Parental Responses to Social Insurance for Children: Evidence from CHIP

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Abstract

This paper estimates the parental responses to a large expansion of children's insurance following the roll-out of the Children's Health Insurance Program (CHIP) in the US. Although CHIP does not cover children in utero, pregnant mothers exposed to the roll-out of CHIP invest more in utero, and birth weight improves for children with in-utero exposure to CHIP. The investments are consistent with a 14.3% reduction in the present bias of mothers exposed to the roll-out. Because mothers highly value the child's birth weight, they value the exposure to CHIP as much as expansions of own insurance due to the benefit on birth weight. In the long run, in-utero investments increase college enrollment and predict higher earnings and tax payments that lower the net cost of the program by 8.4%. The private and social benefits of the investment responses provide strong motivations for outreach efforts engaging parents in children's insurance programs.

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1 Introduction

A growing literature highlights the importance of early life investments for the long-run outcomes of the child. The long-run benefits have motivated social insurance for children in low-income families, where parental investments may be inadequate due to limited resources. While targeting children, insurance programs rely on the behavior of parents to enroll and to invest in the child. Despite serving the role of agency in children's insurance programs, parents have seldom been the focal point of studies on children's insurance programs. As a result, there exists little evidence on how parents respond to children's insurance, or how their investments could impact the effectiveness of the program.

This paper provides evidence on these open questions exploiting the roll-out of the Children's Health Insurance Program (CHIP) in the US. The roll-out doubled the share of children eligible for public insurance from 15% to 30% , but did not expand insurance for pregnant mothers or children in utero. Thus, CHIP is unlikely to affect the birth outcomes of children. Nonetheless, birth outcomes may improve if pregnant mothers increased investments in response to CHIP. Therefore, I examine mother's in-utero investments during the roll-out of CHIP to understand the parental responses to social insurance for children.

I have three main findings from the analysis. First, mothers exposed to the roll-out of CHIP have earlier onset of pre-natal care and smoke less during pregnancy. These investments are consistent with CHIP exposure lowering the present bias of mothers. Second, the investments suggest that mothers highly value the child's birth weight. Due to the benefit on birth weight, mothers value the exposure to CHIP as much as expansions of own insurance. Third, children exposed to CHIP in utero are more likely to attend college. The predicted gains in earnings and tax payments imply that parental responses to the roll-out of CHIP can lower the net cost of the program by 8.4% in the long run.

To motivate the investment responses, I model CHIP as lowering the health expenditures when parents invest in a less healthy child. The insurance allows parents to invest more in the child and narrows the gap in child outcomes by child health. Because CHIP protects parents from the utility loss from child health, it may lower the incentive for parents to invest in utero in the child. Yet, empirically, I find overwhelming evidence of an investment "crowd-in," suggesting the existence of additional mechanisms besides moral hazard. I motivate and show empirical support for a behavioral effect on the present bias of mothers as the leading mechanism.

Empirically, I estimate the investment responses exploiting two variations generated by the roll-out. First, mothers exposed to CHIP in early stages of the pregnancy have a longer

window of exposure to CHIP. Second, mothers in states adopting higher income limits are exposed to greater expansions of insurance. To capture both variations, I calculate in-utero 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. By construction, in-utero exposure increases with income limits, and increases within states for mothers with earlier exposure to CHIP. I then examine parental investments across different levels of exposure to children's insurance.

In-utero exposure significantly improves the early onset of pre-natal visits and reduces smoking during pregnancy. Exposure to the roll-out of CHIP lowers late care onset past the first trimester by 5.6%, and lowers very late onset in the third trimester by 11.2%. Despite earlier onset of care, the number of pre-natal visits does not increase with exposure. Exposure to the roll-out further reduces smoking rates by 4%, increases birth weight by 8.5 grams, and decreases low birth weight by 3.6%. These effects are concentrated among single mothers exposed to CHIP since the first trimester of pregnancy. By contrast, CHIP exposure has no effect on married mothers whose children have low predicted eligibility for CHIP.

To understand mechanisms, I examine whether the exposure to children's insurance increased mother's take-up of own insurance and cash benefits. These resources may allow the mother to spend more on pre-natal investments. Drawing data from the Survey of Income and Program Participation, I find that CHIP exposure has no effect on mother's insurance, cash transfer income, or health expenditures during pregnancy. The data further reveals that mothers investing more in utero are also more likely to enroll the child in the first year of life, but these mothers do not have higher expected education for the child. This result suggests that the investments are not motivated by the long-run effects on the education outcome of the child.

After ruling out mother's insurance, income, and the long-run effects of investments as mechanisms, I explore two behavioral mechanisms whereby CHIP exposure adjusted mother's perception of in-utero investments. First, the exposure may have increased mother's altruism for the child, shifting utility weights from own consumption to child outcomes. Second, the exposure may have shifted mother's inter-temporal weights towards future benefits for the child, lowering the present bias of mothers.

I formally investigate the behavioral mechanisms using a dynamic model of in-utero investments. In the model, mothers invest in each trimester and the child is born at the end of the third trimester. Mother's utility depends on the child's birth weight net of the costs of investments in utero. Because investments occur over multiple periods, mothers face an inter-temporal choice between early versus late onset of investments, in addition

to the trade-off between birth weight and costly investments in utero. An increase in altruism tends to increase mother's investments in the child, whereas a decrease in present bias tends to shift investments to earlier stages of the pregnancy. I therefore quantify the behavioral mechanisms matching moments on the level and the timing of investments in utero. I find that the investments are consistent with a 14.3% reduction in the present bias of mothers exposed to the roll-out. By contrast, CHIP exposure has little effect on the altruism of mothers.

Turning to welfare, I simulate mother's counterfactual utility in the absence of CHIP to reveal her valuation of the exposure. I find that mothers highly value the child's birth weight. The utility gain from birth weight alone is sufficient to offset the cost of exposure measured by the spending on program outreach. Net of investments, mothers value the exposure to CHIP at 69% of the outreach spending, placing the marginal value of public funds (MVPF) of CHIP exposure in the same range as insurance expansions for low-income adults (Finkelstein and Hendren 2020; Hendren and Sprung-Keyser 2020). This result suggests that mothers value the exposure to CHIP as much as expansions of own insurance due to the benefit on birth weight.

In addition to improving mother utility, CHIP exposure further impacts the cost-effectiveness of the program through the long-run effects on earnings. To quantify the fiscal impacts, I first show that exposure to the roll-out of CHIP increases college enrollment by 1.37 percentage points for children of single mothers. This effect predicts higher earnings over the life cycle by \$1,101.1, and higher tax payments by \$209.1. Compared to the cost of program investments in childhood, the tax payments reduce the net cost of the program by 8.4%, implying significant fiscal externality from parental responses to children's insurance.

These findings suggest that parental investments can powerfully impact the ultimate effects of insurance on children. Positive investment responses not only improve child outcomes before the onset of the program, but improve the long-run effectiveness of the program through better economic outcomes later in life. Investigations into the mechanism of the responses reveal that parents highly value child outcomes, but may suffer from behavioral biases that lower their investments in the child. Information correcting the biases can effectively increase investments and the utility of parents. These benefits strongly motivate outreach efforts engaging parents in children's insurance programs.

This paper contributes to the literature on children's insurance programs by highlighting parental responses as a critical pathway for the effects on child outcomes. While numerous studies have documented the beneficial effects of Medicaid insurance for children (Currie and Gruber 1996a; Currie and Gruber 1996b; Goodman-Bacon 2018), less

is known about how parents respond to children's insurance, or whether parental investments improve child outcomes over and above the direct effects of insurance. This paper shows that information correcting the behavioral biases of parents significantly increases investments and improves the long-run outcomes of the child. Therefore, children's insurance should foster positive investments from parents. Parental investments have received similar attention in the literature of early-childhood interventions (Heckman and Mosso, 2014), where programs improving parenting skills through information and preference change are shown to have larger impacts on child outcomes than simple transfer programs.

This paper also contributes to a growing literature that evaluates the welfare of social insurance programs by estimating beneficiaries' valuation of the insurance (Finkelstein *et al.* 2019a; Finkelstein *et al.* 2019b). Here, I quantify mother's valuation of the exposure to CHIP by first estimating the behavioral effects of exposure implied by her investment responses. In doing so, I also contribute to the literature on structural behavioral models, in particular 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.

Lastly, this paper illustrates how insurance programs could harness behavioral insights to improve the effectiveness of insurance. Although the existence of behavioral biases calls for taxes and subsidies as the standard corrective of the bias (Herrnstein *et al.* 1993; Gruber and Köszegi 2001; O'Donoghue and Rabin 2006), in the absence of such policies, information nudges (Thaler and Sunstein, 2008) provide an alternative, light-touch approach to combating the biases. In the roll-out of CHIP, for instance, exposure to children's insurance increased investments and mother utility as effectively as expansions of mother's own insurance. Thus, I add to the growing evidence base of nudging applications in social policies (see Benartzi *et al.* 2017 for a survey) by documenting the significant welfare benefits of in-utero exposure to CHIP.

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

2 Children's Health Insurance Program

The Children's Health Insurance Program, or CHIP, was created by the Balanced Budget Act (BBA) of 1997 under a new Title XXI of the Social Security Act. Title XXI, which became effective on Oct. 1st, 1997, offered states the option to enroll uninsured children ineligible for Medicaid either through an expansion of the existing Medicaid program or by establishing a separate insurance program for children. States opting for either type of expansion were eligible for federal funding totaling $40 billion in the first ten years of Title XXI (FY1998-FY2007). States can only use the funding to expand insurance for children (age 0 to 18), but not for adult parents.

Nearly all states expanded insurance for children between 1997 and 2000.[1] Table 1 lists the timing of CHIP onset by states, along with changes in the income limit of the program for different ages of childhood.[2] Of the 50 states that expanded insurance for children, 11 states also expanded insurance for adult parents using state funding, and the remaining 39 states expanded insurance only for children.[3] I focus on the latter set of states to understand the parental responses to social insurance for children.

The expansion significantly increased the *expected* insurance eligibility for children born in 1997-2000. I calculate expected eligibility as the probability of being eligible for Medicaid/CHIP insurance during childhood (age 0-18), according to income limits (Table 1) known at the time of pregnancy.[4] Figure 1 illustrates the increase in insurance eligibility during the roll-out of CHIP. Cohorts born in Jan. 1997 had an average eligibility of 0.15, or an expected 2.88 years of Medicaid/CHIP insurance during childhood. Eligibility then increased significantly for later cohorts in 1998-1999 as more states started the CHIP program. By Dec. 2000, all states (except Tennessee) had started enrolling children under CHIP. As a result, expected insurance eligibility increased to 5.68 years for the Dec-2000 birth cohort.

[1] The only exception is Tennessee, where the Medicaid program diserolled a large number of enrollees in 2002. Prior to 2002, individuals with income up to 400% FPL are eligible for the state's Medicaid program.

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

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

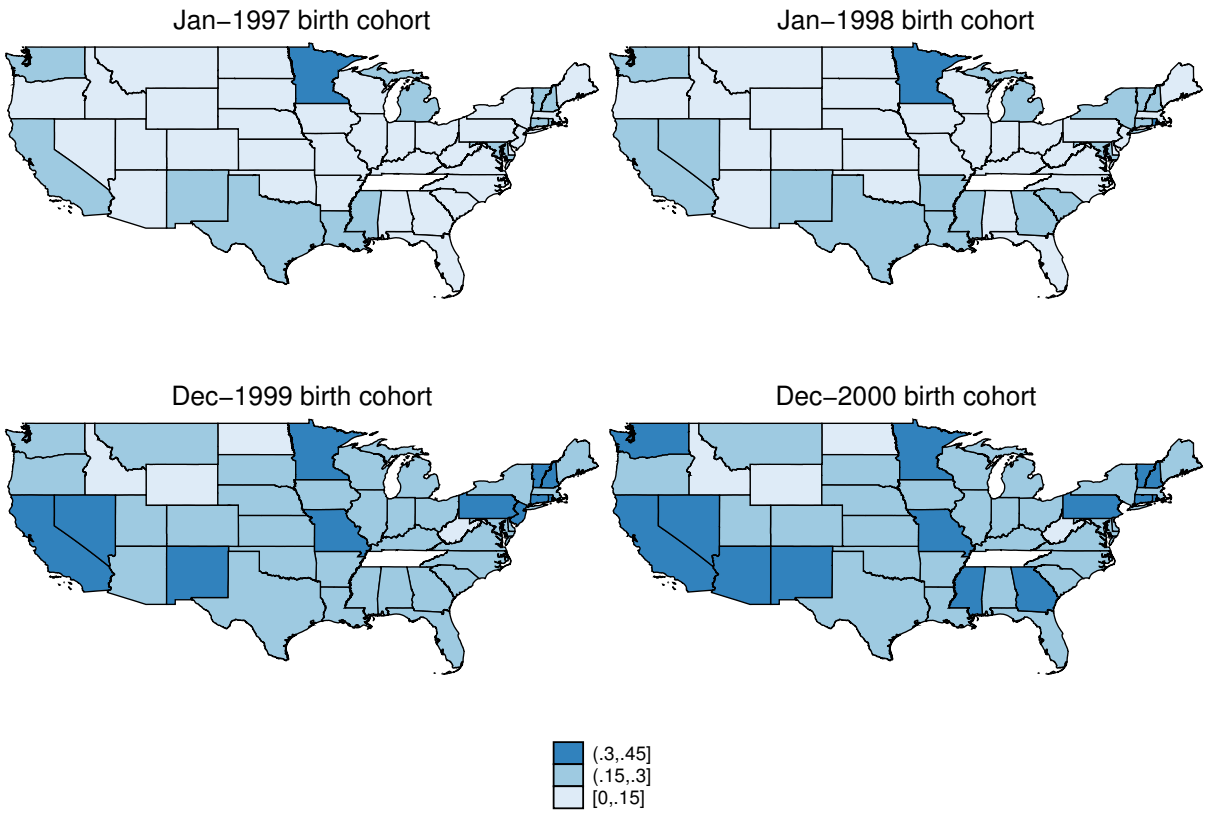
[4] I follow the standard "simulated eligibility" approach pioneered by Currie and Gruber (1996a) and Currie and Gruber (1996b) to calculate the expected eligibility. I show details of the calculation in Appendix A.

