increases utility by $\zeta_i + \omega_{it}$, where ζ_i is the taste (net of costs) for smoking, and ω_{it} is a taste shock. The utility of smoking $s_{it} \in \{0, 1, 2\}$ in trimester t is the follows

$$\psi(s_{it}\,; \omega_{it}) = s_{it}\left(\zeta_i + \omega_{it}\right). \tag{16}$$

Birth Weight. Birth weight b_i depends on the mother's pre-natal visits and smoking in

[23]The larger number of visits in the third trimester matches the guideline recommendation of weekly visits for near-term mothers.

[24]86% of the pre-natal visits incurred zero out-of-pocket costs (see details in Appendix D). Due to the small amount of costs, I assume that investment costs were paid in each trimester rather than financed by loans against future incomes.

pregnancy. I specify a flexible birth weight production function as follows

$$log(b_i) = \phi_i + \phi_1 \cdot V_i + \phi_2 \cdot V_i^2 + \phi_3 \cdot smoke_i + \phi_4 \cdot heavy_i + \Phi(V_i, V_i^2, smoke_i, heavy_i) + \sigma \xi_{i3}, \tag{17}$$

where $V_i = 3\sum_{t=1}^{3} v_{it}$ is the total number of visits, and $\phi_1 + 2\phi_2 \cdot V_i$ is the marginal benefit of visits. $smoke_i$ and $heavy_i$ are binary variables based on average smoking $\bar{s}_i = \frac{1}{3}\sum_{t=1}^{3} s_{it}$. Specifically, $smoke_i$ indicates smokers with more than 5 cigarettes daily ($\bar{s}_i \geq 5$), and $heavy_i$ indicates heavy smokers with more than 15 cigarettes daily ($\bar{s}_i \geq 15$). ϕ_4 captures the incremental effect of heavy smoking.

I further interact pre-natal visits with smoking in $\Phi(V_i, V_i^2, smoke_i, heavy_i)$. The interactions allow the marginal benefit of visits to differ by smoking intensity. I allow for unobserved heterogeneity in the investment returns across mothers using the intercept ϕ_i. Larger values of ϕ_i imply greater returns of investments on birth weight. Finally, health shock ξ_{i3} impacts birth weight through the parameter σ.

Altruism. 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 raises α, increasing the utility from birth weight $L(b_i)$ 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 focus on the short-term patience β and fix the quarterly discount factor $\delta = 1$. In the third trimester, present-biased mothers choose investments to maximize utility

$$U_3\Big(v_{i3}, s_{i3}\,; \varepsilon_{i3}, \mathcal{I}_{i3}\Big) = \vartheta(v_{i3}\,; \upsilon_{i3}, \xi_{i3}, a_i) + \psi(s_{i3}\,; \omega_{i3}) + \beta\, \mathbb{E}\Big[L(b_i) | \mathcal{I}_{i3}, v_{i3}, s_{i3}\Big], \tag{18}$$

where $\varepsilon_{i3} = (\upsilon_{i3}, \xi_{i3}, \omega_{i3})$ is the vector of transitory shocks, and $\mathcal{I}_{i3} = (3\sum_{t=1}^{2} v_{it}, \sum_{t=1}^{2} s_{it}, X_i)$ is the state vector containing previous 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

$$\mathcal{U}_3\Big(v_{i3}^*, s_{i3}^*\,; \varepsilon_{i3}, \mathcal{I}_{i3}\Big) = \vartheta(v_{i3}^*\,; \upsilon_{i3}, \xi_{i3}, a_i) + \psi(s_{i3}^*\,; \omega_{i3}) + \mathbb{E}\Big[L(b_i) | \mathcal{I}_{i3}, v_{i3}^*, s_{i3}^*\Big]. \tag{19}$$

Compared to the long-run utility in equation 19, present-biased mothers over-discount the utility from birth weight with $\beta < 1$ in equation 18 and hence under-invest in $t = 3$.

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

$$U_2(v_{i2}, s_{i2}; \varepsilon_{i2}, \mathcal{I}_{i2}) = \vartheta(v_{i2}; \upsilon_{i2}, \xi_{i2}, a_i) + \psi(s_{i2}; \omega_{i2}) + \beta\, \mathbb{E}[\mathcal{U}_3 | \mathcal{I}_{i2}, v_{i2}, s_{i2}], \tag{20}$$

where $\mathcal{U}_3$ is the long-run utility implied by investments in $t = 3$ (equation 19). Maximizing equation 20 yields investments (v^*_{i2}, s^*_{i2}) in $t = 2$. Recursively, present-biased mothers over-discount the long-run utility implied by (v^*_{i2}, s^*_{i2}) with $\beta < 1$ when investing in $t = 1$.[25] I hence solve for mother i's investments $\left(v^*_{it}, s^*_{it}\right)_{t=3,2,1}$ from equation 18 to 21 given the short-term patience β.

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 $\Delta\ell_{js} = eliginc_{js} - inc^{pre}_s$ 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 ($-9 \leq j \leq -1$), $\Delta\ell_{js} = (1 + \frac{j}{9}) \cdot \Delta inc_s$ increases with j for mothers with earlier exposure to CHIP, and increases with expansion size $\Delta inc_s = inc^{post}_s - inc^{pre}_s$. Mothers gaining full exposure to CHIP ($j \geq 0$) have $\Delta\ell_{js} = \Delta inc_s$, and mothers never exposed to CHIP in pregnancy ($j \leq -10$) have $\Delta\ell_{js} = 0$.

I calculate $\Delta\ell_{js}$ for 324,400 non-college-educated single mothers starting pregnancy 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.[26] I discretize $\Delta\ell_{js}$ into 5 nodes, corresponding to 0%, 10%, 30%, 50%, and 70% FPL exposure. I assign

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

$$U_1(v_{i1}, s_{i1}; \varepsilon_{i1}, \mathcal{I}_{i1}) = \vartheta(v_{i1}; \upsilon_{i1}, \xi_{i1}, a_i) + \psi(s_{i1}; \omega_{i1}) + \beta\, \mathbb{E}[\mathcal{U}_2 | \mathcal{I}_{i1}, v_{i1}, s_{i1}], \tag{21}$$

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

[26]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.

mothers with $j \le -10$ to the zero exposure node, and assign mothers with $j \ge -9$ 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

$$\alpha_i = \alpha_0 + \alpha_1 \Delta\ell_i , \tag{22}$$

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 $\alpha_0 = 1$.[27] Similarly, I specify a behavioral equation for present bias

$$\beta_i = \beta_0 + \beta_1 \Delta\ell_i , \tag{23}$$

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 $(\alpha_1, \beta_0, \beta_1)$ to quantify the behavioral effects of CHIP exposure.

Moment Conditions. Based on equation 22 and 23, 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 $\Delta\ell_i$,

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

To estimate the birth weight production function in equation 17, I construct moment conditions exploiting the exposure levels in $\Delta\ell_i$ as instruments.[28] Specifically, I match

[27] 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.

