The Effect of Cognitive Skills on Fertility Timing*

Agustín Díaz Casanueva†

February 15, 2026
Latest Version

Abstract

Teen childbearing varies sharply with cognitive skill: in a nationally representative U.S. cohort, 28% of women in the bottom quartile of an adolescent cognitive test had a first birth by ages 14–17, compared with 3% in the top quartile. I estimate a dynamic life-cycle model of schooling, work, marriage, and contraceptive effort to ask whether standard opportunity-cost channels can explain this gap. They cannot: matching the teen-birth gradient requires that cognitive skill also raises the effectiveness of contraceptive effort in reducing pregnancy risk. This finding introduces a novel mechanism to the structural fertility literature—ability-dependent contraceptive effectiveness—that operates beyond standard opportunity-cost channels. Counterfactuals imply that equalizing contraception access to high-skill levels lowers pregnancies before age 18 by 50% and raises college attendance by 13%. Welfare gains exceed 11% of lifetime consumption for the bottom ability quartile and are concentrated among low-skill women.

JEL codes: J13, J12, I21, J24, C61.

*I am grateful to my committee members Dirk Krueger, José Víctor Ríos-Rull, and Andrew Shephard for invaluable guidance. I also thank Agustin Arias, Sofía Bauducco, Sara Casella, Alessandro Dovis, Mario Giarda, David Gill, Mario Gonzalez, Jincheng Huang, Joachim Hubmer, Min Kim, Sean McCrary, Guillermo Ordoñez, Germán Sánchez, Raül Santaeulàlia-Llopis, and participants at the University of Pennsylvania Macro Seminars, the University of Pennsylvania Population Studies Center Colloquium, Universidad de los Andes, and the Central Bank of Chile, as well as the Midwest Macro Spring Meeting 2023, the European Society of Population Economics Annual Meeting 2023, SEHO 2024, the BSE Summer Forum 2024, the SED Winter Meeting 2024, SECHI 2024, and the Society for the Study of Economic Inequality 2025, for helpful comments and suggestions. This paper received the Étienne van de Walle Prize for the best graduate student paper in demography from the University of Pennsylvania Population Studies Center. The views expressed herein are solely those of the author and do not necessarily reflect the views of the Central Bank of Chile. All errors are my own.

†Central Bank of Chile, adiaz@bcentral.cl, Address: Agustinas 1180, Santiago, Chile.

1 Introduction

Teen childbearing varies sharply with cognitive skill. In a nationally representative cohort of U.S. women born in the late 1950s and early 1960s—the 1979 National Longitudinal Survey of Youth (NLSY79)—28% of women in the bottom quartile of an adolescent cognitive test had a first birth by ages 14–17, compared with 3% in the top quartile. First birth hazard rates are sharply decreasing in ability during the teenage years but converge across ability groups by the late twenties; mean age at first birth differs by 5.4 years across quartiles. These patterns are not artifacts of measurement timing or cohort trends: they appear in conditional hazards and survive controls for family background.

The correlation between cognitive ability and fertility cannot be dismissed as a mechanical consequence of ability's correlation with schooling and income. Even within educational categories, higher-ability women have lower teen fertility; the within-education ability gradient is almost as steep as the raw gradient. Reduced-form evidence from other settings corroborates this pattern. Heckman et al. (2006) show that both cognitive and noncognitive skills independently predict teen pregnancy in the NLSY79, with effects that remain significant after controlling for education. Fe et al. (2022) find that theory-of-mind and cognitive ability measured in childhood both predict lower fertility at age 25 in the Avon Longitudinal Study of Parents and Children (ALSPAC), with effects operating partly through educational participation but partly through direct channels. These patterns motivate the question addressed in this paper: through what mechanisms does cognitive ability shape fertility timing?

To answer this question, I develop and estimate a structural life-cycle model in which cognitive ability is an early, persistent trait[1], and in which women jointly choose schooling, labor supply, experience accumulation, marriage, and fertility control. In particular, women choose contraceptive effort. By contraceptive effort, I mean the deliberate actions and resources women devote to preventing pregnancy—incurring social, monetary, and psychological costs. This includes paying for and accessing contraceptive methods, learning about options, negotiating use with partners, using contraception consistently, and managing side effects, stigma, and the cognitive burden of planning and adherence. The model's key

[1]Measured cognitive ability is highly stable from late adolescence through adulthood (Almlund et al., 2011; Heckman et al., 2006).

innovation is a fertility-control technology in which cognitive ability shifts the effectiveness of contraceptive effort—the rate at which effort translates into reduced pregnancy risk—in addition to the standard channels through which ability affects fertility via schooling and wage incentives. This mechanism is motivated by medical evidence documenting large gaps between "perfect use" and "typical use" contraceptive failure rates that vary systematically with user characteristics (Black et al., 2010; Trussell, 2011), suggesting that ability may affect not only the quantity but also the quality of fertility-control investments.