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 * in the "infant" column expanded insurance for children as well as adult members of the family. See footnote 2 in the main text for the sources of the information.

Figure 1: Expected insurance eligibility for birth cohorts, 1997-2000



Notes. The map shows the expected insurance eligibility for cohorts born between Jan. 1997 and Dec. 2000. Expected insurance eligibility is the fraction of childhood years (age 0-18) in which the child is eligible for Medicaid/CHIP based on program rules known at the time of pregnancy. Appendix A details the calculation.

3 Conceptual Framework

To motivate the investment responses to CHIP, consider a two-period model where parents invest in the child both 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 period utility $u(c_t)$ – and costly investment v_t in the child. In-utero investments affect the health status of the child in $t = 1$. Children born with low health, such as those with disability, require larger medical expenses in childhood. CHIP provides partial insurance against the medical costs when parents invest in the low-health child. I analyze the effect of this insurance on investments in childhood and in utero below.

3.1 Childhood Investments

Let superscript $h = 0, 1$ denote the health status of the child, with $h = 1$ indicating high child health. Parents spend out-of-pocket medical expenses $OOPC$ when investing in a low-health child. 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, parental investments in $t = 1$ maximize the following utility

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

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

It is easy to see that medical expenses $OOPC$ decreases non-health investments v_1^h in the low-health child, reducing the education outcome of the low-health child.[5] By lowering $OOPC$, CHIP increases v_1^0 and narrows the education gap $\Delta s = s(v_1^1) - s(v_1^0)$ by child health. The reduction in the education gap further reduces the gap 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.

[5] I show detailed proofs in Appendix B.

3.2 In-Utero Investments

In $t = 0$, forward-looking parents choose in-utero investments to maximize the sum of utility in utero and in childhood. Specifically, parents maximize the following utility

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

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

Optimal in-utero investments satisfy the following first-order condition

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

The first term $\delta\rho'(v_0)\Delta\tilde{U}_1 = \delta\rho'(v_0)\,(\Delta u + \Delta\Gamma + \delta\Delta V)$ is the marginal benefit of investments on the future utility of parents. $w'(v_0)$ is the marginal benefit on birth outcomes. Optimal investments balance the marginal benefits with the marginal cost $u'(c_0)$.

CHIP affects the trade-off in equation 3 by lowering the benefit of in-utero investments on future utility. Because CHIP reduces the gap in child outcomes by child health, it also reduces the gap in parental utility $\Delta\tilde{U}_1 = \Delta u + \Delta\Gamma + \delta\Delta V$ by child health. Due to the risk protection of CHIP, in-utero investments have smaller benefits on the future utility of parents. Since CHIP did not affect the marginal cost of in-utero investments but lowered the marginal benefits, equation 3 predicts smaller in-utero investments in response to CHIP.

3.3 Investment Crowd-In

Equation 3 is consistent with the standard prediction that public insurance can "crowd-out" private insurance. However, empirical evidence from the roll-out of CHIP overwhelmingly shows increased in-utero investments. The crowd-in response suggests the existence of additional mechanisms that increased the marginal benefit of investments rather than decreasing it.[6] I focus on two behavioral mechanisms in this paper. First, CHIP shifted the utility weights from parental consumption to child outcomes, increasing the altruism of parents. Second, CHIP shifted the inter-temporal weights towards future benefits for the child, decreasing the present bias of parents.

[6] I focus on marginal effects assuming that incomes or in general the resources of pregnant mothers did not increase after CHIP. I provide empirical support for the assumption in Section 5.5.

Altruism. I model altruism as the weight on child outcomes in the parent's utility. Altruism may increase if CHIP exposure increased parent's awareness of the child's well-being. In this case, increasing the child's weight to $\alpha > 1$ revises the first-order condition for in-utero investments according to

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

where the utility gap $\tilde{U}_1(\alpha) = \Delta u + \alpha(\Delta\Gamma + \delta \Delta V)$ now depends on the consumption gap Δu and the gap in child outcomes $\Delta\Gamma + \delta\Delta V$ multiplied by the altruism parameter α. Higher altruism increases parent's perceived benefit of investments. With sufficiently large increases in altruism, the perceived benefits of investments could offset the reduction in $\Delta\Gamma + \delta\Delta V$, motivating the crowd-in of in-utero investments.

Present Bias. Investment responses to CHIP also depend on parent's inter-temporal preferences over investments and child outcomes. Since investments have immediate costs but delayed benefits, parents who are are over-sensitive to short-term costs may fail to take on actions that are beneficial in the long run. For health investments, present bias has been linked to smoking (Gruber and Köszegi, 2001), cancer screening (Fang and Wang, 2015), and food choice (Sadoff *et al.*, 2020). Following the literature, I adopt the $\beta - \delta$ representation (Laibson, 1997) to illustrate the implications of present bias for in-utero investments.

In the $\beta - \delta$ representation, present bias is captured by the short-run discount factor $\beta < 1$. δ is the long-run discount factor. Present bias modifies the first-order condition for in-utero investments according to

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

Present-biased mothers ($\beta < 1$) discount the marginal benefit of investments more than her long-run self would, and invest less in utero compared to the long-run optimum given by equation 4. Exposure to CHIP could shift mother's inter-temporal weights towards future benefits for the child, resulting in less present bias (higher β) and more in-utero investments.

Although both altruism and present bias could explain the increase in in-utero investments, they have different implications for the timing of investments. In equation 5, increasing either α or β increases investment v_0. However, because β generates present bias in each stage of the pregnancy, increasing β also reduces the delay in the onset of investments and shifts investments towards earlier stages of the pregnancy. Therefore, an

increase in β could explain earlier onset of investments absent increases in the level of investments during pregnancy. I exploit this distinction to interpret the empirical evidence in Section 5.5, and to structurally estimate the effect of CHIP exposure on present bias in Section 7.

4 Data

I use data on the universe of birth certificates in the US to study the effect of CHIP exposure on in-utero investments and birth outcomes. The birth certificate contains information on the child's birth weight, demographic information of the mother, prenatal care utilization, and health behavior such as smoking. In the main analysis I focus on the 39 states that expanded insurance only for children (or the CHIP states) during the roll-out of CHIP, and restrict the age of mother to 21-40 at the time of delivery. I therefore exclude teen pregnancies and pregnancies above age 40 from the analysis.[7]

Table 2 summarizes the CHIP eligibility, birth weight, and pre-natal investments for children born in 1997-2001. CHIP eligibility is almost twice as large for children of single mothers (44% compared to 23% on average). Single mothers invest less in the child in utero. Specifically, they are less likely to start pre-natal cate in the first trimester, more likely to delay care till the third trimester, and are more likely to smoke intensely (over 15 cigarettes daily) during pregnancy. Due to the investment differences, birth weight is lower by 100 grams for children of single mothers.

5 In-utero Investments

5.1 Empirical Strategies

I examine the investment responses exploiting two variations generated by the roll-out of CHIP. First, mothers exposed to CHIP in earlier stages of the pregnancy have a longer window of exposure to CHIP. Second, mothers in states expanding insurance to higher income levels are exposed to greater expansions of CHIP. I exploit both variations and calculate mother's exposure to children's insurance using the average income limit during

[7] Teen pregnancies account for 17% of all births in 1997-2001. Since some states extended maternity coverage for CHIP enrollees up to age 20, I do not include teen pregnancies in the main analysis. 82% of the births are given by women between age 21-40, and the remaining 1% are by women above age 40.

Table 2: Summary statistics, birth sample

	Full Sample		Single Mothers	
	Observations	Mean	Observations	Mean
CHIP				
income limit (100% FPL)	12,094,302	1.75	2,978,094	1.74
simulated eligibility	12,094,302	0.23	2,978,094	0.44
birth weight (grams)	12,407,979	3339.43	3,067,358	3234.10
low birth weight (% <2,500 grams)	12,407,979	7.10	3,067,358	9.64
month prenatal care started	12,117,214	2.45	2,966,116	2.98
care started in 1st trimester (%)	12,117,214	84.99	2,966,116	72.67
care started in 3rd trimester (%)	12,117,214	5.44	2,966,116	11.29
# doctor visits	12,000,696	11.72	2,929,395	10.79
≥ 5 cigarettes daily (%)	9,727,610	8.13	2,365,340	15.49
≥ 15 cigarettes daily (%)	9,727,610	2.96	2,365,340	5.55
smoking intensity (half packs daily)	9,727,610	0.11	2,365,340	0.21

Notes. Table summarizes the birth cohorts between Jan. 1997 and Dec. 2001 in the 39 CHIP states that expanded insurance only for children during the roll-out in 1997-2000. I restrict the sample to births given by mothers between age 21 and 40 at the time of delivery. Simulated eligibility is the probability of being eligible for public insurance according to the income limits known at the time of pregnancy. Appendix A details the construction of the simulated eligibility.

pregnancy. Formally, I construct in-utero exposure, $eliginc$, as follows

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

where $j = t - T_s$ is the gap between the pregnancy onset time t and the CHIP onset time T_s in state s. inc_s^{pre} and inc_s^{post} denote the income limit of children's insurance before and after CHIP, respectively.[8]

In equation 6, in-utero exposure is a 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 mothers starting pregnancy within 9 months before CHIP ($-9 \leq j \leq -1$), exposure to CHIP begins in month $|j|$ of the pregnancy, implying a weight of $\frac{|j|}{9}$ for 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 is larger in states with higher income limits for children's insurance, and increases within states for mothers with earlier exposure to CHIP. In the empirical analysis, I focus on mothers starting pregnancy 16 months before till 4

[8] I express both limits in 100% of federal poverty level (FPL) following the convention of income eligibility rules. For instance, an income limit at 200% FPL for CHIP is parametrized as $inc_s^{post} = 2$.

months after CHIP ($-16 \leq j \leq 4$) to exploit the roll-out of CHIP.

I use $eliginc$ to estimate the investment responses in the following specification

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

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

The empirical strategy estimates the causal effects of CHIP exposure on investments if both the timing and the level of exposure are exogenous to pregnant mothers. This requires that mothers do not selectively enter pregnancy or single motherhood in response to CHIP, and that the income limits of insurance are not set according to local demographic factors such as single motherhood or incomes. I examine and rule out fertility responses to the roll-out of CHIP in Appendix Table I1. To address concerns of endogenous income limits, I control for unobserved differences by single motherhood across local areas (counties) using $\beta_c \cdot single$. Within counties and mother groups, I exploit investment differences by the timing of exposure across cohorts to estimate the investment responses to CHIP. I illustrate the identifying variation by estimating cohort-specific effects in the event study below. I further explore additional heterogeneity across mother groups with the simulated eligibility strategy in Section 5.4, finding similar effects for single mothers.

5.2 Birth Outcomes

I first examine the effect of CHIP exposure on birth outcomes. Because CHIP does not cover the pre-natal care of pregnant mothers, the roll-out of CHIP is unlikely to improve the birth outcome of children. However, birth outcomes may improve if pregnant mothers

increase private investments in the child. In Table 3, I estimate the effect of CHIP exposure on birth weight using equation 7 and 8.

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

Table 3: Effects of CHIP exposure on birth outcomes

	(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 CHIP exposure on birth weight (grams) and low birth weight (<2,500 grams). I estimate separate effects for single and married mothers using equation 7 in column 1 and 3, and estimate effects on single mothers using equation 8 in column 2 and 4. Robust standard errors clustered at the level of states in the parenthesis.

I then examine the effects by the timing of exposure to CHIP using an event study specification

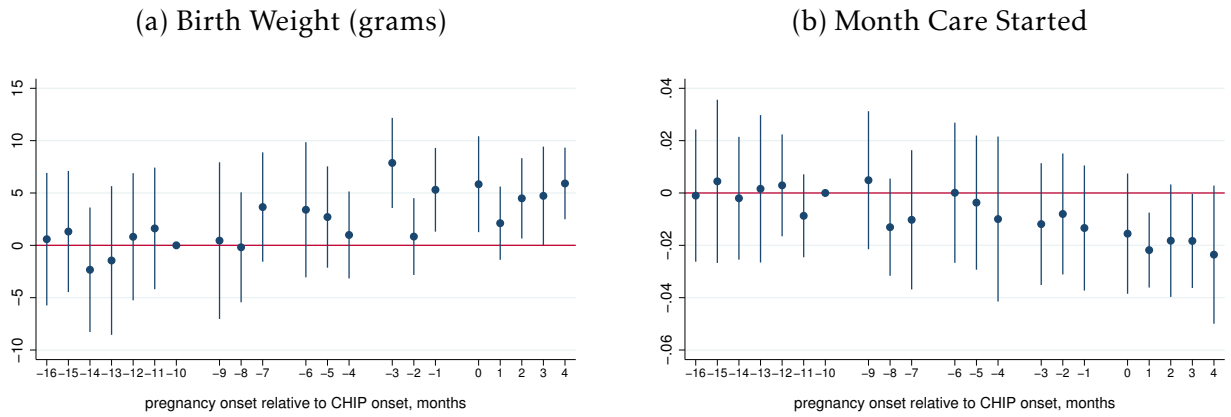
$$y_{itc} = \sum_{\substack{j=-16 \\ j\neq -10}}^{4} \beta_j \cdot eliginc_{ts(c)} \cdot single \cdot 1\{t - T_{s(c)} = j\} + \gamma \cdot eliginc_{ts(c)} + \beta_c \cdot single + \alpha_c + \tau_t + \alpha_{s(c)} \cdot \tau_{y(t)} + \epsilon_{itc}, \quad (9)$$

where I expand the term $\beta_1 \cdot eliginc_{ts(c)} \cdot single$ in equation 7 by the timing of exposure j, and estimate separate effects by j with β_j. I normalize the effects on children conceived 10 months before CHIP to zero. These children and earlier cohorts ($j \leq -10$) are already born

by the onset time of CHIP, and hence are not exposed to CHIP in utero. In-utero exposure then increases with j for later cohorts.