[28] The production function in equation 17 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.

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

$$P_i^k = P^k\left(X_i\,;\pi^k\right) = \frac{F(\pi^k \cdot X_i)}{\sum_{n=0,1,2} F(\pi^n \cdot X_i)}, \tag{24}$$

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 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% · 0.13/0.75).

I illustrate the identification of the behavioral effects comparing simulated investments with empirical counterparts in the data. In Figure 4, 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 J2 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 J3).

Birth Weight. The lower panel of Table 7 estimates the birth weight production function in equation 17. 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 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

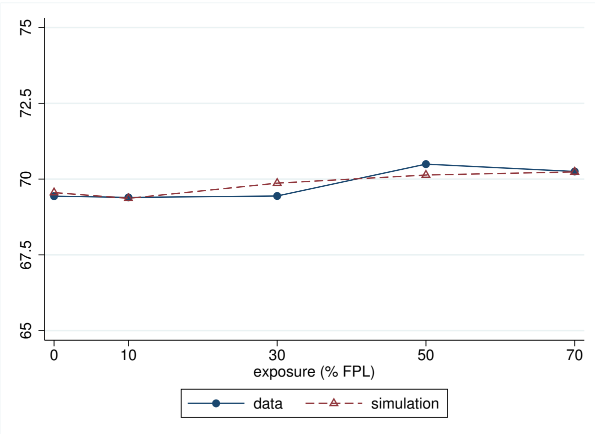
Table 7: Estimated model parameters

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)		

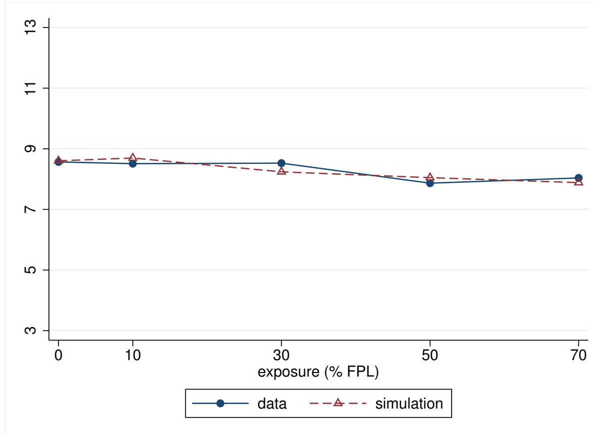
Notes: Table shows estimates of the model parameters. The top panel shows estimates of the behavioral effects in equation 22 and 23. The middle panel shows estimates of mother types – in terms of visits, smoking, and the birth weight endowment – as well as the share of each type in the population. The last panel shows estimates of the birth weight production function (equation 17) and mother's marginal utility from birth weight governed by θ. Standard errors of the estimated parameters in the parenthesis.

Figure 4: Investment responses to CHIP exposure, model fit

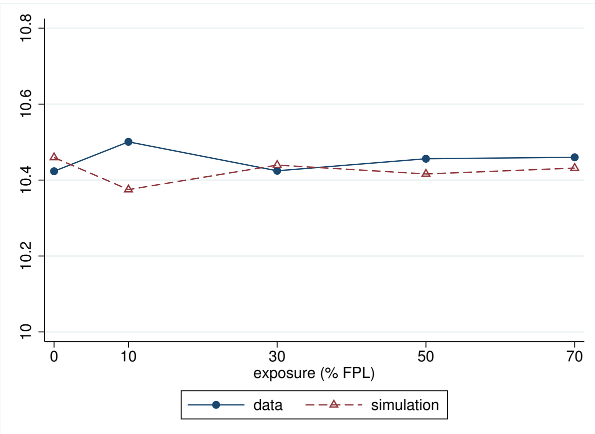
(a) First Trimester Onset (%)



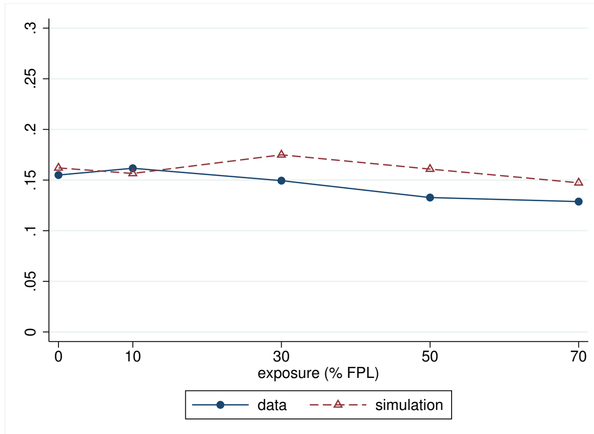
(b) Third Trimester Onset (%)



(c) Number of Pre-Natal Visits



(d) Smoking (Half Packs)



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.

response to the exposure. To illustrate this point, I simulate investments and birth weight across mother types in Appendix Figure J4. 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 $\mathcal{U}^*$.[29] 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, 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.[30] Investments have larger costs on utility for type 0 and type 1 mothers, but the benefits on birth weight

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

$$\mathcal{U}(I) = \mathbb{E}\left[\sum_{t=1}^{3} \vartheta(v_t; \varepsilon_t, \mathcal{I}_t) + \sum_{t=1}^{3} \psi(s_t; \varepsilon_t, \mathcal{I}_t) + L\left(b^i; \varepsilon_3, \mathcal{I}_3\right)\right], \tag{25}$$

which sums over utility in each trimester applying the long-run discount factor $\delta = 1$. Optimal investments I^* maximizing equation 25 give the long-run utility $\mathcal{U}^* = \mathcal{U}(I^*)$.

[30] 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.

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

$$WTP_i = \frac{\mathcal{U}_i^1 - \mathcal{U}_i^0}{\Delta\ell_i} = \frac{C_i^1 - C_i^0}{\Delta\ell_i} + \frac{M_i^1 - M_i^0}{\Delta\ell_i}, \tag{26}$$

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 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.[31]

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

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

$$MVPF = \varphi \frac{WTP}{\Delta G} = \varphi \frac{WTP^C}{\Delta G} + \varphi \frac{WTP^M}{\Delta G}, \tag{27}$$

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 $\Delta inc_{s(i)} = inc^{post}_{s(i)} - inc^{pre}_{s(i)}$ 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.[32] 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 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, because 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

[32] 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.

tax payments from college enrollment.

Specifically, exposure to the roll-out increased college enrollment by $80\% \cdot 1.45 = 1.16$ percentage points for children of single mothers (Table 6). Under the assumption that college students induced by the exposure attend college for two years, and that each year of college increases earnings by 11.3% (Zimmerman, 2014), the exposure predicts higher earnings by $2 \cdot 11.3\% \cdot 0.0116 = 0.26\%$ for children of single mothers. Discounted to the program onset in 1997 using a 2% annual discount rate, the life-cycle earning benefit amounts to \$946.38 per child of single mother. Under a 18.9% marginal tax rate (Hendren and Sprung-Keyser, 2020), the exposure increases tax payments by $18.9\% \cdot \$946.38 = \$178.87$ per child of single mother, or by $\frac{\$178.87}{\$2{,}483.10} = 7.2\%$ of the program cost in childhood.