The model's structure delivers a test of whether ability affects fertility only through opportunity costs or also through fertility control. The key comparison is between a benchmark specification, in which ability can shift both schooling incentives and the effectiveness of contraceptive effort, and a restricted specification that shuts down the direct effect on contraceptive effectiveness. If the standard opportunity-cost channels were sufficient, the restricted model would fit the data as well as the benchmark. The nested test shows that it does not: restricting the effectiveness channel causes the model to substantially underpredict the ability gradient in teen births while simultaneously degrading fit on contraception use patterns.

This paper makes a novel contribution to the structural literature on fertility and human capital. While recent work models imperfect fertility control (Choi, 2017; Ejrnæs and Jørgensen, 2020), these papers do not allow innate ability to directly affect the productivity of contraceptive effort conditional on education. Choi (2017) models fertility risk and abortion in a life-cycle framework where conception probability depends on effort and age, but the mapping from effort to risk reduction is common across individuals. Ejrnæs and Jørgensen (2020) model abortion as insurance against income shocks but do not introduce ability heterogeneity in contraceptive effectiveness. Similarly, while Fe et al. (2022) document robust reduced-form associations between cognitive skills and fertility using ALSPAC data, they do not embed these patterns in a structural framework that identifies the mechanism or separates ability-driven differences in opportunity costs from ability-driven differences in pregnancy risk. The nested specification test in this paper provides formal evidence that standard opportunity-cost channels alone cannot rationalize the data: matching the teen-birth gradient requires cognitive ability to also shift the effectiveness of contraceptive effort.

This question is at the center of several literatures in economics—human capital and labor supply, family formation, and the determinants of inequality—because the timing of fertility shapes women's schooling, career experience, marriage trajectories, and the intergenerational persistence of education and earnings. It is also directly policy-relevant because the main policy tools used to influence early childbearing are (i) education-and-opportunity policies—such as compulsory-schooling reforms, school-quality investments, and college-aid expansions that raise educational attainment and the returns to experience—and (ii) contraception access-and-cost policies—such as subsidized contraception, clinic expansions, and insurance coverage that lower the monetary and social costs of using effective methods. If ability-related differences in contraceptive effectiveness operate beyond these policy margins—as the nested specification test indicates—then the welfare gains from policies that expand contraceptive access will be heterogeneous across skill groups, with the largest benefits accruing to those who face the highest baseline risk and lowest effectiveness. Moreover, policies that reduce user-dependent variation in contraceptive failure rates—such as subsidizing long-acting reversible contraceptives (LARCs) that minimize scope for user error—may be particularly effective for low-ability women. The 50% reduction in teen pregnancies predicted under the fertility-control counterfactual is comparable in magnitude to effects documented in evaluations of LARC programs such as the Contraceptive CHOICE Project (Secura et al., 2014), providing external validation of the mechanism's quantitative importance.

Understanding the link between cognitive ability and fertility timing also matters for assessing the consequences of early childbearing for mothers and children. If early fertility among low-ability women reflects primarily lower opportunity costs, then policies that delay childbearing may have limited effects on human capital accumulation. But if early fertility partly reflects difficulty controlling fertility, then the same policies could generate large gains by allowing women to time births when they are better prepared. For children, maternal ability and the timing of birth interact to shape early investments and long-run outcomes; disentangling these channels is necessary for evaluating the intergenerational effects of fertility-timing interventions.

This paper makes two main contributions to the structural literature on fertility and human capital. First, I estimate a life-cycle model that jointly determines schooling, wage growth through experience, marriage, and fertility timing, where both education and cognitive ability can independently shift effective fertility control. The model introduces a novel parameter—ability-dependent contraceptive effectiveness ($\eta_{\theta,g}$)—that governs how cognitive skill shifts the mapping from contraceptive effort to realized pregnancy risk. This extends the conception-risk specifications in Choi (2017) and Ejrnæs and Jørgensen (2020) by allowing heterogeneity in the *productivity* of effort, not merely its cost or baseline risk levels. The nested specification test provides formal evidence that this extension is empirically necessary: restricting $\eta = 1$ (no ability heterogeneity) causes the model to underpredict the ability–fertility gradient by a factor of two to five.

Second, I use the estimated model to quantify the policy-relevant implications of this decomposition. The counterfactuals show that the direct "fertility-control" channel is quantitatively important: equalizing contraception frictions to those faced by high-ability teens reduces pregnancies before age 18 by 50% (36% before age 22) and increases college attendance by 13%, while aligning both contraception and schooling opportunities raises college attendance by 33% and reduces pregnancies before age 18 by 57%. The welfare analysis reveals that heterogeneity in effective fertility control has substantial consumption-equivalent value: giving low-ability women the contraception environment of college graduates is worth 11% of lifetime consumption for the bottom ability quartile, while equalizing contraceptive effectiveness alone is worth 5%. These magnitudes underscore that ability-dependent contraceptive effectiveness is not merely a statistical artifact but an economically meaningful source of inequality in life outcomes.