Figure 2 plots estimates of β_j for birth weight in panel (a). CHIP has little effect on birth weight for children never exposed to CHIP in utero ($j \leq -10$). For children exposed to CHIP in the third and the second trimester ($-9 \leq j \leq -4$), the exposure has no significant impact on birth weight. By contrast, CHIP exposure significantly increases birth weight for children exposed in the first trimester ($-3 \leq j \leq -1$) and those with full exposure in utero ($j \geq 0$). Among these children, gaining a 100% FPL exposure increases birth weight by 4.1 grams, and decreases the probability of low birth weight by 1.6% (Appendix Table I2).[9]

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



Notes. Figure plots the effects of CHIP 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 indexed by j. Mothers starting pregnancy more than 10 months before CHIP ($j \leq -10$) are not exposed to CHIP in utero. In-utero exposure then increases with j for later cohorts. I plot estimates of β_j from equation 9 as well as 95% confidence intervals based on robust standard errors clustered by states. Effects on the $j = -10$ cohort are normalized to zero.

5.3 In-Utero Investments

The effect on birth weight suggests that CHIP exposure may have increased mother's private investments in the child. To detect the investment responses, I examine mother's pre-natal care visits and smoking during pregnancy, and estimate effects of CHIP exposure

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

on the *timing* and the *level* of investments using equation 7 and 8. I find that single mothers with greater exposure to CHIP have earlier onset of pre-natal visits, are less likely to delay care till the third trimester, and smoke less during pregnancy.

Investment Timing. I examine the effect of CHIP exposure on the timely onset of pre-natal care in Table 4. Pre-natal care begins when the pregnant woman has the first pregnancy-related doctor visit. The Guidelines for Perinatal Care (Freeman and Poland, 1992) recommends that pregnant women have one doctor visit each month in the first two trimesters, and have 4 visits each month in the final months of the pregnancy. However, around 15% of the mothers delay the onset of care till the second or third trimester, and 5% start care in the third trimester. Gaining a 100% FPL exposure to CHIP lowers late care onset past the first trimester by 1.1 percentage points, or by 7% below the mean, and reduces third trimester onset by 14%. The time to first pre-natal visit decreases by 0.05 months. These responses are fully concentrated among single mothers.

Panel (b) of Figure 2 plots the event study estimates for the month of care onset based on equation 9. Month of care onset did not improve for mothers without in-utero exposure to CHIP, and improved by a small and insignificant amount for mothers with partial exposure in utero. The overall effect on the timing of care onset is concentrated among single mothers with full exposure to CHIP ($j \geq 0$). For these mothers, gaining a 100% FPL exposure lowers late care onset by 2.5%, and reduces the time to first pre-natal visit by 0.02 months (Appendix Table I3).

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

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

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

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

Investment Levels. I then examine if improvements in the early onset of pre-natal visits led to greater number of visits by the end of pregnancy. In Table 5, gaining a 100% FPL exposure to CHIP increases pre-natal care by 0.09 visits, and the effect becomes marginally significant in the full specification in column 2. Effects by the timing of exposure in Appendix Table I4 show a similar null effect on the number of visits, including for mothers with full exposure to CHIP ($j \geq 0$). For these mothers, despite earlier onset of pre-natal visits, the number of pre-natal visits did not increase significantly with CHIP exposure.

Table 5: Effects of CHIP exposure on the number of visits and smoking

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

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

Notes. Table shows the effect of CHIP exposure on the number of pre-natal visits and smoking. I define smoking status using the intensive margin of daily cigarette consumption. Specifically, columns 3-4 focus on the probability of consuming 5 or more cigarettes daily, and columns 5-6 focus on the probability of consuming 15 or more cigarettes daily. I estimate separate effects for single and married mothers using equation 7 in odd-numbered columns, and estimate effects on single mothers using equation 8 in even-numbered columns. Robust standard errors clustered at the level of states in the parenthesis.

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

5.4 Heterogeneity

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

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

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

Simulated Eligibility. Complementary to the main analysis, I estimate investment responses using the simulated eligibility strategy (Currie and Gruber 1996a; Currie and Gruber 1996b). Given the income limit, the strategy simulates the probability of being eligible for insurance for a fixed sample of children, and use the probability to parameterize the income limit. Because children of low-income mothers are more likely to be eligible, I

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

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

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

[11] The largest expansion state among this group is Maine, where income limit increased by 55% FPL. States such as Louisiana, South Dakota, Wyoming, Iowa, and Mississippi expanded income limits by only 22.58% FPL. Around 25% of all births occurred in the small expansion states.

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

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

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

simulate separate probability by mother demographics – specifically, by race, education, and marital status – to calculate insurance eligibility for children.[15] I use the average eligibility during pregnancy to calculate in-utero exposure $eligCHIP$, and estimate the effect of in-utero exposure on investments in the following specification

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

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

By construction, in-utero eligibility is larger for mother demographics with higher predicted eligibility for CHIP, for cohorts exposed to CHIP earlier in the pregnancy, and in states expanding insurance to higher income limits. I control for time-varying factors across states with $\alpha_s \cdot \tau_t$, and control for unobserved differences across states and mother demographics with $\alpha_s \cdot \gamma_d$. Therefore, within states and mother demographic groups, I exploit eligibility differences by the timing of exposure across cohorts to estimate the investment responses in equation 12.[16]

I find similar effects of CHIP exposure on birth weight and investments using the simulated eligibility strategy in Appendix Table I5. Increasing CHIP exposure by 10 percentage point eligibility increases birth weight by 3.2 grams, and the effect is concentrated among children of single mothers. For these children, the roll-out increased insurance eligibility from 0.33 to 0.50, and increased birth weight by 8.1 grams. This effect is comparable to the 8.5 gram increase implied by estimates from equation 8 in Table 3.[17] Similarly, investments by eligibility differences are comparable to the effects of expanded income limits on single mothers,[18] supporting the results from equation 8.

5.5 Mechanism

The empirical evidence shows compelling patterns of investment crowd-in following the roll-out of CHIP. To understand the mechanisms of the response, I first examine whether

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

[16] Instead of controlling for group-level fixed effects, Borusyak and Hull (2020) computes and controls for a re-centered measure of insurance eligibility based on counterfactual policy shocks. The counterfactual policy shocks further allow for efficient confidence intervals based on randomization inference.

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

[18] Specifically, the simulated eligibility strategy implies a 0.9 percentage point reduction in late care onset and a 0.2 percentage point reduction in heavy smoking among single mothers during 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.

the exposure to children's insurance increased mother's take-up of own insurance and safety net benefits. I also examine whether mothers increased in-utero investments to improve the long-run outcomes of the child. I find little support for these mechanisms. Instead, behavioral mechanisms on the altruism and the present bias of mothers could explain responses in the level and the timing of investments observed in the data.

Budget Constraint. One mechanism of the crowd-in is that CHIP exposure may have increased the resources of pregnant mothers by inducing higher take-up of safety net benefits. I investigate this possibility using the Survey of Income and Program Participation (SIPP) in Appendix Table I6. I find no evidence that CHIP exposure increased mother's cash transfer incomes or her spending on health services. I also find no evidence of increased borrowing in response to CHIP. Moreover, CHIP exposure has no significant impact on mother's insurance or the type of insurance (public or private) during pregnancy (Appendix Table I7). These results are inconsistent with a resource-based mechanism where CHIP increased investments by relaxing the budget constraint of pregnant mothers.

Investment Complementarity. The crowd-in could also occur if mothers internalize the complementarity between investments in utero and in childhood. With complementarity, in-utero investments can magnify the benefits of program investments in childhood, thus motivating the crowd-in response to CHIP. One implication of the mechanism is that mothers investing more during the roll-out should also expect better outcomes for the child in childhood. I test this implication examining mother's decision to enroll the child in CHIP and her belief about the child's education outcome in SIPP. In Appendix Table I8, mothers exposed to CHIP since the first trimester, in addition to investing more in utero, are also more likely to enroll the child in the first year of life, but expected education for the child does not differ by the exposure to CHIP. These results suggest that the investments are not motivated by the long-run effects on the education outcome of the child.

Altruism. I next examine the two behavioral mechanisms which I take to the data in the structural analysis. CHIP exposure may increase mother's altruism for the child by increasing mother's awareness of the child's well-being. Higher altruism for the child predicts higher levels of investments, but has less obvious implications for the timing of investments. In the event that mothers started pre-natal care earlier primarily to use more care, altruism could also predict earlier onset of investments. Empirically, however, the increase in the early onset of visits did not lead to a significant increase in the number of visits by the end of pregnancy. This suggests that responses in the timing of investments are driven by additional mechanisms apart from the effects on altruism.

Present Bias. To explain responses in the timing of investments, I explore the effect of CHIP exposure on the time preferences of mothers. Specifically, CHIP exposure may have shifted mother's intertemporal weights towards future benefits for the child, making mothers less sensitive to the immediate costs of investments. A reduction in present bias predicts less delay in costly investments and more self control over additive consumption such as smoking. In particular, the reduction in present bias could explain the increase in the early onset of visits absent significant increases in the number of visits. To formally investigate the behavioral mechanisms, I develop a dynamic model of in-utero investments in Section 7, where I exploit the level and the timing of investments to quantify the behavioral effects of CHIP exposure.

6 Education Outcomes

I next estimate the long-run effects of in-utero exposure on children's education outcomes using the American Community Survey (ACS). I find that cohorts with greater exposure to CHIP in utero are more likely to graduate high school and enroll in college. In high school, they are more likely to attend the grade appropriate for their age. These effects are concentrated among children of single mothers.

6.1 Empirical Strategy

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

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

where y_{ibqt} is the education of child i born in year-quarter q and state b surveyed in year t. $eliginc_{ibq}^{utero}$ is the in-utero insurance exposure of child i, calculated from a 3-quarter average of income limits during pregnancy. $single$ indicates children of single mothers. Since in-utero responses to CHIP are 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). In X_{ibqt}, I include childhood exposure $eliginc_{ibqt}^{child}$, constructed as the average income limit from birth till year t, and child age.[19]

I control for unobserved differences by single motherhood across states in $\beta_b \cdot single$.

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

Within states, I exploit differences in the timing of exposure across cohorts to estimate the effect of CHIP exposure on education. In addition, I use state-year fixed effects to account for state-specific trends during the roll-out and in the long-run follow-up.[20] In the robustness check, I further include *single*-year fixed effects to absorb the long-term trends of single motherhood. I estimate equation 13 for children conceived 7 quarters before till 2 quarters after CHIP to exploit the roll-out of CHIP.[21]

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

Equation 13 may yield biased estimates of the effect of CHIP exposure, if mothers adjusted the probability of single parenthood in response to CHIP. Empirically, I examine and rule out the effects of CHIP exposure on the marital status of mothers in Appendix Table I9, and rule out fertility responses to the roll-out of CHIP in Appendix Table I1. These results suggest that differences in the timing of exposure are plausibly exogenous for children of single mothers. To make explicit the variation by the timing of exposure, I plot event study estimates by the quarter of exposure on education outcomes below.

6.2 Effects on Education

I study the education outcomes of children expected to enter Grade 9 or above in 2010-2018. Following the academic progress of these children through high school and into college, I estimate the effect of CHIP exposure on their grade-for-age status, high school graduation, and college enrollment applying equation 13. I focus on college enrollment first.

College Enrollment. Table 6 estimates the effects on college enrollment. Column 3-4 estimates the preferred specification in equation 13. Gaining a 100% FPL exposure to CHIP increases college enrollment by 2.91 percentage points for children of never married mothers, or by 18.44% above the mean. For children of single mothers in general, the

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

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

exposure increases college enrollment by 1.71 percentage points. Controlling for the long-run trends of single motherhood in column 5-6 yields similar estimates. Removing year-specific effects for both states and single motherhood in column 1-2 also yields similar estimates for children of single mothers. Overall, the long-run impacts of in-utero exposure on college enrollment are not sensitive to the choice of controls in the specification.

To illustrate the identifying variation, Appendix Figure J2 plots the effects on college enrollment by the timing of exposure across cohorts. Children conceived more than 4 quarters before CHIP were not exposed to CHIP in utero, and college enrollment did not increase for these children. College enrollment increased by a small and insignificant amount for children exposed to CHIP in the first and second trimester. The overall effect on college enrollment is concentrated among the full exposure cohort, where a 100% FPL exposure to CHIP increased college enrollment by 1.14 percentage points for children of never married mothers, and by 0.69 percentage points for children of single mothers (Appendix Table I10).

Table 6: Effects of CHIP exposure on college enrollment

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

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

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

High School. I also examine the effect of CHIP exposure on children's academic progress through high school, focusing on whether the child attends the grade appropriate for her age (the "grade-for-age" status), and whether the child graduates high school. Appendix

Table I11 shows the estimates. In-utero exposure significantly improves grade-for-age. For children of never married mothers, gaining a 100% FPL exposure in utero lowers late grade entry by 2.36 percentage points, or by 20% below the mean. For children of single mothers, the exposure lowers late grade entry by 1.56 percentage points.

In-utero exposure further improves high school graduation rates for children of single mothers. Gaining a 100% FPL exposure increases high school graduation by 1.71 percentage points for children of never married mothers, or by 5.94% above the mean. Compared to the effect on college enrollment, the increase in high school graduation is smaller in magnitude, suggesting that CHIP exposure increased college enrollment among high school graduates who would not have attended college absent the exposure. Across cohorts, the effects on high school graduation is concentrated among children gaining full exposure to CHIP in utero (Appendix Table I10).

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) finds that a ten percentage point increase in Medicaid eligibility in utero and in the first year of life increases college enrollment by 0.35 percentage points.[22] This effect implies that the roll-out of CHIP would increase college enrollment by 0.60 percentage points.[23] In practice, the exposure to CHIP increased college enrollment by 1.13 percentage points for children of single mothers, or by 0.29 percentage points for children on average.[24] Therefore, in-utero exposure to CHIP increased college enrollment by around half the direct effect of insurance to pregnant mothers and infants.