These calculations suggest that, prior to program investments in children, parental investments during the roll-out could lower the social cost of insurance by 7.2% over the long run. To gauge the magnitude of the fiscal impact, I consider alternative assumptions in Appendix H. Parental investments can offset 13.2% of the program cost when students enroll in college for 4 years rather than 2 years, and offset 5.2%-9.5% of the cost with a 3% annual discount rate. To account for uncertainties in the estimated effects on education and earnings, I calculate 95% confidence intervals based on bootstrap draws of effect sizes (Appendix Table H2). Across scenarios, parental investments predict significant reductions in the social cost of insurance, with the median estimate suggesting a 5.0%-7.0% reduction in costs when children attend college for two years.

Finally, I compare the fiscal externality of parental investments with that of program investments in children. Focusing on children born in the early 1980s, Brown *et al.* (2020) estimates that each year of Medicaid eligibility in childhood increased earnings in age 28 by \$214.81.[33] Assuming two years of college enrollment, exposure to the roll-out of CHIP predicts higher earnings by \$40.85 in age 28 for children of single mothers, or by $\$40.85 \cdot 28.28\% = \$11.55$ for children on average. Thus, parental investments magnify the fiscal externality of program investments and could further lower the social cost of insurance by $\frac{\$11.55}{\$214.81} = 5.4\%$ over the long run.

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.[34] 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

[33] The original estimate is an increase of \$280 (in 2011 dollars) shown in Figure 5 and Appendix Table OA.5 of Brown *et al.* (2020). I index the earning gain to 2000 dollars using CPI-U.

[34] 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.

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 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 7% 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 insurance eligibility using the full sample of women between age 21 and 40 in the 2000 decennial census. I apply the income limit of Medicaid/CHIP in state s and time t for children in age band b to the reference sample, assuming all women have a child in the given age band b. Specifically, the child is eligible for Medicaid/CHIP if family income $finc_i$ is below the income limit inc_{st}^b. I therefore parameterize the income limit using the share of children eligible for insurance as follows

$$eligCHIP_{st}^b = \frac{1}{N}\sum_i 1\{finc_i \leq inc_{st}^b\}, \tag{A1}$$

where $N = 1,948,731$ is the number of women in age 21-40 in the 2000 census. Because the income limit inc_{st}^b is applied to a fixed population of mothers, differences in $eligCHIP_{st}^b$ capture exogenous variation in program rules that shifted income limits across state, time, and child age.

I calculate $eligCHIP_{st}^b$ for three age bands: infants (age 0), small children (age 1-5), and older children (6+). Table 1 lists the changes in the income limits across states and age bands. I average out age b to simulate insurance eligibility in childhood $eligCHIP_{st}$:

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

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

Because children in low-income families are more likely to be eligible given the income limit, I calculate eligibility separately for mother demographic groups that differ by marital status, race, and education. Specifically, eligibility for children in demographic group g is given by

$$eligCHIP_{gst}^b = \frac{1}{N_g}\sum_{i\in\mathcal{G}} 1\{finc_i \leq inc_{st}^b\}, \tag{A3}$$

where $\mathcal{G}$ is the pool of children in group g. $eligCHIP_{gst}^b$ is the share of children in age b and group g eligible for Medicaid/CHIP given the income limit. Within group g, differences in eligibility $eligCHIP_{gst}^b$ capture exogenous policy variations in income limits across state, time, and child age. I then average out age b to simulate insurance eligibility in childhood $eligCHIP_{gst}$

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

To calculate in-utero exposure, I first simulate eligibility $eligCHIP_{gs\tau}$ based on income limits in month τ of the pregnancy, and then average the monthly eligibility over a 9-month pregnancy as follows

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

where t is the pregnancy onset time, and $eligCHIP_{g(i)st}$ is the in-utero exposure of mothers starting pregnancy in month t. I plot $eligCHIP_{g(i)st}$ across states and cohorts during the roll-out in Figure 1. I also use it as the simulated exposure measure in Section 5.4. Simulated 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 mothers' in-utero exposure to children's insurance. Specifically, in-utero exposure is given by

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

where $inc_{\tau s} = \frac{1}{19} inc^{0}_{\tau s} + \frac{5}{19} inc^{1-5}_{\tau s} + \frac{13}{19} inc^{6+}_{\tau s}$ is the income limit known in state s and month τ of pregnancy. This calculation is equivalent to the definition in equation 6. $eliginc_{ts}$ 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. Non-health investment v_1^h improves the child's education $s(v_1^h)$. $V^h(s(v_1^h))$ is the utility from the child's adult outcomes, which may depend on education and child health. A less healthy child ($h = 0$) incurs medical expenses $OOPC$. Optimal investment v_1^{h*} satisfies 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 the 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 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 $c_0 = Y_0 - v_0$ is consumption, 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 investing in a 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 investment in $t = 1$ now solves

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

and in-utero investment solves

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

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

When CHIP increases altruism α and reduces $OOPC$, 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, the response in consumption is ambiguous. In the case that 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 the investment responses and the marginal effects $\Gamma' s' + \delta V' s'$ by child health. These quantities are indeterminate from equation B5. In general, the exposure could increase parents' perception of investment benefits by increasing their valuation of $\Delta \tilde{U}_1(\alpha) = \Delta u + \alpha (\Delta\Gamma + \delta \Delta V)$,[35] hence increasing investments in utero 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 immediate costs but delayed payoffs, present bias results in under-investments in the short run. Specifically, present bias modifies investments in childhood according to

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

and modifies investments in utero according to

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

where utility gap $\Delta \tilde{U}_1(\alpha, \beta) = \Delta u + \alpha (\Delta\Gamma + \delta \Delta V)$ is adjusted by both present bias β and altruism α.

When CHIP reduces present bias (higher β) in addition to increasing altruism, non-health investments increase even more for children of both health types. However, due to the decrease in $OOPC$, the consumption response is ambiguous for parents of a less healthy child, and the gap in child outcomes may increase or decrease depending on the investment responses and the marginal effects by child health. In general, larger behavioral effects on either altruism or present bias result in greater increases in the perceived benefits

[35] 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 follows 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 due to larger α from the exposure.

of investments $\beta\delta\rho'(v_0^*)\Delta\tilde{U}_1(\alpha,\beta)$,[36] leading to larger increases in investments based on equation B8.