The remainder of the paper is organized as follows. Section 2 summarizes the literature. Section 3 describes the data and documents the key empirical patterns. Section 4 presents the life-cycle model. Section 5 describes the estimation strategy and identification. Section 6 presents the parameter estimates and model fit. Section 7 conducts the counterfactual policy experiments. Section 8 concludes.

2 Literature

This paper contributes to the large literature that models fertility choices as the outcome of forward-looking household optimization. Foundational work places fertility within household decision-making and the quantity–quality trade-off (Becker, 1960; Becker and Lewis, 1973; Ben-Porath, 1976; Willis, 1973). Dynamic structural models then endogenize the timing and spacing of births in a life-cycle framework, including early discrete-choice models (Heckman and Walker, 1990; Hotz and Miller, 1988; Wolpin, 1984). Building on this tradition, a subsequent wave of life-cycle models jointly determines family formation and labor-market choices: Van der Klaauw (1996) study women's marital status and labor supply, Francesconi (2002) estimate married women's joint fertility–labor decisions, Sheran (2007) develop a model with endogenous schooling, marriage, and fertility, and Keane and Wolpin (2010) integrate schooling, work, marriage, fertility, and welfare participation. Related work quantifies how marriage and labor markets shape family structure and birth timing (Caucutt et al., 2002; Regalia et al., 2019).

This paper contributes to this structural tradition by introducing cognitive ability as a innate, time-invariant state that shapes both opportunity costs (through schooling and wage growth) and fertility control (through an ability-dependent conception hazard). Empirically, I discipline these channels using targeted moments to identify an ability-dependent fertility technology. In the estimated model, allowing contraception costs to vary by education is not enough: matching the ability gradient in first-birth timing requires a direct ability shifter in the conception hazard, beyond standard opportunity-cost channels.

A second, closely related strand emphasizes imperfect fertility control and policy-driven changes in reproductive technologies. Choi (2017) incorporate fertility risk and abortion, Ejrnæs and Jørgensen (2020) model abortion as insurance against income risk, and Amador (2017) analyze how abortion and contraception policy affects reproductive choices, schooling, and work. These papers formalize the idea that fertility outcomes reflect both preferences and the effectiveness/cost of avoiding conception. This paper builds on this insight but introduces cognitive ability as a determinant of the effectiveness (or effort cost) of contraceptive control, providing a channel that helps explain why similarly educated women display different fertility timing profiles by cognitive skills. On the interaction between fertility and careers, Adda et al. (2017) quantify the career costs of children; the model complements this by showing that the incentives created by career costs are not sufficient to match the ability gradient without a direct ability channel in fertility control.

Third, the paper relates to empirical work on the income–education–fertility relationship and the role of unintended childbearing. Rosenzweig and Schultz (1989) show that schooling increases contraceptive knowledge and effectiveness in use, and Musick et al. (2009) document that the education gradient in births is primarily driven by unintended childbearing. Policies and technologies that lower the cost of fertility control also shape both timing and human-capital investment: Goldin and Katz (2002) and Bailey (2006) show that pill access delayed first births and facilitated educational and career investment; Kearney and Levine (2009) find that Medicaid family-planning expansions reduced births via increased contraception use; and a recent randomized intervention by Bailey et al. (2023) shows that eliminating out-of-pocket costs at Title X clinics substantially increases uptake of highly effective methods and implies a meaningful reduction in undesired pregnancies. Finally, quasi-experimental evidence on education's causal effect on fertility finds small or context-dependent effects (Fort et al., 2016; McCrary and Royer, 2011). Relative to this reduced-form literature, I contribute a structural interpretation that explicitly accounts for innate cognitive skills when mapping education and contraception policies into fertility timing and educational attainment.

Fourth, the paper connects to a broader literature documenting that cognitive (and noncognitive) skills predict a wide range of life outcomes.[2] In this tradition, Heckman et al. (2006) show that higher cognitive and noncognitive skills reduce risky behaviors, including teen pregnancy and early marriage, while Fe et al. (2022) links childhood cognition to adult behaviors and outcomes, including lower fertility in young adulthood. The paper contribution is to embed these empirical patterns in a disciplined life-cycle model and to rationalize these patterns through a mechanism consistent with the data: an ability-dependent fertility-control technology that operates in addition to education and wages.

Finally, the paper speaks to the economics of U.S. teen childbearing and its decline. Kearney and Levine (2012) provide a synthesis of the evidence and mechanisms, and related work quantifies the roles of improved contraceptive access and changing incentives (e.g., Kearney and Levine, 2009, 2015). In the estimated model, cohort decompositions instead assign the central role to improved schooling opportunities while changes in contraception frictions account for only a small share of the 1990s decline in teen births.