6.3 Discussion

Empirical results from Section 5 and 6 show that in-utero exposure to the roll-out of CHIP significantly improved the birth weight and the college enrollment of children. Specifically, the exposure decreased low birth weight by 3.6% and increased college enrollment by 1.13 percentage points for children of single mothers. To understand the magnitude of the effect on birth weight, I compare the effect of CHIP exposure with the direct effects

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

[23] 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.

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

of transfer programs for single mothers. For instance, Hoynes *et al.* (2015) estimates that single mothers receiving a $1,000 payment of Earned Income Tax Credit (EITC) have lower rates of low birth weight by 6.7%. By comparison, in-utero exposure to the roll-out of CHIP resulted in around half the reduction in low birth weight. Therefore, for both birth weight and college enrollment, in-utero exposure to CHIP improved child outcomes by around half the direct effects of transfers to low-income families and children.

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 in each trimester to invest in the birth weight of the child. Because investments occur over multiple trimesters, mothers may delay the onset of investments and end up under-investing in the child. The exposure to CHIP shifted the timing and the level of investments, which I exploit to estimate the behavioral effects of the exposure. I then evaluate welfare based on the model estimates.

7.1 Setting

Pre-Natal Visits. Let v_{it} be the monthly number of visits chosen by mother i in trimester t, where $t = 1, 2, 3$. Following the medical guideline, I allow the maximum number of visits each month to increase from 1 visit in the first trimester to 2 visits in the second trimester, and finally to 4 visits in the third trimester. The higher frequency of visits in the third trimester matches the guideline recommendation of weekly visits for near-term mothers. In the model, mothers can take a maximum of 21 visits during pregnancy. Empirically, mothers on average take 11 visits during pregnancy.

The out-of-pocket cost of a pre-natal visits is c_{it}. I allow the cost to vary by mother age a_i and a health shock ξ_{it}. The health shock is assumed to be $i.i.d.$ $N(0,1)$, and determines whether the mother pays zero out-of-pocket cost or pays a positive amount, in which case the cost is a quadratic function of mother age. I match the probability of paying positive costs and the level of the costs with empirical moments observed in the Medical Expenditure Panel Survey (MEPS). I show details of the cost calibration in Appendix D.

Mother's utility from a pre-natal visit depends on her taste for the visit relative to the cost c_{it}. Her taste has a permanent component η_i and a transitory component υ_{it}. η_i is drawn from the type distribution of mother i. I assume three types of mothers in the population, each with a different permanent taste for visits. The distribution of η_i

across mother types depends on mother characteristics X_i. The transitory taste shock v_{it} is assumed to be *i.i.d.* $N(0, \sigma_v^2)$. I measure mother's tastes and utility in dollars. Specifically, her utility from taking v_{it} visits each month in trimester t is given by

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

Smoking. In trimester t, mother i also chooses smoking intensity s_{it}. I let s_{it} take on three potential levels using cut-points at 5 and 15 cigarettes daily. Non-smokers ($s_{it} = 0$) consume fewer than 5 cigarettes daily. Light smokers ($s_{it} = 1$) consume 5 to 15 cigarettes, or around half a pack daily. Heavy smokers ($s_{it} = 2$) consume over 15 cigarettes daily, or a full pack on average. I assume that the utility from an additional level of smoking – roughly a half pack daily – depends on a permanent taste ζ_i and a transitory taste shock ω_{it}. ζ_i is drawn from the type distribution of mother i, and ω_{it} is drawn from *i.i.d.* $N(0, \sigma_s^2)$. Since the price of tobacco does not vary by mother characteristics, I absorb the money cost of smoking inside taste ζ_i, and write the utility from smoking s_{it} in trimester t as

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

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

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

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

$smoke_i$ and $heavy_i$ are binary variables derived from the average smoking intensity $\bar{s}_i = \frac{1}{3} \sum_{t=1}^{3} s_{it}$ in pregnancy. Specifically, $smoke_i = 1$ for mothers smoking more than 5 cigarettes daily ($\bar{s}_i \geq 5$), and $heavy_i = 1$ for heavy smokers with more than 15 cigarettes daily ($\bar{s}_i \geq 15$). The effect of smoking on birth weight is captured by ϕ_3, and the effect of heavy smoking on birth weight is captured by $\phi_3 + \phi_4$.

I further include flexible interaction terms between pre-natal visits and the smoking indicators in $\Phi(V_i,\, V_i^2,\, smoke_i,\, heavy_i)$. I therefore allow the marginal benefit of pre-natal visits to vary by the smoking intensity of mothers. Moreover, birth weight depends on an endowment effect ϕ_i drawn from the type distribution of mother i. Larger ϕ_i increases the

return of investments on birth weight. The error term ϵ_i is assumed to be $i.i.d.$ $N(0, \sigma_b^2)$.

Altruism. Mothers derive utility from the child's birth weight according to $L(b_i) = \alpha\, b_i^{\theta}$, where θ governs the marginal utility of birth weight, and α is the utility weight on child outcomes. I use α to measure mother's altruism for the child. Larger α increases mother's valuation of birth weight relative to her own utility $\vartheta(v_{it}; v_{it}, \xi_{it}, a_i)$ and $\psi(s_{it}; \omega_{it})$ from investments.

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

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

where $\varepsilon_{i3} = (v_{i3}, \xi_{i3}, \omega_{i3})$ is the vector of transitory shocks in $t = 3$. $\mathcal{I}_{i3} = (3\sum_{t=1}^{2} v_{it}, \sum_{t=1}^{2} s_{it}, X_i)$ is the state vector summarizing previous investments and mother characteristics X_i. Let (v_{i3}^*, s_{i3}^*) denote mother's investments in $t = 3$. The long-run utility implied by the investments is

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

Compared to equation 17, the long-run utility places higher weights on the utility from birth weight, $\mathbb{E}\Big[L(b_i)|\mathcal{I}_{i3}, v_{i3}^*, s_{i3}^*\Big]$, discounting it by the long-run factor $\delta = 1$.

In $t = 2$, mother anticipates her investments in $t = 3$ but discounts future utility by the present bias term β. Specifically, investments in $t = 2$ maximize the following utility

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

where $\mathcal{U}_3$ is the long-run utility implied by investments in $t = 3$ (equation 18). Maximizing equation 19 yields investments (v_{i2}^*, s_{i2}^*) in $t = 2$. Recursively, the long-run utility implied by investments in $t = 2$ is discounted by the present bias term β to determine investments in $t = 1$.[25] Therefore, I solve the investment profile $\left(v_{it}^*, s_{it}^*\right)_{t=3,2,1}$ of mother i from equation 17 to 20, discounting the long-run utility in the next period by the present bias term β. I then match the model solutions with observed investments in the data to estimate the

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

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

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

model parameters.

7.2 Estimation

I estimate the birth weight production function (equation 16), mother preferences (α, θ, β), and her tastes (η_i, ζ_i, ϕ_i, ε_{it}) using the method of simulated moments (MSM). To estimate the behavioral effects of CHIP, I allow altruism α and present bias β to vary by CHIP exposure $\Delta\ell_i$. I model the behavioral effects and construct moment conditions identifying the model parameters below.

CHIP Exposure. Similar to the empirical strategy in Section 5, I construct CHIP exposure $\Delta\ell_{js}$ exploiting the timing of exposure for cohort j and the size of expansion in state s. Building on the definition of in-utero exposure $eliginc$ (equation 6), I calculate CHIP exposure $\Delta\ell_{js} = eliginc_{js} - inc_s^{pre}$ as the change in $eliginc$ due to the onset of CHIP. For mothers starting pregnancy within 9 months before CHIP ($-9 \leq j \leq -1$), $\Delta\ell_{js}$ equals $(1 + \frac{j}{9}) \cdot \Delta inc_s$, which increases with j for cohorts with earlier exposure to CHIP, and increases with the size of expansion $\Delta inc_s = inc_s^{post} - inc_s^{pre}$. $\Delta\ell_{js}$ equals Δinc_s for cohorts gaining full exposure to CHIP ($j \geq 0$), and equals 0 for cohorts never exposed to CHIP in utero ($j \leq -10$).

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 pre-CHIP income limit was between 110% and 130% FPL, and the expansion was between 20% and 90% FPL. I therefore estimate the behavioral effects starting from a common baseline exposure level across states.[26] I discretize $\Delta\ell_{js}$ in these states into 5 nodes, corresponding to 0%, 10%, 30%, 50% and 70% FPL exposure to CHIP. I assign mothers with $j \leq -10$ to the zero exposure node, and assign mothers with $j \geq -9$ to the nearest positive exposure node to construct the discretized exposure $\Delta\ell_i$ for mother i.

Behavioral Effects. I use $\Delta\ell_i$ to study the effect of CHIP on altruism α and present bias β. I specify that mother's altruism α_i responds to CHIP exposure $\Delta\ell_i$ according to a linear equation

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

where the slope α_1 is the effect on altruism for a unit increase in CHIP exposure, and α_0 is the baseline altruism prior to CHIP ($j \leq -10$). I normalize $\alpha_0 = 1$.[27] Similarly, I specify a

[26] 91% of single mothers lived in states with pre-CHIP income limit between 110% and 130% FPL. I show details of the sample construction in Appendix E.

[27] This is because mother's utility weight for her own investments is already estimated in her taste types

linear response function for present bias

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

where β_0 is the baseline present bias for $j \leq -10$, and β_1 is the effect on present bias for a unit increase in CHIP exposure. Using these equations, I determine the altruism and the present bias of mother i based on her exposure $\Delta\ell_i$ and the baseline preferences. I therefore estimate parameters $(\alpha_1, \beta_0, \beta_1)$ to quantify the behavioral effects of CHIP exposure.

Moment Conditions. I quantify the behavioral effects exploiting CHIP exposure as shifters of mother preferences in equation 21 and 22. The shift in mother's present bias affects her valuation of future utility, and hence impacts the timing of investments across trimesters. The shift in altruism affects the trade-off between birth weight and mother's own utility from investments, and hence impacts the level of investments in utero. I therefore match the following moment conditions to quantify the behavioral effects

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

To estimate the birth weight production function in equation 16, I construct moment conditions exploiting the exposure levels in $\Delta\ell_i$ as instruments.[28] Specifically, I match the reduced-form relationship between birth weight and $\Delta\ell_i$ in addition to the first-stage relationship between investments and $\Delta\ell_i$. The relative shifts in birth weight and investments in response to $\Delta\ell_i$ inform the production of birth weight from investments. I also match the empirical patterns between 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 moments receive lower weights in the estimation. In total, I employ 272 moment condi-

η_i and ζ_i. Different scaling of the child's weight α_0 does not affect the relative utility weights between the mother and the child.

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

tions to estimate the model parameters. I detail the full list of moment conditions and the estimation procedure in Appendix F.

Mother Types. Finally, 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 mother types in the population. Specifically, the probability of being type $k = 0, 1, 2$ for mother i is the follows

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

where F is the cumulative distribution function of a standard normal. X_i includes mother age, whether the mother had fetal death in previous pregnancies, has any maternal risk factor on the birth certificate, and the smoking rate in the mother's county of residence. I summarize mother characteristics and the construction of the variables 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

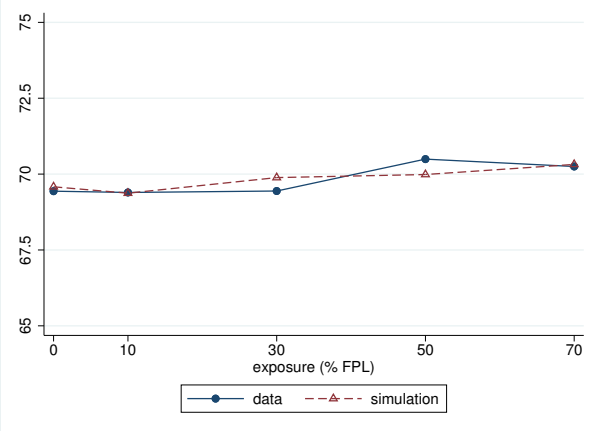
Behavioral Effects. The top panel of Table 7 estimates the behavioral effects of CHIP exposure on altruism and present bias. The exposure has little effect on the altruism of mothers. The estimate of the slope parameter α_1 is small and indistinguishable from zero. The investments therefore are not driven by higher altruism for the child. By contrast, CHIP exposure significantly lowered the present bias of mothers. Gaining a 100% FPL exposure increases mother's short-term patience by $\beta_1 = 0.13$, and the effect is significant at 95% level with a p-value of 4.92%. Compared to the short-term patience before CHIP ($\beta_0 = 0.75$), 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 14.4% ($= 80\% \cdot 0.13/0.75$).

I illustrate the identification of the behavioral effects comparing simulated investments with empirical patterns in the data. In Figure 3, the share of mothers staring care in the first trimester increased with CHIP exposure (panel a), and the share starting care in the second trimester decreased with the exposure (panel b). The simulation matches these patterns in the data. Despite earlier onset of visits, the number of visits did not increase by the end of pregnancy (panel c), whereas smoking intensity decreased with exposure

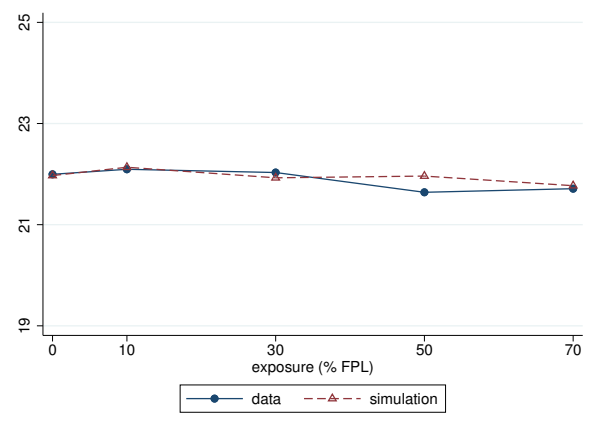
in panel (d). The simulation also matches these responses in the level of investments. Therefore, the early onset of visits and the reduction in smoking are primarily driven by the behavioral effect on the present bias of mothers.