[36]Continuing the example in footnote 35, allowing for present bias, perceived investment benefit $\beta\delta\rho'(v_0^*)\Delta\tilde{U}_1(\alpha,\beta) = \rho'(v_0^*)\beta\delta(1+\alpha+\alpha\beta\delta k)\log\left(\frac{Y_1}{Y_1-OOPC}\right)$, which may 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 through 2 quarters after CHIP in the American Community Survey (ACS). To focus on education attainment in high school and in college, I further restrict the sample to children age-ready for high school (Grade 9) or above in the ACS. Because the earliest cohort – those conceived 7 quarters before CHIP – were born in the second quarter of 1996 and became age-ready for Grade 9 in 2010-2011, I use the 2010-2019 waves of ACS to examine the education attainment. The average child in the sample should complete high school (Grade 12) by 2016-2017. Appendix Table C1 summarizes the sample.

Table C1: Sample summary, education attainment ($N = 304,367$)

	mean	s.e.		mean	s.e.
Enrolled in college (%)	17.73	0.07	Expected year		
Graduated high school (%)	31.47	0.08	entering high school	2012.77	0.002
Insurance exposure			entering college	2016.77	0.002
in utero (100% FPL)	1.60	0.001	Mother never married (%)	8.07	0.05
childhood (100% FPL)	2.34	0.001	Mother unmarried in t (%)	28.28	0.08

Notes: Table summarizes the estimation sample for education outcomes. Sample includes children conceived 7 quarters before through 2 quarters after CHIP who were age-ready for high school or above in 2010-2019 waves of the American Community Survey (ACS). I link children to mothers using the family interrelationships variables developed by Ruggles *et al.* (2020), requiring that the mother was between age 21 and 40 at the time of childbirth. Based on mothers' marital history, I summarize the share of mothers who had never married, or were unmarried in survey year t.

Variable Definition. I determine the child's school entry age based on the school entry law in the state. Specifically, children turning five before the cut-off month can start kindergarten in the same year, whereas those turning five after the cut-off month start in the next year. I assume that children born in the same quarter as the cut-off were born after the cut-off month, and hence adopt the more generous criterion in determining the school entry age.[37] I then focus on children who were age-ready for high school or above in the 2010-2019 waves of the ACS.

I link children to mothers using the family interrelationships variables developed by Ruggles *et al.* (2020). To be consistent with the birth sample, I restrict the long-run sample in the ACS to children whose mothers were in age 21-40 at the time of childbirth. Based on mothers' marital history, I define single motherhood requiring that the mother had never married, or was unmarried in survey year t. 8.07% of children were in households where the mother never married, and 28.28% were in households where the mother was unmarried in survey year t.

[37] 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). The "Event Files" contain expenditure data for all inpatient and outpatient visits made by household members in a calendar year. The "Full-Year Files" contain the demographic information of individuals. I focus on non-college-educated single women between age 21 and 40 in the 1997-2001 surveys. Among this group, I identify pregnant women who had a hospital visit where the reason of the visit was to "give birth to a child" in the Event Files.

For pregnant women, I examine pre-natal visits in the 9-month period before the birth event. Specifically, pre-natal visits should take place in an office setting where the mother consulted directly with a medical doctor over conditions related to the pregnancy. I construct pregnancy-related conditions based on the Clinical Classification Codes provided by MEPS. Appendix Table D1 summarizes the out-of-pocket cost (OOPC) per visit for low-educated single mothers in 1997-2001.

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

	(1)	(2)	(3)
	$OOPC$	$OOPC > 0$	$OOPC(> 0)$
age	0.80	0.10***	-15.32
	(1.05)	(0.024)	(9.79)
age^2	-0.01	-0.002***	0.25
	(0.02)	(< 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 mother age. Column 1 predicts the expected cost per visit. Column 2 predicts the probability of incurring a positive out-of-pocket cost. Column 3 predicts the cost conditional on incurring a positive cost. Sample includes pre-natal visits by non-college-educated single mothers giving birth to a child between 1997 and 2001 in MEPS. All dollars indexed to the 2000 level applying the CPI-U.

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 mother age. To approximate the empirical distribution, I model out-of-pocket costs as following a two-node distribution over zero cost and a positive amount depending on mother age. The mass at zero is determined by the regression coefficients in column 2. The positive cost level is determined by the regression coefficients in column 3. I then calibrate out-of-pocket costs across four age groups in the structural model as follows

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

where $g = 0, 1, 2, 3$ indicates age 21-25, ..., 36-40. z_g is the probability of positive out-of-pocket costs in 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.[38] Larger health shocks increase the probability of 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.

[38] 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.[39] 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 22 and 23, 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.

[39] 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 22 and 23. 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 24. 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 22 and 23, and the birth weight production in equation 17. 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

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

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 $\mathbb{E}\Big[d_i^l|\Delta\ell_i = k\Big]$.

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

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

and the sample counterpart is given by

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

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.[40] Stacking up, $m = \Big(m^l\Big)$, $l = 0,\ldots,271$ 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.[41] The estimate $\hat{\Theta}$ is asymptotically normal: $\sqrt{I}\Big(\hat{\Theta} - \Theta_0\Big) \sim N(0,\mathbf{V})$, and the

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

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

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

[41] 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

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

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 18 to 21. 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."[42] 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.[43] 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.[44]

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.

[42] 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.

[43] 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.

[44] 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, ΔG = \$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 ΔG = \$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 $80\% \cdot 1.45 = 1.16$ percentage points (Table 6). Following Hendren and Sprung-Keyser (2020), I assume that students induced by the exposure to attend college enroll in college for two years. Assuming that each year of college increases earnings by 11.3% (Zimmerman, 2014), I calculate that CHIP exposure can increase earnings by $2 \cdot 11.3\% \cdot 0.0116 = 0.26\%$ for children of single mothers.

I then apply the 0.26% increase in earnings 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).[45] I adjust the earning profile in the population to reflect the earning loss due to single parenthood based on estimates from Lopoo and DeLeire (2014).[46] Upon adjustment, earnings for children of single mothers are lower by 21% compared to the population average. Moreover, because the 0.26% earning benefit is relative to that of children without college education, I calculate earnings absent college education based on college enrollment rates.[47] Consistent with findings

[45] I assume a 0.5% wage growth rate when predicting future earnings for children. Results are very similar using static wages observed in 2014-2018.

[46] 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.

[47] Specifically, because college enrollment rate is 45% among children of single mothers in the ACS, under the assumption that students attend college for two years, the implied earning loss for those without college

Table H1: Program costs of CHIP, fiscal year (FY) 1998-2016

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 index all dollars to the 2000 level 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.

in Zimmerman (2014), I assume that the earning benefit of college education appears from age 23 onward, while in age 19-22, college enrollment lowers annual earnings by 12.80%.[48] Discounted to 1997 applying a 2% annual discount rate, the life-cycle earning benefit amounts to \$946.38 per child of single mothers.