[2] See Heckman and Mosso (2014) for a survey; see also Almlund et al. (2011) and Cunha and Heckman (2007).

3 Empirical Evidence

This section documents the relationship between cognitive skills and fertility using the National Longitudinal Survey of Youth 1979 (NLSY79). First, I describe the survey, sample construction, and key measures—cognitive skills, fertility timing (teen pregnancy and age at first birth), schooling, marriage formation, and work-experience accumulation. I then present descriptive facts linking cognitive skills to early pregnancy and first-birth timing, and how this is related to education, marriage, and on-the-job experience.

3.1 Data Description

The NLSY79 follows a nationally representative cohort of individuals born between 1957 and 1964 who were ages 14–22 at the initial interview in 1979. The survey provides detailed longitudinal information on schooling, labor market outcomes (employment, hours, and earnings), marital status and partnership histories, and fertility (pregnancies and births). Because the cohort is observed for more than four decades, women have largely completed their reproductive years and much of their working lives, making the NLSY79 well suited to study fertility timing.

Cognitive ability is proxied by the Armed Forces Qualification Test (AFQT), obtained from the NLSY79 created ability-score files derived from the ASVAB administered early in the panel. I treat invalid/nonresponse codes as missing and exclude women with missing AFQT. After applying these restrictions, the working sample contains 5,634 women. Additional details on sample construction, variable definitions, cleaning conventions, and the mapping to the model are provided in Appendix OA.1.

3.2 Descriptive Statistics

This subsection documents a set of empirical facts that motivate and discipline the model. The objective of paper study is to investigate the relationship between cognitive skills and fertility timing. Since pregnancies interact with schooling choices, labor-market experience accumulation, and marriage formation, the analysis focuses on joint patterns linking cognitive skill, the timing of first births, education, wages, and marital outcomes.

Table 1. Fertility Timing and Outcomes by Ability Quartile

Age / Outcome	Ability Quartile 1	2	3	4
Panel A. Conditional first-birth probability by age bin				
14–17	28%	16%	9%	3%
18–21	49%	38%	25%	16%
22–29	54%	53%	46%	45%
Panel B. Age at first birth and completed fertility				
Age at First Child	20.14	21.66	23.45	25.56
Married at First Pregnancy	0.38	0.56	0.72	0.84
At least one child by age 40	0.87	0.82	0.74	0.72

Notes: Panel A reports conditional first-birth probabilities by age bin and ability quartile; the denominator is women childless at the start of the bin. Panel B reports the mean age at first birth, the share married at first pregnancy, the share with at least one child by age 40, and the total number of children.

3.2.1 Cognitive Ability and the Timing of First Birth

A central goal of the paper is to quantify how cognitive ability shapes the timing of entry into motherhood. I begin by documenting the ability gradient in first-birth timing using conditional first-birth probabilities and completed fertility outcomes.

Panel A of Table 1 reports conditional first-birth probabilities by age bin and cognitive-skill quartile. Each cell is computed among women who are childless at the beginning of the age bin, so cross-quartile differences isolate the timing of entry into motherhood rather than differences in parity at earlier ages. For example, the entry 54% in the first-ability-quartile, ages 22–29 cell means that among bottom-quartile women who had not given birth before age 22, 54% had a first birth between ages 22 and 29. Panel B reports unconditional summary fertility outcomes by quartile: mean age at first birth, the fraction married at first pregnancy, and the share with at least one child by age 40.

The table shows a strong negative ability gradient in the likelihood of early first births that attenuates with age. At ages 14–17, 28% of women in the lowest quartile versus 3% in the highest quartile have a first birth (a 25 pp gap). The gap remains large at ages 18–21 (49% vs. 16%, a 33 pp gap) and largely dissipates by ages 22–29 (54% vs. 45%, a 9 pp gap), indicating that higher-ability women predominantly postpone, rather than avoid, first births.

Consistent with postponement, mean age at first birth rises by about 5.4 years from quartile 1 to quartile 4 (20.14 to 25.56). High-ability women are also much more likely to be married at first pregnancy (0.84 vs. 0.38), less likely to have a first birth by age 40 (0.72 vs. 0.87).

3.2.2 Ability and Education

A key role of the structural model is to disentangle how much of the observed ability gradient in fertility can be accounted for by this education gradient, versus how much reflects additional ability-related mechanisms beyond schooling.

Table 2 shows a strong, monotone relationship between cognitive ability and educational attainment. Relative to women in the lowest AFQT quartile, those in the highest quartile are far less likely to leave school as high school dropouts (1% vs. 29%, a 28 pp gap) and far more likely to complete college (52% vs. 4%). College attendance also rises sharply with ability—from 11% in quartile 1 to 67% in quartile 4—while the middle of the distribution is concentrated in high-school completion.