Figure 3: Investment responses to CHIP exposure, model fit

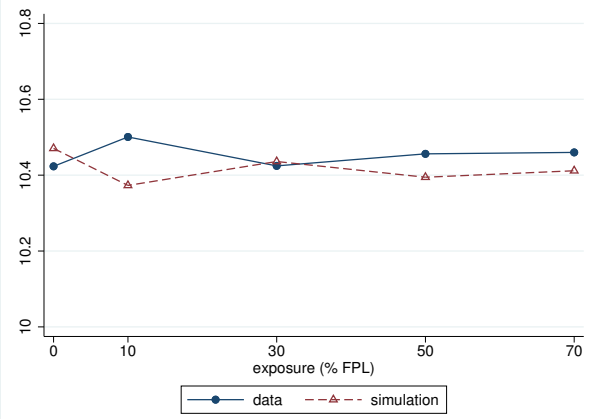
(a) First Trimester Onset (%)



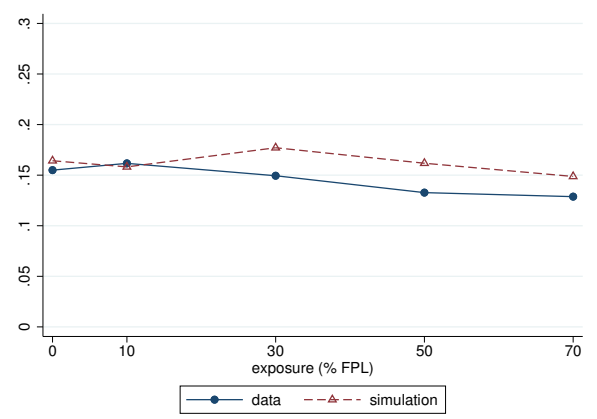
(b) Second Trimester Onset (%)



(c) Number of Pre-Natal Visits



(d) Smoking Intensity (Half Packs)



Notes. Figure compares simulated investments with observed investments 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 non-college educated single mothers and plot simulated investments by exposure levels in dotted lines. I plot the empirical counterparts in solid lines.

Mother Types. The middle section of Table 7 summarizes the taste types and the birth weight endowment of mothers. The majority of mothers (52.74%) are type 2 mothers who derive positive utility from pre-natal visits and negative utility from smoking. Another large share of mothers (37.68%) are type 1 mothers with significant disutility from smoking.

Table 7: Estimated model parameters

Behavioral Effects			
α_0:	1	α_1:	0.001
	–		(0.14)
β_0:	0.75	β_1:	0.13
	(0.048)		(0.068)
Mother Types	Type 0	Type 1	Type 2
Taste for visits η_i	-0.017	-0.38	3.75
	(0.86)	(0.45)	(0.48)
Taste for cigar. ζ_i	38.42	-677.60	-17.68
	(4.27)	(<0.001)	(1.97)
Endowment ϕ_i	3.33	2.16	2.02
	(0.29)	(0.19)	(0.18)
Share (%)	9.58	37.68	52.74
Birth Weight Production			
V_i	1.54	$V_i \cdot smoke$	0.61
	(0.009)		(0.009)
V_i^2	-0.093	$V_i \cdot heavy$	4.72
	(<0.001)		(2.46)
$smoke$ ($\bar{s}_i \geq 5$)	-10.52	$V_i^2 \cdot smoke$	0.025
	(0.094)		(<0.001)
$heavy$ ($\bar{s}_i \geq 15$)	-4.55	$V_i^2 \cdot heavy$	-0.77
	(8.95)		(0.15)
Birth Weight Valuation			
θ:	0.53		
	(0.006)		

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

Notes. Table shows estimates of the model parameters. The top panel shows estimates of the behavioral effects in equation 21 and 22. The middle panel shows estimates of mother types – her tastes for visits, smoking, and the birth weight endowment – and the share of each type in the population. The last panel shows estimates of the birth weight production function (equation 16) and θ, which determines mother's marginal utility from birth weight. I estimate the model parameters using the Method of Simulated Moments where I match the investment profiles and the birth outcomes of ten million low-educated single mothers with empirical counterparts in the data. I show standard errors of the estimated parameters in the parenthesis.

These mothers almost never smoke in pregnancy, and their tastes for pre-natal visits are not statistically different from zero. The remaining share of mothers (9.58%) are type 0 mothers who have strong tastes for smoking, almost always smoke in pregnancy, and are indifferent about pre-natal visits. The birth weight endowment is also largest among type 0 mothers.

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

Birth Weight Production. The lower panel of Table 7 estimates the birth weight production function in equation 16. Pre-natal visits significantly increase birth weight with diminishing marginal benefits. By contrast, smoking more than 5 cigarettes daily significantly lowers birth weight. The magnitude of these two effects suggests that the negative impacts of smoking are roughly offset by 7 additional visits in pregnancy. The interaction terms between visits and smoking imply that the optimal number of visits is around 9 for non-smoking mothers, and around 15 for smokers.

Birth weight further depends on endowment ϕ_i. High-endowment mothers have higher returns to investments and may invest more in response to the exposure. To illustrate this point, I simulate investments and birth weight by exposure $\Delta\ell_i$ and mother types in Appendix Figure J5. Consistent with higher endowment, type 0 mothers increased the number of pre-natal visits by a small amount (panel b) despite having nearly zero tastes for visits. The endowment further contributes to the significant reduction in smoking for type 0 mothers (panel c) despite strong tastes for smoking among these mothers. Due to the investments, 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 effects on the utility of mothers. To do so, I simulate counterfactual investments in the absence of CHIP, and use the utility difference to reveal mother's valuation of the exposure. I then ask how mothers value the exposure to CHIP compared to expansions of own insurance using the marginal value of public funds (Finkelstein and Hendren, 2020).

Utility. I measure welfare adopting mother's long-run utility as the normative criterion.[29] Under the criterion, optimal investments maximizing the long-run utility generate welfare $\mathcal{U}^*$.[30] However, because investments of present-biased mothers deviate from the long-run optimal, the welfare loss from present bias is $\frac{\mathcal{U}^*-\mathcal{U}^i}{\mathcal{U}^*}$ relative to the long-run utility $\mathcal{U}^*$, where $\mathcal{U}^i$ denotes the welfare of investments in the status quo ($i = 1$) and in the absence of CHIP ($i = 0$). The exposure to the roll-out lowered 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 0.06%. Across mother types, the welfare effect is larger for type 0 mothers, where long-run utility increased by 0.16%. To understand how mother's investments contribute to the welfare effect, I calculate utility separately for in-utero investments M^i and for the child's birth weight C^i.[31] Investments decreased long-run utility by 0.047% but increased the utility from birth weight by 0.11%, with larger increases of 0.20% for type 0 and type 1 mothers. Type 0 mothers increased birth weight at substantially lower costs, deriving the largest welfare gain from CHIP exposure.

MVPF. Since I measure mother 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 of mother i as

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

where I normalize the utility difference $\mathcal{U}_i^1 - \mathcal{U}_i^0$ by the level of 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 then compare mother's WTP with the cost of exposure to the program to construct

[29] This is a common practice in the literature to evaluate the welfare consequences of time inconsistency (e.g., Herrnstein *et al.* 1993; O'Donoghue and Rabin 2006; Duflo *et al.* 2011).

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

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

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

[31] Specifically, mother utility $\mathcal{U}^i = C^i + M^i$ is the sum of utility from the child's birth weight C^i and own investments M^i. 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.

Table 8: Effects of CHIP exposure on birth weight and investments

	All	Type 0	Type 1	Type 2
$\frac{\mathcal{U}^1-\mathcal{U}^0}{\mathcal{U}^*}$ (%)	0.061	0.16	0.063	0.041
	(<0.001)	(0.001)	(<0.001)	(<0.001)
$\frac{C^1-C^0}{\mathcal{U}^*}$ (%)	0.11	0.19	0.21	0.020
	(<0.001)	(0.001)	(<0.001)	(<0.001)
$\frac{M^1-M^0}{\mathcal{U}^*}$ (%)	-0.047	-0.028	-0.15	0.021
	(<0.001)	(0.001)	(<0.001)	(<0.001)
Share (%)	100	9.58	37.68	52.74

Notes. Table summarizes the welfare effect of CHIP exposure relative to the long-run utility $\mathcal{U}^*$ of mothers. I calculate separate utility for the child's birth weight C^i and for mother's investments M^i, where subscript i indicates outcomes in the status quo ($i = 1$) and in the absence of CHIP ($i = 0$). I then examine welfare effects by the effect on birth weight and on investments according to $\frac{\mathcal{U}^1-\mathcal{U}^0}{\mathcal{U}^*} = \frac{C^1-C^0}{\mathcal{U}^*} + \frac{M^1-M^0}{\mathcal{U}^*}$. Standard errors of the welfare effects from ten million simulated individuals in the parenthesis.

the marginal value of public funds (MVPF) for the exposure (Finkelstein and Hendren 2020; Hendren and Sprung-Keyser 2020). I measure the cost of the exposure 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, and calculate the cost of exposure ΔG to be \$0.42 per household in the roll-out.[32]

I calculate the MVPF for CHIP exposure as follows

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

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

Table 9 calculates the MVPF. Mothers are willing to pay \$0.43 for the benefit of the exposure on birth weight, and the valuation is sufficient to offset the \$0.41 cost of the exposure. Net of investments, mothers are willing to pay \$0.29 for the exposure, and

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

hence value the exposure at $\frac{\$0.29}{\$0.41} = 71\%$ of the cost. To understand magnitude, I ask how mothers value the exposure compared to expansions of own insurance. For instance, recent Medicaid expansions in Oregon and Massachusetts suggest that low-income adults value the expansion of own insurance between 55% and 116% of the cost (Finkelstein *et al.* 2019a; Finkelstein *et al.* 2019b). By comparison, the MVPF of CHIP exposure falls within if towards the lower end of these estimates.[33] Therefore, consistent with high WTP for child outcomes, mothers value the exposure to children's insurance as much as expansions of own insurance.

Despite high WTP for child outcomes, parents may suffer from behavioral biases that lower their investments in the child. By adjusting the behavioral biases, information of children's insurance can "nudge" parents to invest more in the child, and the nudge can be highly effective due to high WTP for child outcomes. Thus, in addition to improving child outcomes, outreach efforts encouraging parental investments also improve parents' own utility as effectively as direct expansions of insurance.

Table 9: MVPF of CHIP Exposure

	WTP	WTP^C	WTP^M	$MVPF$
$\varphi = 1$	0.29	0.42	-0.13	0.71
	(0.001)	(0.002)	(0.001)	(0.002)
$\varphi = 2$	0.59	0.85	-0.26	1.44
	(0.002)	(0.003)	(0.002)	(0.004)
$\varphi = 3$	0.88	1.27	-0.39	2.15
	(0.003)	(0.005)	(0.003)	(0.006)

Notes. Table summarizes the marginal value of public funds (MVPF) of CHIP exposure. I calculate the MVPF normalizing mother's WTP for the exposure 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 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.

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

7.5 Fiscal Externality

Because I calculate MVPF based on mother's WTP for the exposure, social benefits of the exposure not internalized by mother investments are not captured in the welfare analysis. In particular, mothers investing more in utero did not expect higher education outcome for the child, but investments increased the child's college enrollment, which may lead to higher earnings and tax payments that lower the net cost of the program. The fiscal externality is under-stated in mother's WTP for the exposure. Here, I separately quantify the fiscal externality predicting earnings and tax payments from the effect on education.

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

Applying a 18.9% marginal tax rate (Hendren and Sprung-Keyser, 2020), CHIP exposure increases tax payments by $18.9\% \cdot \$1,101.11 = \$208.11$ per child of single mothers. The increase in tax payment amounts to $\frac{\$208.11}{\$2,483.10} = 8.4\%$ of the initial program cost in childhood. This result suggests that parental responses to the roll-out already reduced the net cost of the program by 8.4% before the onset. I examine robustness in Appendix H. Fiscal externality increases to 15.4% of the cost when students enroll in college for 4 years, and drops to 6.0% under a 3% discount rate and a 2-year enrollment. These estimates suggest that parental responses could magnify the fiscal externality of program investments by over 6% in the long run.[34]

8 Discussion and Conclusion

Social policies for children increasingly harness parental investments to augment the policy impacts on children. In K-12 and pre-school, for instance, parent-school partnerships and family-based interventions lower the informational and behavioral frictions facing parents, improving their investments and the education outcome of the child.[35] To effectively

[34] Focusing on Medicaid insurance for children, Brown *et al.* (2020) estimates that each childhood year of eligibility increases tax payments in age 19-28 by \$178 in 2000 dollars. In-utero exposure to CHIP predicts higher tax payments between \$12 and \$32 by age 28, increasing the fiscal externality of the program by 6.7% to 18.0% in the long run.

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

engage parents, policymakers need information on how parents invest in the child and how responses to policies might impact investments and child outcomes. In the context of social insurance for children, I provide evidence on these questions exploiting the roll-out of the Children's Health Insurance Program (CHIP) in 1997-2000.

I find that expanding insurance for children increases parental investments in utero. Pregnant mothers exposed to higher CHIP eligibility reduced smoking and improved the timely onset of pre-natal visits. Using a structural model of in-utero investments, I find that CHIP exposure increased investments by lowering the present bias of mothers, and increased mother utility primarily through the effects on birth weight. This result suggests that parents highly value child outcomes, but nonetheless under-invest due to behavioral biases over-weighting the short-term costs of investments.

The behavioral mechanism has several implications for policy. First, parents may exhibit short-term bias 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 benefits for more present-biased parents (Mayer *et al.*, 2019). Second, effective engagement strategies can feature low-cost, light-touch approaches without financial incentives to parents. In particular, I find that "nudging" parents with in-utero exposure to CHIP increases utility as effectively as expansions of mother's own insurance coverage.

Finally, combating the behavioral biases also generates substantial benefits to the society in terms of 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), implying high social externality of parental investments. In-utero exposure to CHIP, for instance, lowers the cost of program investments by 8.38% through the benefits on adult earnings and tax payments. These benefits provide strong motivations for outreach efforts engaging parents in children's insurance programs.