Tax Payments. Following Hendren and Sprung-Keyser (2020), I assume that the earning gains are subject to a marginal tax rate of 18.9%.[49] The implied increase in tax payment, $18.9\% \cdot \$946.38 = \$178.87$, amounts to $\frac{\$178.87}{\$2,483.10} = 7.2\%$ of the program costs in childhood. Therefore, parental investments in the roll-out of insurance can offset 7.2% of the program costs in childhood.

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 1,000 effect sizes from the asymptotic distribution of the estimates.[50] For each draw, I calculate the implied fiscal externality as the percent of program costs offset by tax payments. I show the empirical 95% confidence intervals under alternative assumptions in the calculation in Appendix Table H2.

Increasing college enrollment from 2 to 4 years tends to double the fiscal externality. Maintaining the assumption that children induced by the exposure attend college for 2 years, increasing the annual discount rate from 2% to 3% reduces the fiscal externality from 7.2% to 5.2% of the program costs. In all cases, parental investments in the roll-out predict significantly lower social costs of insurance at the 95% confidence level.[51] The median fiscal externality from the bootstrap draws is comparable to the point estimates based on the main results.

education is $9.09\% = 1 - \frac{1}{45\% \cdot (1+2 \cdot 11.3\%) + 55\%}$ below the average earning among children of single mothers.

[48] Zimmerman (2014) shows that college students have lower earnings in the first four years after high school. Scaled by the first-stage effect on college enrollment, each additional year of college lowers annual earnings in age 19-22 by 12.08%.

[49] 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.

[50] I bootstrap effects on college enrollment based on $\hat{\beta} = 1.37\%$, s.e.=0.32% from column 3 of Table 6, and bootstrap effects on earnings based on $\hat{\beta} = 11.3\%$, s.e.=3.83% from Zimmerman (2014).

[51] In all cases, the fiscal externality is further significant at the 99% confidence level.

Table H2: Fiscal externality under alternative assumptions

	$r = 3\%$	$r = 2\%$
2 years in college	5.2%	7.2%
	[5.0%]	[7.0%]
	{0.4%, 15.4%}	{0.6%, 21.4%}
4 years in college	9.5%	13.2%
	[9.2%]	[12.8%]
	{0.8%, 28.3%}	{1.1%, 39.2%}

Notes: Table calculates the fiscal externality of CHIP exposure under alternative assumptions of the annual discount rate r and the duration of college enrollment, To account for uncertainties, I follow Hendren and Sprung-Keyser (2020) and calculate fiscal externality for 1,000 bootstrap draws of the effects on college enrollment and earnings. I calculate the implied fiscal externality for each draw, and show the empirical 95% confidence interval in the curly brackets and the median estimate in the square brackets.

I Additional Tables

Table I1: Effects of insurance exposure on fertility rates and single motherhood

	(1) Fertility Rates (‰)	(2) Single Mothers (‰)
eliginc	0.05	-0.01
	(0.12)	(0.04)
Estimates across Exposure Timing		
eliginc · exposure in		
4-7 months of age	0	0
	(0.05)	(0.01)
1-3 months of age	0	0
	–	–
3rd trimester	0.01	0.01
	(0.05)	(0.02)
2nd trimester	0.08	0.01
	(0.06)	(0.02)
1st trimester	0.07	0.01
	(0.05)	(0.02)
0-4 months pre-utero	0.08	-0.01
	(0.06)	(0.02)
y mean	6.60‰	1.58‰
R^2	0.92	0.94
N	808	808

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

Notes: Table shows the effects of insurance exposure on fertility rates and single motherhood, both in per-thousand shares of the female population between age 21 and 40 in the state. To calculate the fertility rates, I combine the universe of live births in the birth certificate records with the fetal death records to arrive at the full count of mothers giving birth in each year-month. I then use the gestation estimates in these records to infer the pregnancy onset time and to construct fertility rates by state-year-month. I define single motherhood for live births where the mother was unmarried at the time of delivery, and measure single motherhood in rates relative to all women between age 21 and 40 in the state. I show event study estimates grouping by the timing of exposure to CHIP in the second half of the table, where I normalize the estimates on mothers starting pregnancy 10-12 months before CHIP (whose children would be 1-3 months of age at the CHIP onset) to zero. Robust standard errors clustered at the level of states in the parentheses.

Table I2: Effects of insurance 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 effects of insurance exposure on birth weight (grams) and the percentage of children with low birth weight (<2,500 grams). I group children by the trimester of exposure and show estimates for six exposure groups in the table. I normalize the estimates on children conceived 10-12 months before CHIP (hence 1-3 months of age at the CHIP onset) to zero. Robust standard errors clustered at the level of states in the parentheses.

Table I3: Effects of insurance exposure on the timing of care onset

	(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	0.10	-0.02
	(0.01)	(0.23)	(0.18)
1-3 months of age	0	0	0
	–	–	–
3rd trimester	-0.01	0.03	-0.10
	(0.01)	(0.24)	(0.10)
2nd trimester	0	-0.10	-0.13
	(0.01)	(0.23)	(0.18)
1st trimester	-0.01	-0.25	-0.27
	(0.01)	(0.19)	(0.17)
0-4 months pre-utero	-0.02**	-0.38**	-0.30**
	(0.01)	(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 insurance exposure on the month of 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 in the table. I normalize the estimates on mothers starting pregnancy 10-12 months before CHIP (whose children would be 1-3 months of age at the CHIP onset) to zero. Robust standard errors clustered at the level of states in the parentheses.

Table I4: Effects of insurance 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	-0.01	0.12	0
	(0.02)	(0.15)	(0.07)
1-3 months of age	0	0	0
	–	–	–
3rd trimester	0	0.12	0.03
	(0.02)	(0.14)	(0.09)
2nd trimester	0	-0.01	-0.09
	(0.02)	(0.10)	(0.06)
1st trimester	0.02	-0.11	-0.16**
	(0.02)	(0.10)	(0.07)
0-4 months pre-utero	0.03	-0.20**	-0.19***
	(0.02)	(0.08)	(0.06)
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 effects of insurance exposure on the number of pre-natal visits and smoking in pregnancy. I group mothers by the trimester of exposure and estimate effects across six exposure groups in the table. I normalize the estimates on mothers starting pregnancy 10-12 months before CHIP (whose children would be 1-3 months of age at the CHIP onset) to zero. Robust standard errors clustered at the level of states in the parentheses.

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 cigarettes daily)	
eligCHIP	26.75**	8.59	-3.87**	-1.87	-2.23***	-1.65***
	(12.31)	(12.36)	(1.79)	(1.77)	(0.53)	(0.41)
eligCHIP · *single*		48.16***		-5.34***		-1.46**
		(10.43)		(1.28)		(0.66)
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 insurance exposure as the predicted probability of being eligible for Medicaid/CHIP, applying the income limit of insurance to a fixed sample of children. I show details of the simulation in Appendix A. Robust standard errors clustered at the level of states in the parentheses.