Table 2. Educational Attainment by Cognitive Ability Quartile

	Cognitive Ability (AFQT) Quartile				
Education outcome	**Q1 (lowest)**	**Q2**	**Q3**	**Q4 (highest)**	**Total**
HS dropout	29%	9%	2%	1%	10%
HS graduate	68%	80%	75%	47%	68%
College attendance	11%	25%	41%	67%	36%
College graduate	4%	11%	23%	52%	22%

Notes: Sample includes women from the NLSY79. Educational attainment is measured as highest degree completed. College attendance includes those who attended college between ages 18-22. Cognitive ability is measured using AFQT percentile scores and divided into quartiles. Entries report the share of women in each AFQT quartile whose completed education falls in the indicated category (column percentages).

3.2.3 Pregnancy Timing and Education

Early childbearing can lower educational attainment through time and resource constraints, while schooling can delay fertility by raising opportunity costs and by improving the effectiveness of fertility control. Table 3 summarizes how the timing of the first childbirth varies with completed schooling by reporting, for each education group, the share of women whose first birth occurs in each displayed age bin.[3]

Table 3. Conditional Distribution of Age at First Pregnancy by Education Outcomes

	Education Outcome		
Age at First Pregnancy	**HS Dropout**	**HS Graduate**	**College Graduate**
14–17	42%	14%	3%
18–21	32%	31%	8%
22–29	14%	28%	37%

Notes: For each education outcome, entries report the share of women whose first childbirth occurred in the indicated age group.

Two patterns stand out. First, early motherhood is concentrated among less educated women: by ages 14–17, the first-birth share is 42% for high-school dropouts, compared with 14% for high-school graduates and 3% for college graduates. By age 21 (14–17 plus 18–21), roughly 74% of dropouts have had a first birth versus 11% of college graduates. Second, more educated women shift first births into later ages: in the 22–29 bin, the share is 37% for college graduates versus 28% for high-school graduates and 14% for dropouts, consistent with postponement along the education gradient.

3.2.4 Early Pregnancies and Marriage

Marriage is a central state in the model because it shapes household resources, risk-sharing, and the incentives to invest in schooling and labor-market experience. A long tradition emphasizes that childbearing outside marriage can reduce subsequent marriage prospects by changing economic circumstances and the costs/returns to partner search (Becker, 1991). [4]

I summarize two relationships by whether a first pregnancy occurs or not before the first marriage: (i) the probability of ever marrying over the observed life cycle and (ii) spousal earnings conditional on marriage. Throughout, these comparisons are descriptive: they may reflect causal effects of early/out-of-wedlock (OOW) fertility, but also selection on background characteristics, marriage-market conditions, and preferences.

[3]Entries are computed within education groups as shares of all women in the group. The table reports only the displayed age bins, so column totals need not sum to one; the omitted residual corresponds to first births after the last reported bin or no observed first birth by the end of the sample.

[4]Bronars and Grogger (1994) document that women with unplanned births are less likely to be married when their children are young.

Table 4. Probability of Ever Marriage: Premarital Pregnancy vs. No Premarital Pregnancy

Group / Age at Pregnancy	HS Dropout	HS Graduate	College Graduate
	Education Outcome		
(A) Premarital First Pregnancy			
14–17	67%	81%	83%
18–21	58%	75%	72%
22–29	46%	59%	69%
(B) No Premarital Pregnancy			
All ages	94%	96%	98%

Notes: Panel A conditions on having a first pregnancy before the first marriage (i.e., the woman is not yet legally married at the time of her first pregnancy). Panel B conditions on having no pregnancy prior to first marriage (including women who never marry during the survey window). For Panel A, probabilities are shown by age at first pregnancy; for Panel B, the probability is pooled across ages. The ever-married indicator equals one if the respondent reports at least one legal marriage during the survey window.

Table 4 reports the probability of ever marrying separately for women whose first pregnancy occurs before first marriage (Panel A) and those with no premarital pregnancy (Panel B). Two patterns emerge. First, within Panel A, ever-marriage rates are increasing in completed education and declining with the age at premarital first pregnancy. For example, among high-school graduates with a premarital first pregnancy, the probability of ever marrying falls from 81% (ages 14–17) to 59% (ages 22–29); among high-school dropouts it falls from 67% to 46%, and among college graduates from 83% to 69%. Second, among women with no premarital pregnancy (Panel B), ever-marriage rates are uniformly high and only mildly increasing with education (94%–98%). Taken together, the table indicates that premarital fertility is associated with lower marriage —especially for the least educated and for women whose premarital first pregnancy occurs at older ages—consistent with a combination of selection and marriage-market penalties tied to premarital childbearing.