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Appendix

A Simulated Eligibility

I calculate simulated eligibility using the full sample of women between age 21 and 40 in the 2000 decennial census. I assume that woman i has a child of age a_i belonging to age band $b(a_i)$. The child is eligible for Medicaid/CHIP if the woman's family income $finc_i$ is less than the income limit inc^b_{st}. To parametrize the income eligibility rules, I apply income limits from different states s and time t, and calculate the implied share of children eligible for Medicaid/CHIP by age band b as follows

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

where $N = 1,948,731$ is the sample size of all women in age 21-40 in the 2000 census. The simulated eligibility $eligCHIP^b_{st}$ calculates the share of children of age band b who would be eligible for Medicaid/CHIP for a fixed composition of mothers and their incomes. Given age band b, differences in $eligCHIP^b_{st}$ reflect exogenous variation in program rules that shifted income limits across states and over time.

I calculate $eligCHIP^b_{st}$ for three age bands: infants (age 0), small children (age 1-5) and older children (6+). The income limits in each state before and after CHIP by age bands are listed in Table 1. In expectation, childhood eligibility $eligCHIP_{st}$ is a weighted average over childhood years:

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

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

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

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

where $\mathcal{G}$ is the collection of children in demographic group g. The simulated eligibility $eligCHIP^b_{gst}$ calculates the share of children of age b in group g who would be eligible for Medicaid/CHIP for a fixed composition of mothers and incomes. Within group differences in eligibility $eligCHIP^b_{gst}$ reflect exogenous variation in income limits across states and over time.

Childhood eligibility for group g is given by

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

For pregnant mother i in the birth sample, I calculate childhood eligibility

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

as the average eligibility over a 9-month gestation, where $eligCHIP_{gs\tau}$ is the childhood eligibility according to policy rules in effect in month τ of the pregnancy, whereas subscript t refers to the month of fertility as in the main text. I plot $eligCHIP_{g(i)st}$ across states and cohorts during the CHIP roll-out in Figure 1. Eligibility increased substantially from 0.15 to 0.30 between the 1997 and the 2000 cohort (or from 2.85 eligible years to 5.70), and increased even more for children of single mothers from 0.33 to 0.50 over the same period.

In most of the empirical analyses, I simply calculate the average income limit during childhood as a measure of insurance eligibility:

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

where $inc_{s\tau} = \frac{1}{19} inc_{s\tau}^{0} + \frac{5}{19} inc_{s\tau}^{1-5} + \frac{13}{19} inc_{s\tau}^{6+}$ is the average income limit according to eligibility rules in effect in state s and month τ of the pregnancy. Averaged over a 9-month gestation, $eliginc_{st}$ gives the childhood income limit for newbornes conceived in year-month t in state s.

B Detailed Proofs

I solve the parents' investment problem backwards, starting from the childhood stage $t = 1$. Given child health $h = 0, 1$, parents choose the schooling 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 $u\left(Y_1 - v_1^h - OOPC \cdot 1\{h = 0\}\right)$ is the utility from consumption after investing v_1^h and medical expenses $OOPC$ in case of a low health child ($h = 0$). Larger investments improve utility from schooling outcomes $s(v_1^h)$ and adult outcomes $V^h(s(v_1^h))$. Optimal investments v_1^{h*} satisfy the first order condition

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

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

The condition states that optimal investment v_1^{h*} matches the marginal cost of investment on consumption $u'(c_1^{h*})$ with the marginal gains on education and adult outcomes $\Gamma' s'(v_1^{h*}) + \delta V' s'(v_1^{h*})$. As CHIP lowers $OOPC$, decreasing v_1^{h*} lowers the marginal cost on consumption but increases the marginal gains on education outcomes for concave Γ, s, and V. Therefore v_1^{h*} must increase at lower $OOPC$. Moreover, because $OOPC = 0$ for $h = 1$, parents invest more in the high health child ($v_1^{1*} > v_1^{0*}$), and the marginal benefits of investment are higher for the low health child. From equation B2, it follows that the marginal cost of consumption is also larger for the low health child. This implies that total investments are larger in the low health child, but non-health investment v_1^{0*} is smaller due to the medical expense $OOPC$.

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

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

where consumption $c_0 = Y_0 - v_0$, and $w(v_0)$ is the utility on birth outcomes as a function of in-utero investments v_0. Larger v_0 also increases the probability of high child health in $t = 1$, 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 $\Delta\tilde{U}_1 = u(c_1^*) - u(c_0^*) + \Gamma(s(v_1^{1*})) - \Gamma(s(v_1^{0*})) + V^1(s(v_1^{1*})) - V^0(s(v_1^{0*})) = \Delta u + \Delta\Gamma + \Delta V$ is the utility gap in future periods in terms of consumption (Δu), education outcomes ($\Delta\Gamma$), and the child's adult outcomes (ΔV). The gaps are determined by childhood investments v_1^{h*}. Since non-health investments increase for low health children at lower $OOPC$ but remain constant for high health children, CHIP narrows the outcome gap $\Delta\Gamma + \Delta V$ between low and high health children. The investments lower the marginal benefits on the right hand side of equation B2, implying higher consumption levels for parents of low health

children. Therefore, consumption gap Δu also decreases after CHIP. As a result, $\Delta\tilde{U}_1$ is smaller after CHIP. This effect then lowers the marginal benefit of in-utero investment v_0, captured by the term $\delta\rho'(v_0^*)\Delta\tilde{U}_1 + w'(v_0^*)$ in equation B4. In response, v_0 decreases after CHIP.

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

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

and in-utero investment v_0 solves

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

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

When CHIP also increases altruism α in addition to lowering $OOPC$, it is easy to see that non-health investments increase for both health due to equation B5. The additional investments lower consumption c_1^{1*} for parents of high health children. For parents of low health children, the additional investments are potentially offset by smaller medical expenses $OOPC$, rendering the consumption implications ambiguous. In the case that parental consumption is a normal good, lower medical expenses increases consumption c_1^{0*}. This would imply that the consumption gap Δu narrows after CHIP. However, $\Delta\Gamma + \Delta V$ depends on the relative size of investment responses and the marginal effects of investments on outcomes ($\Gamma' s' + V' s'$) by child health. These quantities are indeterminate from equation B5.[36] In general, altruism increases parent's perception of the utility gap $\Delta\tilde{U}_1(\alpha) = \Delta u + \alpha(\Delta\Gamma + \Delta V)$, increasing the perceived benefits of in-utero investments on the left hand side of equation B6.

Present Bias. Present-biased parents discount future benefits of investments by an additional factor β to the present period. The inconsistency in time preference generates oversensitivity to short-term costs relative to long-run benefits, implying under-investment in the short term. Specifically, investments of a present-biased parent satisfy the following conditions in childhood

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

and the following condition in-utero

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

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

When CHIP increases both α and β in addition to lowering $OOPC$, non-health in-

[36] For illustration, consider the special case where $u(c) = \log(c)$, and $\Gamma(s(v)) + V(s(v)) = \log(v)$. It is easy to see that $\Delta\Gamma + \Delta V = \log\left(\frac{Y_1}{Y_1 - OOPC}\right)$, and valuation $\alpha(\Delta\Gamma + \Delta V)$ increases after CHIP with $\alpha > 1$.

vestments increase even more for both high and low health children. However, the consumption implications for parents of low health children are ambiguous, and the gap in child outcomes depends on the relative increase in investments and the marginal effects of investments by child health. As a result, utility gap $\Delta\tilde{U}_1 = \Delta u + \alpha(\Delta\Gamma + \Delta V)$ can either increase or decrease after CHIP. Regardless, larger β increases parent's perceived benefits of investments, given by $\beta\delta\rho'(v_0^*)\Delta\tilde{U}_1$, on future utility, mitigating the potential drop in utility gap $\Delta\tilde{U}_1$. Combined with higher altruism for the child, in-utero investments potentially increase after CHIP.

C Education Outcomes

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

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

	mean	s.e.		mean	s.e.
grade-for-age (%)	88.21	0.052	child age	16.89	0.003
graduate high school (%)	28.79	0.073	birth year	1998.36	0.002
enroll in college (%)	15.78	0.059	survey year (t)	2015.25	0.003
			Grade 1 entry year	2004.72	0.002
single motherhood					
never married (%)	8.64	0.045	$eliginc^{utero}$ (100% FPL)	1.58	0.001
unmarried in t (%)	25.46	0.070	$eliginc^{child}$ (100% FPL)	2.33	0.001

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

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

Variable Definition. I determine the child's grade-for-age status – whether the child attends the grade level expected of her age and graduates high school on time – based on the school entry age in the state. Specifically, children turning five before a cut-off month in a year can enter kindergarten in the same year, and those turning five after the cut-off enter in the next year. Since ACS provides the quarter of birth rather than the month, I assume that children born in the same quarter as the cut-off are born after the cut-off month, and hence adopt the more generous criterion in determining grade-for-age.[37] For children expected to have finished Grade 12, grade-for-age indicates whether the child has obtained a regular high school diploma or is enrolled in college. I also separately examine high school graduation and college enrollment as distinct outcomes after Grade 12.

I identify mothers of school-age children in the ACS using the family interrelationships variables developed by Ruggles *et al.* (2020). Based on mother's marital status, I define

[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).

single motherhood requiring that the mother has never married, or is unmarried in survey year t. 8.64% of the children live in single-mother households where the mother has never married, and 25.46% live in households where the mother is unmarried in year t. Over the sample period, in-utero exposure to CHIP averages 158% FPL, and increased from 122% FPL before CHIP to 202% FPL after. Childhood exposure averages 233% FPL, and increased from 201% FPL when the average child is age 0 to 263% FPL when the child reaches age 18.

D Calibration of Out-Of-Pocket Costs

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

For pregnant mothers, I identify pre-natal visits if the visit was related to a pregnancy condition during a 9-month period prior to the birth event. I look up pregnancy-related conditions from the Clinical Classification Codes provided by MEPS. I further require that the mother consult directly with a medical doctor in an office setting during the visit. Appendix Table D1 summarizes the out-of-pocket cost per visit for low-educated single mothers who had a birth event in 1997-2001.

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

	(1) $OOPC$	(2) $OOPC > 0$	(3) $OOPC(>0)$
age	0.80	0.10***	-15.32
	(1.05)	(0.024)	(9.79)
age^2	-0.011	-0.0016***	0.25
	(0.018)	(0.0004)	(0.16)
constant	-9.69	-1.41***	249.04
	(15.02)	(0.33)	(144.72)
y mean	3.42	0.14	24.26
N	1,750	1,750	251

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

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

Over 85% of the pre-natal visits had zero out-of-pocket costs (y mean in column 2). The probability of zero costs varied significantly with age. To approximate the empirical

distribution, I model the out-of-pocket cost as following a two-node distribution between zero costs and a positive amount depending on the mother's age. The mass at zero is determined by the regression coefficients in column 2. The level of the positive cost is determined by the regression coefficients in column 3. Although I predict out-of-pocket costs using a quadratic function of mother age, I discretize mother age into four 5-year age groups, and calibrate the cost per visit as follows

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

where $g = 0, 1, 2, 3$ indexes age groups 21-25, ..., 36-40. z_g is probability of positive out-of-pocket costs for group g. In the model, positive out-of-pocket costs occur when the health shock ξ_{it} is greater than $F^{-1}(1-z_g)$, where F is the cumulative distribution function of a standard normal.[38] Larger health shocks increase the probability of paying positive out-of-pocket costs. I use the median age in each age group and the regression coefficients in column 3 of Appendix Table D1 to calibrate the positive cost level.

[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 estimates 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 expansion 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. These states account for 10% of the births by low-educated single mothers. Moreover, 5 states (MN, MI, NM, VT, WA) expanded insurance above 130% FPL prior to CHIP, and the remaining states (91% of the births by low-educated single mothers) have pre-CHIP income limits between 110% -130% FPL. I focus on the latter set of states and estimate the behavioral effects starting from a homogeneous exposure level (110%-130% FPL) prior to CHIP. In equation 21 and 22, the intercept (α_0, β_0) corresponds to the altruism and present bias at this exposure level.

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

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

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 exogenous variables such as 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 her 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.

E.2 Mother Characteristics

The right panel of Table E1 summarizes mother characteristics exploited in the structural analysis. Mother's age group and CHIP exposure $\Delta\ell_i$ enter as state variables in the dynamic model. Mother's age (grouped into 5-year age bands between age 21 and 40) affects out-of-pocket costs and hence the utility from pre-natal visits ϑ. $\Delta\ell_i$ shifts altruism and present bias through equation 21 and 22. The next three characteristics – whether mother has fetal death in previous pregnancies, has any pregnancy risk factor, and the population smoking rate in her county of residence – determine the distribution of taste types η_i and ζ_i and the endowment type ϕ_i according to equation 23. Mothers have previous fetal deaths if they report lower live birth order than the total birth order for the current birth. 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) as 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 examine investment responses specifically to the timing of exposure across cohorts. Because not all states ask mothers about her smoking during pregnancy (affecting 30% of the estimation sample), I treat "missing" as a distinct level of smoking, and calculate the share of smokers including all mothers in the denominator in the moment conditions.

F Moment Conditions and Estimation

Moment Conditions. I construct moment conditions to estimate three key equations in the structural model: the behavioral effects in equation 21 and 22, and the birth weight production in equation 16. To identify the behavioral effects, I exploit responses in the timing and the level of investments by 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 ($\geq$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 ($\leq$6 or $\geq$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 ofpre-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 $\mathbb{E}\Big[\, d_i^l \,|\, \Delta\ell_i = k \,\Big]$.

I transform the conditional moment in equation F1 into an unconditional one 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 of the moment condition 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.[39] Stacking up, $m = \left(m^l\right)$, $l = 0, ..., 271$ is a vector of moment residuals with the variance covariance matrix $\mathbf{S}$.

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

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

where $\mathbf{W}$ is the weighting matrix. I choose a diagonal weighting matrix where the weights are inverse to the variance of moment residuals and are larger for the main identifying moments.[40] The estimate $\hat{\Theta}$ is asymptotically normal: $\sqrt{I}\left(\hat{\Theta} - \Theta_0\right) \sim N(0, \mathbf{V})$, and the variance-covariance matrix $\mathbf{V}$ equals

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

[39] 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 $p = 3, 6, ..., 18$, and $q = 5, 15$.