Table I6: Effects of insurance exposure on mothers' insurance, cash benefits, and incomes

	(1) Medicaid (%)	(2) Food Stamp/WIC (%)	(3) Food Stamp/WIC (thousands $)	(4) Total Incomes (thousands $)
single · *eliginc* · exposure in				
4-7 months of age	6.64	10.28	-0.01	-0.09
	(26.29)	(24.50)	(0.12)	(0.91)
1-3 months of age	0	0	0	0
	–	–	–	–
3rd trimester	28.86	9.88	-0.07	-0.64
	(24.54)	(20.03)	(0.07)	(1.02)
2nd trimester	15.93	5.32	-0.11	0.06
	(19.14)	(20.25)	(0.07)	(0.89)
1st trimester	17.80	1.56	-0.04	-0.38
	(13.66)	(15.01)	(0.06)	(0.60)
0-4 months pre-utero	15.26	-8.40	-0.06	0.30
	(16.02)	(12.42)	(0.05)	(0.59)
y mean	13.52%	14.98%	0.02	1.58
R^2	0.48	0.50	0.57	0.39
N	2,141	2,141	2,141	2,141

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

Notes: Table estimates the effects of insurance exposure on mothers' uptake of own Medicaid insurance (column 1), benefits from the Food Stamp and the WIC programs (column 2-3), and monthly personal incomes (column 4) in pregnancy, using data from the Survey of Income and Program Participation (SIPP). In SIPP, uptake of public insurance and cash transfer programs is recorded for each month using a 4-month recall. I use all months in pregnancy and examine in-utero program uptake across mothers with different timing of exposure to CHIP. Total incomes in column 4 include earned incomes, transfer incomes, property incomes, and other incomes in a given month. I index all dollars to the 2000 level using CPI-U. SIPP sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parentheses.

Table I7: Effects of insurance exposure on mothers' personal debts and account balances (thousands $)

	(1) Credit Card Debt	(2) Personal Loans (bank/credit union)	(3) Third-Party Loans	(4) Checking/Saving Accounts
$single \cdot eliginc$	-0.31	-0.37	-2.00	-0.16
	(0.59)	(0.28)	(1.98)	(0.27)
$eliginc$	-5.89	0.28	-0.06	0.02
	(5.84)	(0.39)	(0.27)	(0.35)
Estimates across Exposure Timing				
$single \cdot eliginc \cdot$ time to CHIP onset				
7-9 months	2.64	0.61	-2.67	0.13
	(1.82)	(0.70)	(3.58)	(0.31)
4-6 months	2.91	1.14	-3.26	0.50
	(2.17)	(0.81)	(4.19)	(0.33)
1-3 months	0	0	0	0
	–	–	–	–
0-2 months post	0.85	0.48*	-0.62	0
	(0.93)	(0.26)	(0.75)	(0.07)
3-5 months post	0.73	0.20	-3.84	-0.34
	(1.10)	(0.43)	(3.37)	(0.37)
6-8 months post	1.41	0.09	-1.53	0.27
	(1.03)	(0.39)	(2.02)	(0.16)
y mean	1.43	0.74	0.55	1.10
R^2	0.01	0.01	0.01	0.01
N	12,930	12,930	12,930	12,930

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

Notes: Table estimates the effects of insurance exposure on mothers' personal debts including credit card debts, bank loans, and third-party loans in column 1-3, and balances in checking and saving accounts in column 4. Because questions about asset holdings are asked only in selected waves of SIPP, restricting the analysis to pregnant mothers greatly reduces the sample size. Instead, I estimate the following difference-in-differences specification

$$y_{its} = \beta_0 \cdot single \cdot eliginc_{st} + \beta_1 \cdot eliginc_{st} + \beta_s \cdot single + \alpha_s + \tau_t + \alpha_s \cdot \tau_{y(t)} + \epsilon_{its},$$

where *eliginc* is the income limit of children's insurance in state s and year-month t. I include in the sample all women in age 21-40 surveyed between 9 months before and 8 months after CHIP. *single* indicates single pregnant mothers, and β_0 estimates the effect of a 100% FPL exposure on their debts and account balances. I show event study estimates grouping by the time to CHIP onset in the second half of the table. Dollar amounts (in thousands) are indexed to the 2000 level using CPI-U. SIPP sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parentheses.

Table I8: Effects of insurance exposure on the uptake of children's insurance and education expectation

	(1)	(2)	(3)	(4)
	Children's Medicaid/CHIP	Expected Education		
		College Degree	Graduate School	Attainment
	(%)	(%)	(%)	(1-5 scale)
single · *eliginc* · exposure in				
4-7 months of age	0.68	-6.88	9.65	0.11
	(11.20)	(8.20)	(11.39)	(0.24)
1-3 months of age	0	0	0	0
	–	–	–	–
3rd trimester	10.80	-6.54	-3.48	-0.09
	(9.28)	(9.28)	(7.30)	(0.19)
2nd trimester	5.40	3.46	-3.96	0.09
	(5.30)	(4.76)	(7.05)	(0.14)
1st trimester	21.05**	3.25	0.54	0.07
	(9.37)	(4.14)	(5.64)	(0.11)
0-4 months pre-utero	15.18**	-4.17	0.84	-0.06
	(7.07)	(4.24)	(4.40)	(0.11)
y mean	19.52%	86.06%	26.91%	4.06
R^2	0.27	0.08	0.01	0.08
N	1,647	1,012	1,012	1,012

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

Notes: Table estimates the effects of insurance exposure on the uptake of Medicaid/CHIP for children in column 1, and mothers' expected education for children in column 2-4, using data from the Survey of Income and Program Participation (SIPP). In SIPP, uptake of public insurance and cash benefit programs is recorded for each month using a 4-month recall. I use the most recent month (the fourth month) and examine the decision to enroll the child in Medicaid/CHIP in the first year of the child's life (age 0) in column 1. Outcomes in column 2-4 are mothers' stated expectation of the child's education attainment. The expectation was asked for all children in SIPP 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; in ascending orders, the integers indicate no degree (less than high school), high school diploma, 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 parentheses.

Table I9: Effects of insurance exposure on mothers' marital status

	(1) Never Married (%)	(2) Unmarried in t (%)
$eliginc^{utero}$	0.60	0.96
	(0.61)	(0.76)
$eliginc^{child}$	0.51	-1.35
	(0.76)	(1.06)
y mean	8.07%	28.28%
R^2	0.01	0.01
N	304,367	304,367

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
Notes: Table estimates the effects of insurance exposure on mothers' marital status. The outcome in column 1 is the share of mothers who have never married by the survey year. In Column 2, the outcome is the share of mothers who are unmarried in survey year t. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parentheses.