Table 5. Average Husband Wage by Education and Women's Childbearing Status at Marriage

	HS Dropout		**HS Graduate**		**College Graduate**	
Age at First Pregnancy	**Out-wed.**	**No out-wed.**	**Out-wed.**	**No out-wed.**	**Out-wed.**	**No out-wed.**
14–17	35089	34563				
18–21	35806	39064	44602	46000		
22–29	33622	35806	43719	55143	66025	73628

Notes: The table reports husbands' average annual wage (2016 dollars) by the woman's completed education, age at first pregnancy, and whether the first pregnancy occurs out of wedlock. The sample is restricted to women who marry during the survey window and to spouse-years in which the husband works at least 2,000 hours and earns at least \$2.50 per hour (in 2016 dollars), as observed in the NLSY79 spouse/partner earnings module.

Table 5 reports average husbands' annual wages (in 2016 dollars) by the woman's completed education, age at first pregnancy, and whether the first pregnancy occurs out of wedlock, conditional on marrying during the survey window. In most education groups and age bins, women with an out-of-wedlock first pregnancy marry lower-earning husbands on average. The implied spousal-earnings differential is largest for high-school graduates—about \$1,400 for ages 18–21 (46,000 vs. 44,602) and about \$11,400 for ages 22–29 (55,143 vs. 43,719). For college graduates (ages 22–29), the gap is about \$7,600 (73,628 vs. 66,025). For high-school dropouts, differences are smaller (roughly \$2,000–\$3,300), and the teen (14–17) dropout cell shows a negligible difference (\$526).

3.2.5 Education, Experience, and Labor-Market Outcomes

In this subsection, I document how fertility intersects with women's labor-market careers across the cognitive-ability distribution, with an emphasis on how ability-related differences in wage growth and experience accumulation translate into heterogeneous opportunity costs of early childbearing. Table 6 summarizes wage levels, wage growth, and experience accumulation by ability and age; all wage statistics are computed among employed women, using the employment and wage definitions stated in Appendix OA.1.

Panel A shows that earnings increase with ability at all ages, and that the level gap widens substantially over the life cycle. At age 20, the gap between quartiles 4 and 1 is about \$3,354 (\$23,042 vs. \$19,688). By age 40 the gap exceeds \$35,000 (\$65,713 vs. \$30,382), consistent with both higher levels and faster growth at the top of the ability distribution.

Panel B shows that returns to experience are substantially steeper at higher ability levels.

After 5 years of accumulated experience, average log wage growth is 24% in quartile 1 versus 57% in quartile 4 (a 33 pp gap). After 10 (15) years, the corresponding figures are 39% vs. 78% (47% vs. 90%). These gradients imply that an additional year of foregone experience early in the career carries a larger earnings penalty for higher-ability women, strengthening incentives to delay childbearing until after key accumulation years.

Panel C documents experience accumulation: higher-ability women accumulate substantially more work experience by a given age. At age 25, quartile 1 averages 1.85 years versus 3.99 years in quartile 4; by age 40, the gap widens to 7.94 vs. 14.44 years. This pattern is consistent with stronger labor-force attachment at higher ability, which raises the extent of experience losses from career interruptions.

Panel D reports average annualized wage growth by ability, which increases monotonically across quartiles (2.69%, 3.12%, 3.53%, 4.33%). Together with Panel B, this provides a simple summary of faster human-capital accumulation and steeper life-cycle profiles at higher ability.

Panel E summarizes labor-market dynamics around the first birth. Following maternity-related gaps, mean log wage changes are weak or negative for lower-ability women (e.g., -0.01 to -0.12 after a 5-year gap in quartiles 1–2) and modestly positive for higher-ability women (0.02 and 0.07 in quartiles 3–4). Moreover, time out of the labor force following the first birth is increasing in ability (0.31, 0.50, 0.56, 0.60 years). These moments suggest that high-ability women both (i) face steeper returns to continuous experience and (ii) spend more time out of work after the first birth, implying a larger opportunity-cost wedge associated with early childbearing.

4 Model

I develop a dynamic life-cycle model to quantify how cognitive ability shapes the timing of first birth and to test whether standard education and opportunity-cost mechanisms can account for the observed ability gradient in early fertility. Time is discrete, with each period representing four years. Women enter the model at age 14 with cognitive ability θ and initial assets $a_1 = 0$. They remain fertile through ages 14–37 and can work until age 61. From ages 62 to 78, households are retired and receive Social Security income that depends on educational attainment. The unit of decision-making is the household: before marriage, it is