[40] 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.

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 bootstrap the estimation sample to generate 10 million individuals in the simulation sample. I draw a vector of standard normal shocks for individual i in trimester t. I fix the z-draws and transform them into taste and health shocks based on model parameters. Given parameter Θ, I solve for optimal investments in state $\mathcal{I}_{it} = (3\sum_{\tau=1}^{t-1} v_{i\tau}, \sum_{\tau=1}^{t-1} s_{i\tau}, X_i)$ from equation 17 to 20. I use the decision rules to generate simulated profiles $D^I(\Theta)$, and calculate the match with sample counterparts according to equation F5. The minimization algorithm tries different parameter values to find the best fitting parameters $\hat{\Theta}$.

G Calculation of MVPF

Outreach Spending. The outreach spending in the roll-out of CHIP is based on program reports in year 2000. According to the Balanced Budget Act of 1997, the national budget for CHIP each year is capped at an amount chosen by the federal government, and states can spend no more than a fixed share of the allotment on program outreach and other administrative costs. Specifically, states can spend no more than 10% of the allotment on program administration, outreach, and additional health assistance and initiatives related to the program.[41] In year 2000, the program allotment at the federal level is $4.3 billion, and spending on program outreach constitutes a small share of total administrative costs subject to the 10% cap, ranging from 6% in Pennsylvania to 14% in California.[42] 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 outreach 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.[43]

Robustness. I calculate alternative MVPFs when the outreach spending increases by a factor of $1+\varpi$, where ϖ captures the additional administrative costs resulting from greater awareness of the program. For instance, program outreach 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 take-up of Medicaid insurance among parents, and the woodwork effect may increase 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.

[41] 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.

[42] 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.

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

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

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

Notes. Table summarizes the marginal value of public funds (MVPF) of CHIP exposure, applying an alternative cost of exposure $\Delta G = \$0.62$. The new cost measure accounts for potential increases in administrative costs as a result of the program outreach, and adjusts 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 spendings 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 spendings of CHIP are capped at the federal level by the annual 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 1998), 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 take-up 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 increases college enrollment by $80\% \cdot 1.71 = 1.37$ percentage points (Table 6). Following Hendren and Sprung-Keyser (2020), I assume that students induced by the exposure to attend college remain in college for two years. Applying a 11.3% return on earnings for each year of college enrollment (Zimmerman, 2014), I calculate that in-utero exposure increases earnings by $2 \cdot 11.3\% \cdot 0.0137 = 0.31\%$ for children of single mothers.

I then apply the 0.31% effect to the life-cycle earning profile for children of single mothers. I construct the profile from average labor incomes in age 19-64 in the 2014-2018 American Community Survey (ACS).[44] I adjust the earning profile of an average individual to match earnings for children of single mothers using estimates from Lopoo and DeLeire (2014).[45] Because the 0.31% effect on earnings is relative to children without college education, I calculate earnings for the latter group using the college enrollment rate among children of single mothers.[46] Consistent with Zimmerman (2014), I assume that the return of college education on earnings begins from age 23 onward, and each

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

[45] 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.

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

Table H1: Cost of program investments, by year

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

Notes. Table calculates the cost of program investments per child in FY1998-FY2016. Each year, CHIP spendings are capped by an allotment determined by the federal government. I divide the allotment by the number of children to determine the cost of investment per child, and discount the cost to year 1997 using a 2% annual discount rate. I adjust all dollars to 2000 levels using CPI-U. Between FY1998 and FY 2016, CHIP invested a total of $1,354.42 per child. For the 1998 birth cohort, this coincides with the cost of program investments in childhood. 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.

year of college lowers annual earnings in age 19-22 by 12.80%.[47] Discounted to 1997, the life-cycle earning benefit amounts to $1,101.11 per child of single mothers.

Tax Payments. Following Hendren and Sprung-Keyser (2020), I assume that the earning benefits are subject to a marginal tax rate of 18.9%.[48] The implied increase in tax payment, 18.9%·$1,101.11 = $208.11, amounts to $\frac{\$208.11}{\$2,483.10}$ = 8.38% of the program costs in childhood. This suggests that the government can expect to recoup 8.4% of the program investments from parental responses to the roll-out.

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

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

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

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

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

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

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

I Additional Tables

Table I1: Effect of CHIP on fertility choice

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

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

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

Table I2: Effects of CHIP exposure on birth outcomes

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

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

Notes. Table estimates the effect of CHIP exposure on birth weight (grams) and low birth weight (<2,500 grams). I group children by the trimester of exposure and estimate effects for six exposure groups. Effects on children already 1-3 months old at the onset of CHIP are normalized to zero. Robust standard errors clustered at the level of states in the parenthesis.

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

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

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

Notes. Table estimates the effects of CHIP exposure on the timing of pre-natal visits, focusing on the month pre-natal care started in column 1, late care onset in the second or third 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 for six exposure groups. Effects on mothers whose children are already 1-3 months old at the onset of CHIP are normalized to zero. Robust standard errors clustered at the level of states in the parenthesis.

Table I4: Effects of CHIP exposure on the number of visits and smoking

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

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

Notes. Table estimates the effect of CHIP exposure on the number of pre-natal visits and smoking. I define smoking status focusing on the intensive margin of daily cigarette consumption. Specifically, columns 2 focus on the probability of consuming 5 or more cigarettes daily, and columns 3 focus on the probability of consuming 15 or more cigarettes daily. I group mothers by the trimester of exposure and estimate effects for six exposure groups. Effects on mothers whose children are already 1-3 months old at the onset of CHIP are normalized to zero. Robust standard errors clustered at the level of states in the parenthesis.

Table I5: Effect of CHIP exposure on birth weight and investments, simulated eligibility

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

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

Notes. Table estimates the effect of CHIP exposure on birth weight (column 1-2), late care onset (column 3-4), and smoking (column 5-6). I measure CHIP exposure using the simulated eligibility implied by the income limits. Specifically, I apply income limits to children in a reference sample, and use the share of children eligible for insurance as the simulated eligibility. I calculate separate eligibility by mother's marital status, race (White, Black, and Other), and education (high school drop-out, high school, some college), and average the eligibility over the 3-quarter pregnancy to construct in-utero exposure *eligCHIP*. I estimate the average effects of the exposure in odd-numbered columns, and estimate the differential effects on single mothers in even-numbered columns. Robust standard errors clustered at the level of states in the parenthesis.

Table I6: Effect of CHIP exposure on cash benefits, health expenditures, and borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
	means-tested cash transfer ($)		out-of-pocket health expenditure (thousands $)		personal debt (thousands $)	
$eliginc \cdot treat \cdot post$	-5.58	58.86	0.056	0.34	2.00	-0.58
	(16.18)	(90.74)	(0.85)	(0.36)	(2.41)	(1.45)
$eliginc \cdot treat$	33.64	-185.74	-2.75	-0.29	-3.68	1.79
	(42.07)	(216.04)	(1.91)	(1.25)	(5.33)	(2.93)
$eliginc$	5.47	6.02	0.36**	0.36**	-0.15	-0.17
	(5.42)	(5.42)	(0.16)	(0.16)	(0.48)	(0.47)
$treat$						
pregnant	Y	Y	Y	Y	Y	Y
single		Y		Y		Y
y mean	46.81	46.82	0.44	0.44	4.00	4.00
R^2	0.02	0.02	0.02	0.02	0.01	0.01
N	33,808	33,803	11,963	11,963	12,219	12,219

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

Notes. Table estimates the effect of CHIP onset on monthly cash benefits from means-tested programs in column 1-2, out-of-pocket health expenditures in 12 months in column 3-4, and personal debt in column 5-6, from the Survey of Income and Program Participation (SIPP). I restrict the analysis to women in age 21-40 surveyed from 8 months before till 8 months after CHIP. I estimate the following difference-in-differences design

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

where $eliginc$ is the income limit in state s and year-month t. Specifically, $eliginc_{st} = inc_s^{pre}$ before CHIP, and $eliginc_{st} = inc_s^{post}$ after CHIP, where $post = 1$. $treat$ indicates pregnant mother in odd-numbered columns, and indicates single pregnant mother in even-numbered columns. The specification controls for cross-state differences by mothers ($\beta_s \cdot treat$) and over time ($\alpha_s \cdot \tau_t$). β_0 estimates the effect of CHIP on (single) pregnant mothers for each 100% FPL exposure to CHIP.

Means-tested cash benefits are asked in the main survey for each month using a 4-month recall. I focus on benefits in the current reference month (the fourth month) in the regression. Out-of-pocket health expenditures include all household payments for the women's healthcare utilization in the past 12 months (including health insurance premiums) net of reimbursements from third parties. Personal debt is the sum of individual credit card or store bill debt, loans, and other debt by the end of the reference month. Both out-of-pocket health expenditures and personal debt are collected in the topical module covering one-third of the sample. Dollar amounts adjusted to the 2000 levels with CPI-U. SIPP sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parenthesis.

Table I7: Effect of CHIP exposure on mother's insurance

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

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

Notes. Table estimates the effect of CHIP onset on mother's insurance and the source of insurance from the Behavioral Risk Factor Surveillance System (BRFSS). I restrict the analysis to women in age 21-40 surveyed from 8 months before till 8 months after CHIP. I estimate the following difference-in-differences design

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

where $eliginc$ is the income limit in state s and year-month t. Specifically, $eliginc_{st} = inc_s^{pre}$ before CHIP, and $eliginc_{st} = inc_s^{post}$ after CHIP, where $post = 1$. $treat$ indicates pregnant mother in odd-numbered columns, and indicates single pregnant mother in even-numbered columns. The specification controls for cross-state differences by mothers ($\beta_s \cdot treat$) and over time ($\alpha_s \cdot \tau_t$). β_0 estimates the effect of CHIP on (single) pregnant mothers for each 100% FPL exposure to CHIP. BRFSS sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parenthesis.

Table I8: Effect of CHIP exposure on enrollment and expected education

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

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

Notes. Table estimates the effect of CHIP exposure on enrollment in column 1 and on mother's expected education for the child in column 2-4. I estimate the specification in equation 7 using the Survey of Income and Program Participation (SIPP), and show separate effects by exposure groups in the table. I construct in-utero exposure *eligine* using equation 6. I determine the time of pregnancy onset from the birth year-month of the child assuming a 9-month pregnancy. In SIPP, respondents are asked to recall monthly enrollment in public insurance over a 4-month period. I focus on enrollment in the most recent month (the fourth month), and examine CHIP enrollment in the first year of the child's life (age 0) in column 1. Outcomes in column 2-4 are mother's stated belief about the child's education attainment. The belief is asked for all children in households surveyed in wave 6 (middle wave) and 12 (final wave) of the 1996-2000 panel, spanning the roll-out of CHIP. In column 4, education attainment is coded on a 1-5 scale. In an ascending order, the integers indicate no degree (less than high school), high school, some college, college degree, and graduate school, respectively. SIPP sampling weights applied in the regressions. Robust standard errors clustered at the level of states in the parenthesis.

Table I9: Effects of CHIP exposure on mother's marital status

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

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

Notes. Table estimates the effects of CHIP exposure on single motherhood, measured by the percentage of mothers who have never married in column 1, and by the percentage of mothers unmarried in the survey year t in column 2. Regressions are weighted by the ACS sampling weights. Robust standard errors clustered at the level of states in the parenthesis.

Table I10: Effects of CHIP exposure on high school graduation and college enrollment

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

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

Notes. Table shows the effects of CHIP exposure on high school graduation rates (column 1-2) and on college enrollment rates (column 3-4), for children of never married mothers and for children whose mothers were unmarried in the survey year. I group children by the timing of exposure and show separate effects for six exposure groups. Effects on children already 1-6 months old at the onset of CHIP are normalized to zero. Regressions are weighted by ACS sampling weights. Robust standard errors clustered at the level of states in the parenthesis.