Table I10: Effects of insurance exposure on high school graduation rates (%)

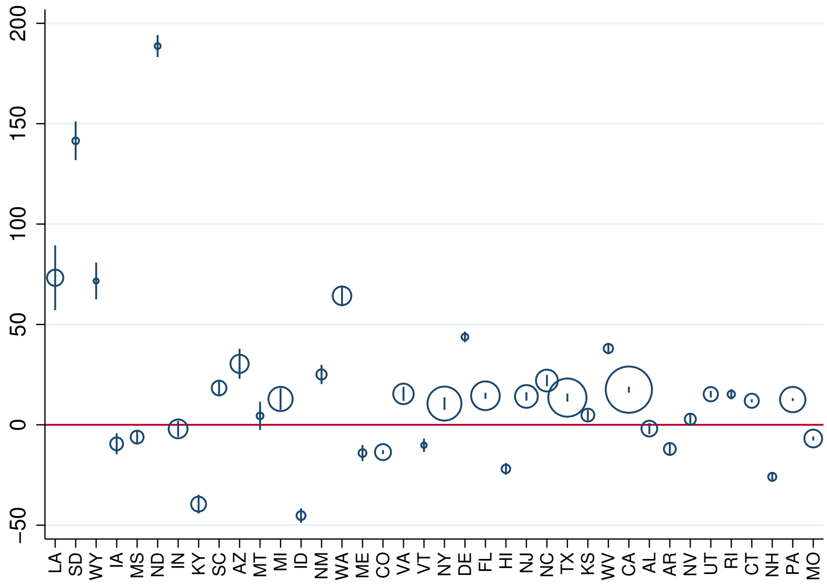
	(1)	(2)	(3)	(4)
$eliginc^{utero} \cdot single$	1.55***	1.54***	0.36	0.34
	(0.54)	(0.56)	(0.36)	(0.37)
$eliginc^{utero}$	-0.01		0.01	
	(0.82)		(0.83)	
never-married mothers	Y	Y		
y mean	31.47%		31.47%	
R^2	0.68	0.68	0.68	0.68
N	304,367		304,367	

*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$
Notes: Table shows the effects of insurance exposure on high school graduation rates. *single* indicates children of single mothers. Single mothers in column 1-2 have never married, and were unmarried in the survey year in column 3-4. I estimate separate effects by single motherhood using equation 13 in column 1 and 3, and focus on children of single mothers using equation 14 in column 2 and 4. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parentheses.

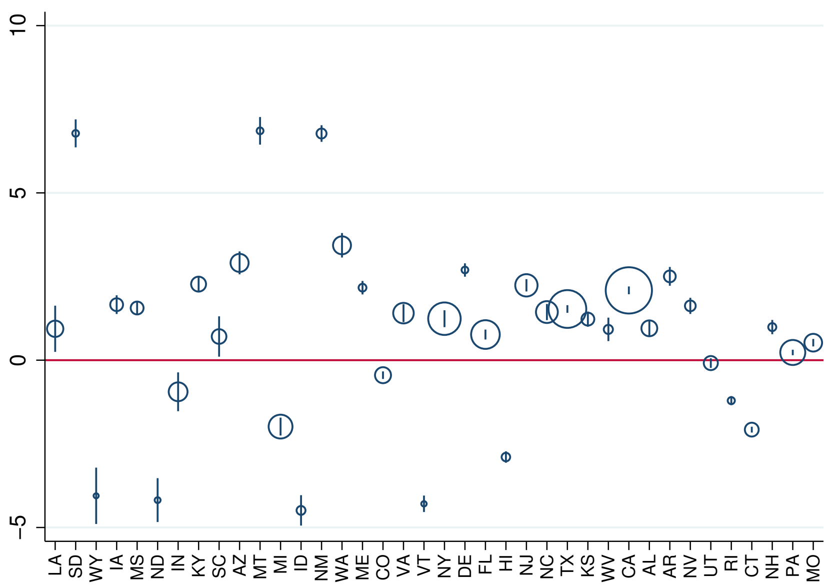
J Additional Figures

Figure J1: Effects of insurance exposure across states

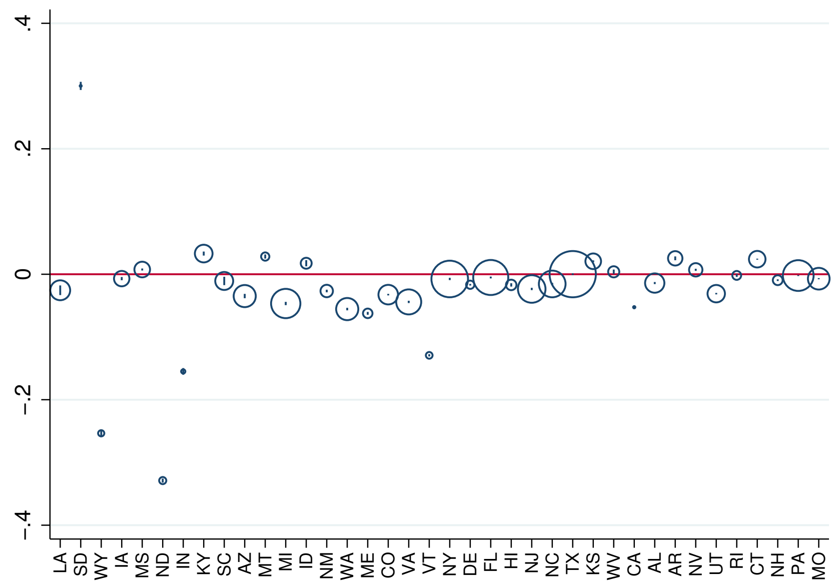
(a) Birth Weight (grams)



(b) First Trimester Care (%)



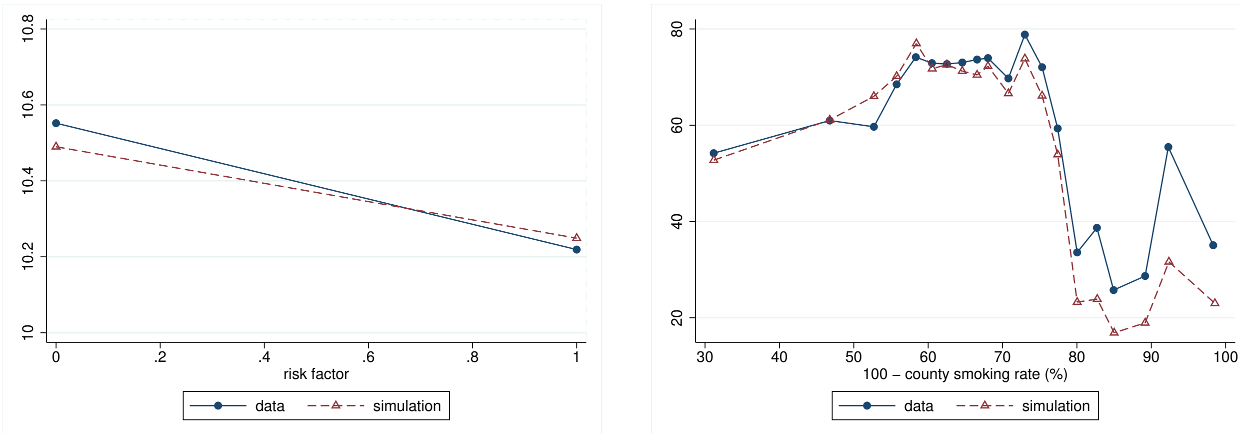
(c) Smoking (half packs)



Notes: Figure plots state-specific effects of insurance exposure on birth weight in panel (a), care onset in the first trimester in panel (b), and smoking intensity in panel (c). I measure smoking intensity in half packs (10s) of cigarettes daily. I rank states by the size of expansion from small to large on the horizontal axis. Small expansion states ranging 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 above the pre-CHIP level (275% FPL). The circle around the estimates is proportional to the number of births in the state during the roll-out. 95% confidence intervals are based on robust standard errors clustered at the level of states.