Table 6. Descriptive Statistics by Ability: Labor Market Outcomes

	Ability Quartile			
Outcome	**1**	**2**	**3**	**4**
Panel A. Wage (workers at given age)				
Wage at age 20	19688	21554	22811	23042
Wage at age 25	23954	27850	32250	38412
Wage at age 30	27778	33689	38978	49126
Wage at age 40	30382	40112	46392	65713
Panel B. Return to experience (log wage growth)				
Potential experience 5 years	24%	35%	45%	57%
Potential experience 10 years	39%	52%	65%	78%
Potential experience 15 years	47%	61%	75%	90%
Panel C. Cumulative work experience (years)				
Experience at age 25	1.85	3.20	3.85	3.99
Experience at age 30	3.60	6.04	7.20	7.51
Experience at age 40	7.94	12.65	14.64	14.44
Panel D. Annualized log wage growth rate				
Avg. log growth rate	2.69%	3.12%	3.53%	4.33%
Panel E. Labor gaps and wage changes around non-work spells				
Log wage change after 1-year gap	0.02	-0.01	0.00	0.04
Log wage change after 3-year gap	-0.02	-0.03	0.05	0.05
Log wage change after 5-year gap	-0.01	-0.12	0.02	0.07
Time out after 1 child (years)	0.31	0.50	0.56	0.60

Notes: Means by ability quartile. "Work" (and thus "experience") is defined at the year level as averaging $\geq$ 20 hours per week for at least 26 weeks and earning at least the minimum hourly wage. Panel A reports average wages at ages 20, 25, 30, and 40 for women who satisfy the work definition at that age. Panel B reports log wage growth after $x \in \{5, 10, 15\}$ years of potential experience, defined as $\ln w_{t+x} - \ln w_t$ with t the first year the individual meets the work definition, where potential experience cumulates only years that meet the work definition. Panel C reports average cumulative years of work experience at ages 25, 30, and 40. Panel D reports the average annualized log wage growth rate among workers. Panel E reports (i) the change in log wages ("1/3/5-year gap") between the last working year and 1, 3, or 5 years after a non-working gap, and (ii) "time out of the labor force after 1 child," defined as total weeks not meeting the work definition during the five years following first birth divided by 52.

a single-adult unit, and after marriage, it is a two-adult unit that pools income and makes joint decisions. There is no divorce.

Each woman can have at most one child. If a birth occurs, the child resides with the household for one period only; parental monetary investment i_t is therefore a one-time choice made in the birth period. Contraception is modeled in reduced form as effort s_t that is costly and imperfect. The model abstracts from divorce and income uncertainty to focus on the joint determination of fertility timing, schooling, work experience, and marriage.

4.1 State variables, choices, and timing

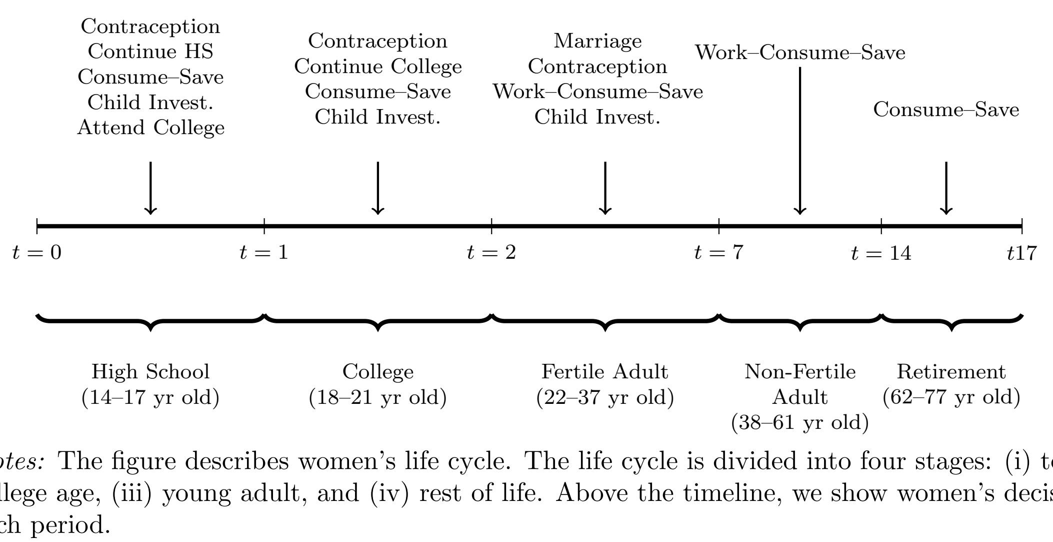
The household state at the beginning of period t is

$$\Omega_{it} = \{a_t, \theta_i, e_t, x_t, m_t, k_t, m_k\},$$

where a_t denotes assets; $\theta_i \in \{1, 2, 3, 4\}$ is the cognitive-ability quartile (1 lowest, 4 highest); $e_t \in \{HSD, HS, C\}$ is education attainment/status; x_t is accumulated labor-market experience; $m_t \in \{0, 1\}$ is marital status; $k_t \in \{1, 2, 3\}$ records childbearing status (1: no prior birth, 2: first birth occurs in period t, 3: first birth occurred in an earlier period); and $m_k \in \{0, 1\}$ records marital status at the first birth (only relevant when $k_t \neq 1$).