Table I11: Effects of in-utero exposure to CHIP on grade progression in high school

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

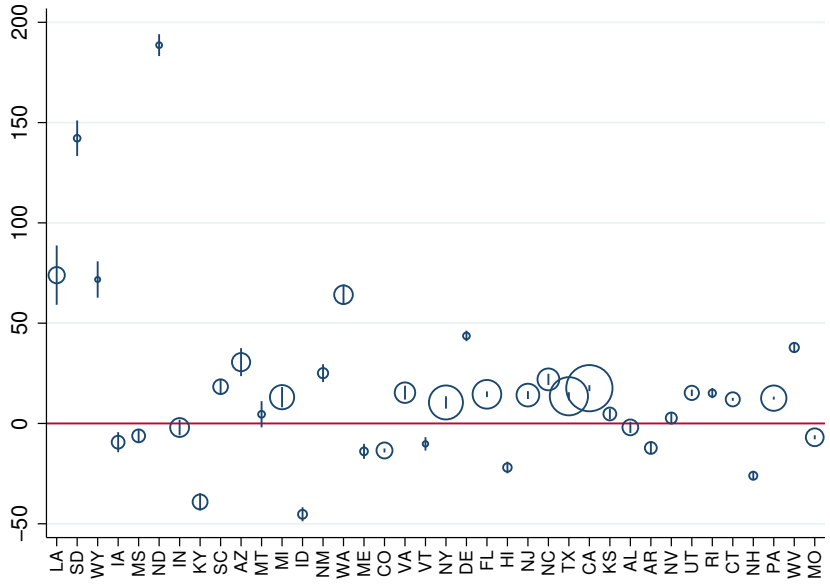
*** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$

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

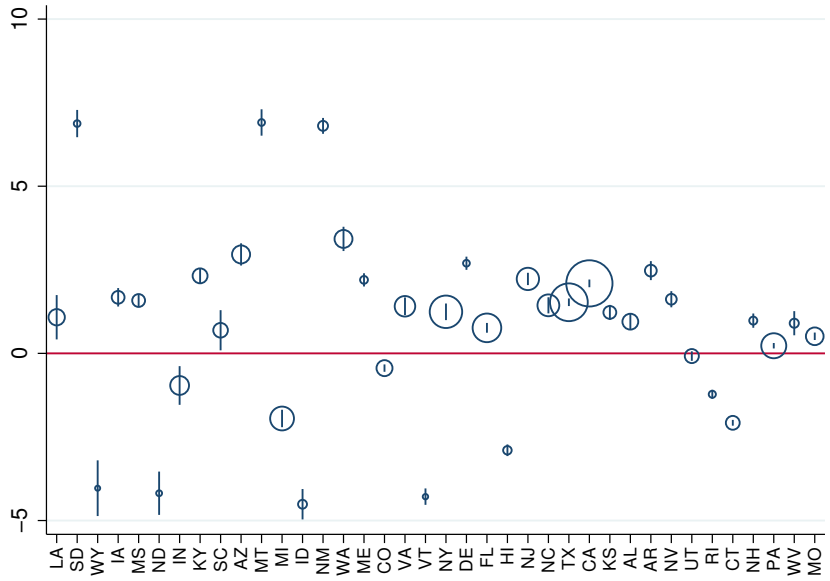
J Additional Figures

Figure J1: Effect of CHIP exposure by states

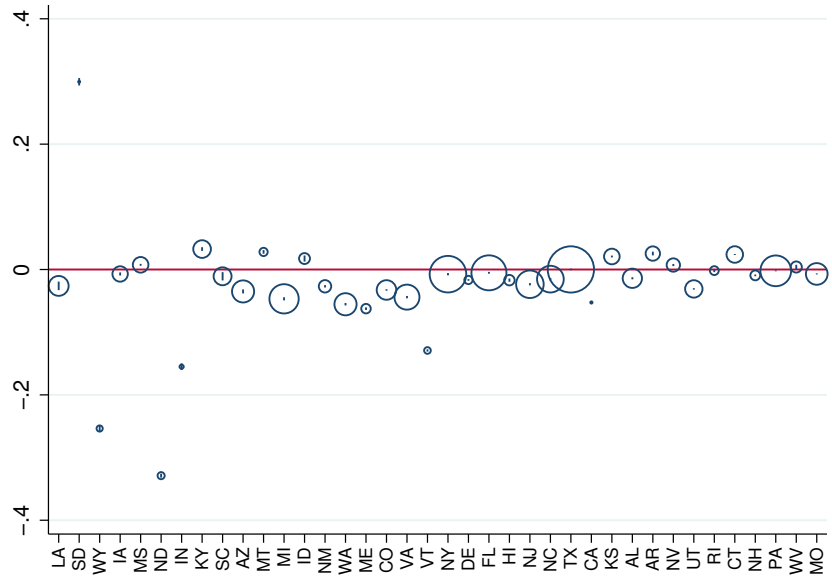
(a) Birth Weight (grams)



(b) First Trimester Care (%)

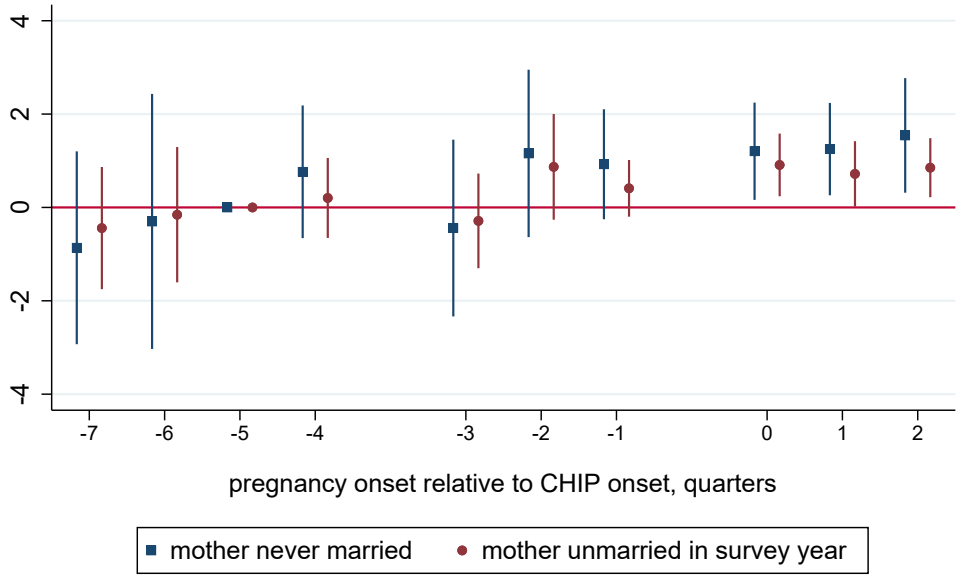


(c) Smoking Intensity (half packs)



Notes. Figure plots the state-specific effects of CHIP exposure on birth weight in panel (a), on first trimester care in panel (b), and on smoking intensity in panel (c). Smoking intensity is measured in half packs (10s) of cigarettes daily. I estimate the state-specific effects from equation 10, and plot the estimates across states, ranking states by the size of expansion from small to large on the horizontal axis. On average, states expanded income limits by 80% FPL. Small expansion states from Louisiana to Maine expanded income limits by less than 70% FPL. States beginning with Rhode Island expanded income limits by over 100% FPL. I plot 95% confidence intervals of the estimates and indicate the sample size of each state with the circle around the estimates. 95% confidence intervals are based on robust standard errors clustered at the level of states.

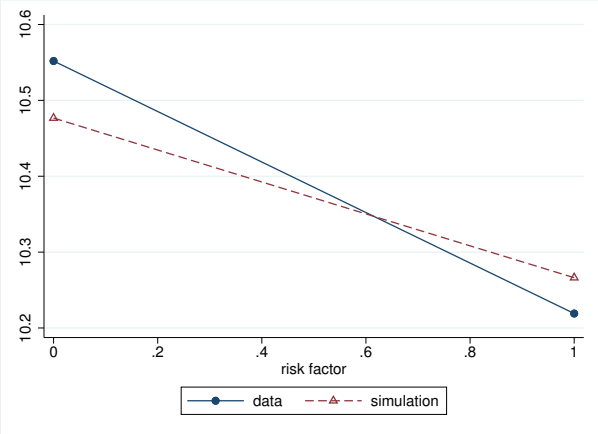
Figure J2: Effect of CHIP exposure on college enrollment (%), event study



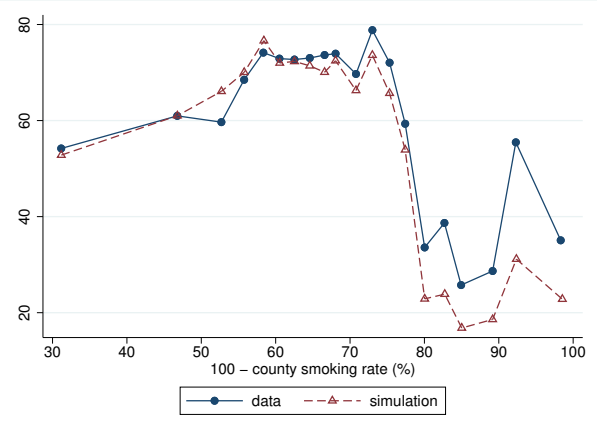
Notes. Figure plots the effect of CHIP exposure on college enrollment by the timing of exposure across cohorts. I show effects for children born to never married mothers and for children of single mothers in the survey year. The horizontal axis compares the pregnancy onset quarter with the CHIP onset quarter. Children conceived more than 4 quarters before CHIP are not exposed to CHIP in utero. In-utero exposure then increases for later cohorts. I normalize the effects on children conceived 5 quarters before CHIP to zero. 95% confidence intervals are based on robust standard errors clustered by states.

Figure J3: Simulated investments by mother characteristics

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



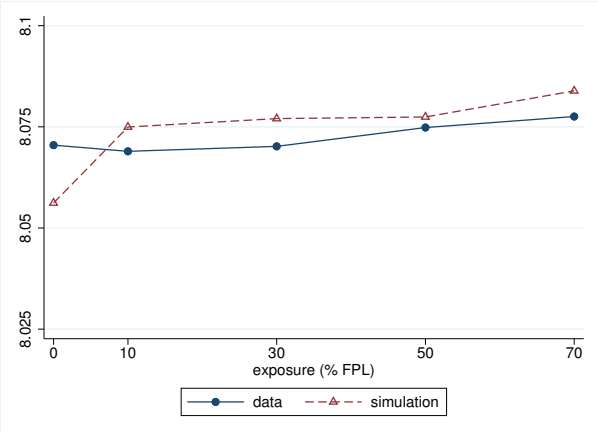
(b) Non-Smokers (%), by County Smoking Rate



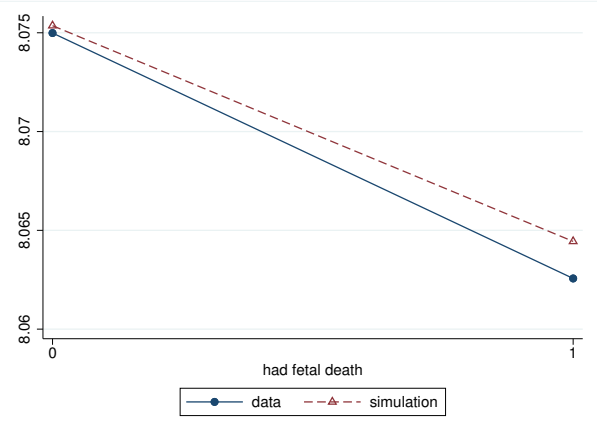
Notes. Figure compares simulated investments with empirical counterparts across mother characteristics that predict mother types in the multinomial Probit. I examine differences in pre-natal visits by the existence of mother risk factors in panel (a), and differences in smoking across county smoking rates in panel (b). 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 non-college educated single mothers and plot simulated investments in the dotted line. I plot empirical counterparts in the solid line.

Figure J4: Effect of CHIP exposure on birth weight

(a) By Exposure $\Delta\ell_i$



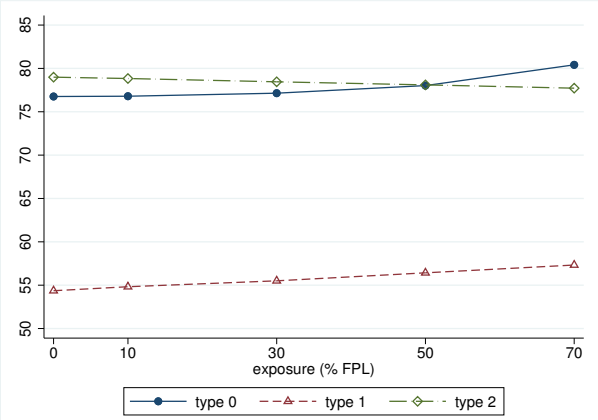
(b) By Prior Fetal Death



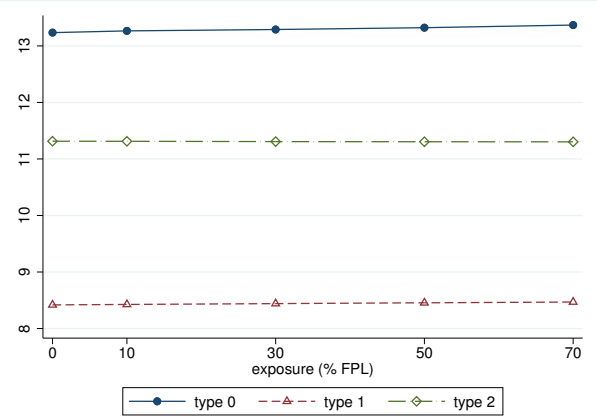
Notes. Figure compares simulated birth weight with empirical counterparts by CHIP exposure $\Delta\ell_i$ in panel (a), and by fetal death in previous pregnancies in panel (b). The mother had fetal death in previous pregnancies if the live birth order of the current birth is smaller than the total birth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

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

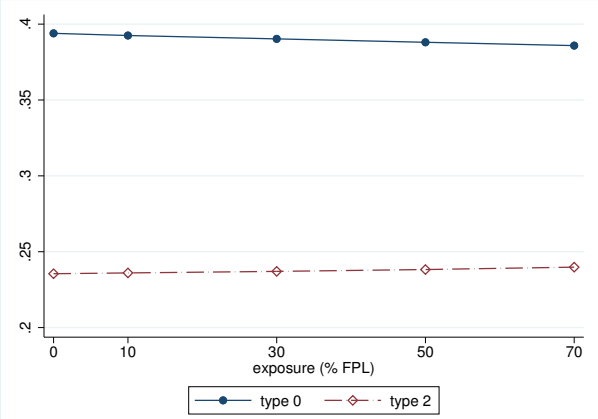
(a) First Trimester Care (%)



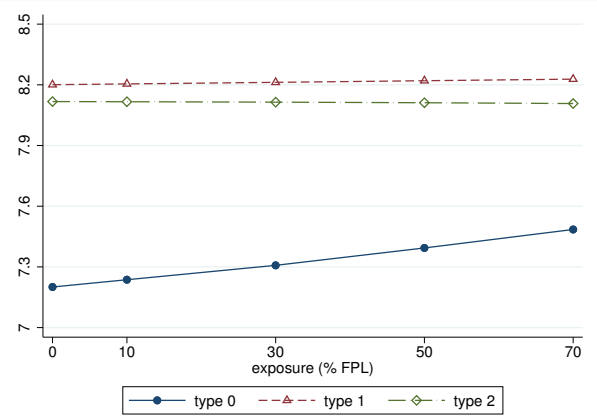
(b) Number of Pre-Natal Visits



(c) Smoking Intensity (Half Packs)



(d) Log Birth Weight



Notes. Figure plots simulated investments and birth weight by CHIP exposure $\Delta\ell_i$ for different mother types. I simulate investments and birth weight for ten million non-college educated single mothers at each exposure level in $\Delta\ell_i$, and plot the results by exposure and mother types. In panel (c), since type 1 mothers never smoked in the simulation due to significant disutility from smoking, I plot simulated smoking intensity only for type 0 and type 2 mothers.

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