Figure J2: Simulated investments by mother characteristics

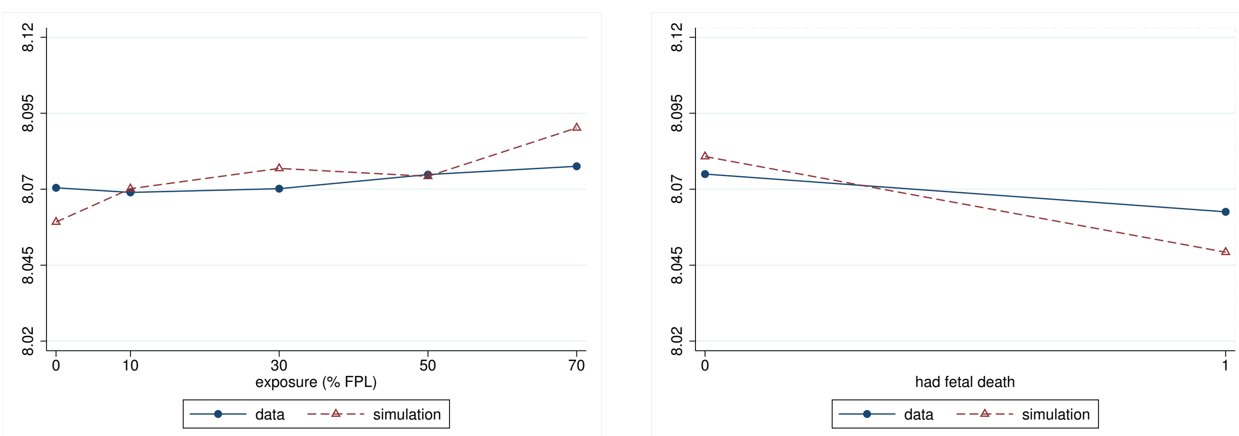
(a) Number of Pre-Natal Visits, by Risk Factor (b) Non-Smokers (%), by County Smoking Rate



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 J3: Effect of CHIP exposure on birth weight

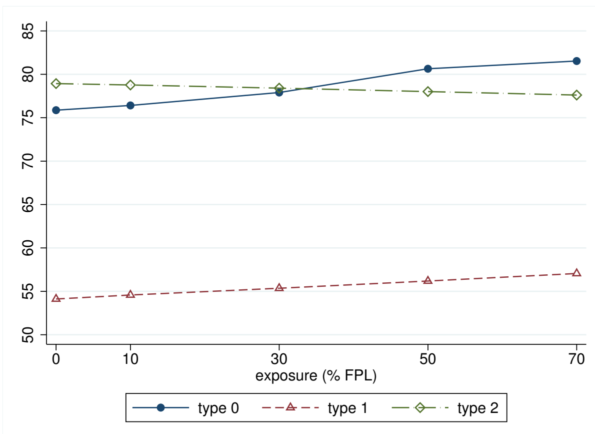
(a) By Exposure $\Delta\ell_i$ (b) By Fetal Death



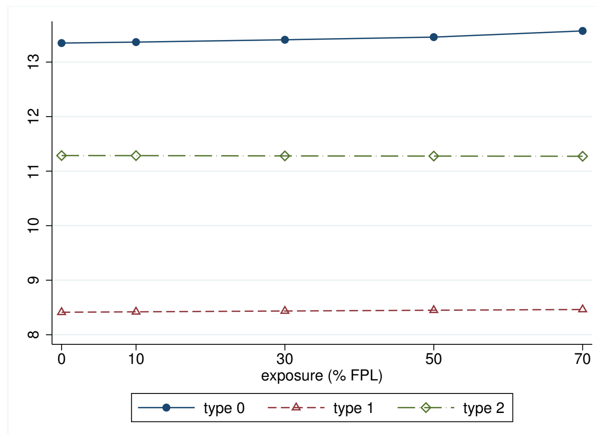
Notes: Figure compares simulated birth weight with empirical counterparts across CHIP exposure $\Delta\ell_i$ in panel (a), and by fetal death in previous pregnancies in panel (b). Mother had fetal death in previous pregnancies if the live birth order of the current birth is smaller than the total birth 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 J4: Effect of CHIP exposure on investments and birth weight, by mother types

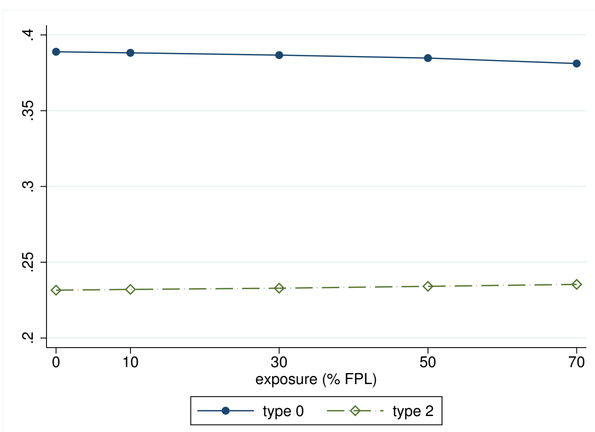
(a) First Trimester Care (%)



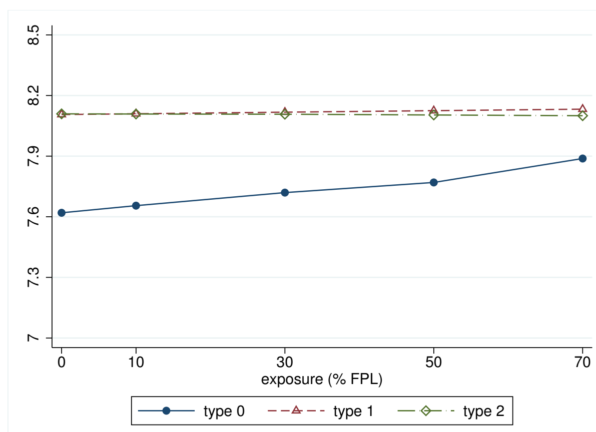
(b) Number of Pre-Natal Visits



(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.

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