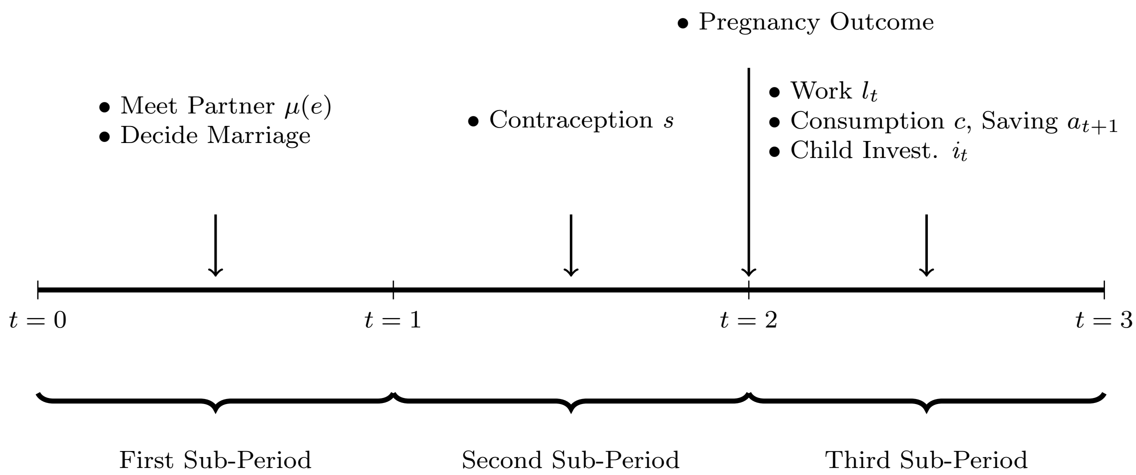
Within-period timing depends on life stage. In fertile ages, single women may meet and accept a partner, childless women choose contraception effort and then face stochastic conception, and households choose labor supply, consumption, saving, and (if a birth occurs) child investment. In schooling periods, schooling continuation decisions occur after the fertility outcome. After fertility ends, the problem reduces to a labor–savings problem, and in retirement labor supply is fixed at zero. Figure 1 and Figure 2 summarize the period mapping and within-period sequencing.

Figure 1. Women Attending College Life Cycle



Notes: The figure describes women's life cycle. The life cycle is divided into four stages: (i) teen, (ii) college age, (iii) young adult, and (iv) rest of life. Above the timeline, we show women's decisions in each period.

Figure 2. Childless Women Between Ages 22–37: Within-Period Timing



Notes: Each period is divided into three sub-periods: (i) marriage (if single), (ii) contraception (if childless and fertile), and (iii) labor supply, consumption–saving, and (if a birth occurs) child investment.

In the next subsection, I describe the key Bellman equations that characterize household decisions over the life cycle. Online Appendix OA.2.1 provides the complete set of Bellman equations by life stage (teen, college, young adult, post-fertile, and retirement) and the associated within-period sequencing.

4.2 Dynamic Household Problem and Value Functions

This section presents the recursive household problem and highlights the main Bellman. The household makes a sequence of interrelated discrete and continuous decisions—schooling and college entry, marriage, work, saving and consumption, contraceptive effort while fertile and childless, and child investment upon a first birth. To keep the exposition transparent, I organize the recursion into four building blocks that correspond to the within-period timing: (i) marriage, which determines whether resources are pooled; (ii) contraception, which determines first-birth risk when childless; (iii) the working-stage labor–consumption–saving problem, which depends on whether a newborn arrives; and (iv) college entry at the end of adolescence.

Working-stage problem with and without a newborn. Because fertility and child presence are state-dependent, it is useful to write the working-stage value functions explicitly. In fertile ages ($t \le T_F$), after the fertility realization, the household solves a labor–consumption–saving problem that depends on whether a first birth occurs in period t. Let j index the fertility/child-status outcome: $j = 2$ if a first birth occurs in t (newborn present), $j = 1$ if no birth occurs and the woman remains childless, and $j = 3$ if the woman had a birth in a previous period. The discrete labor choice $l_t \in \{0, 1\}$ is subject to Type-I extreme value shocks. Conditional on (Ω_{it}, j), the ex-ante value for the working stage is

$$V_t^{3,j}(\Omega_{it}) = \mathbb{E}_\varepsilon\Big[\max_{l\in\{0,1\}} \big\{v_t^{3,j}(\Omega_{it}, l) + \sigma_l \varepsilon_t(l)\big\}\Big].$$

If a first birth occurs in t ($j = 2$), the household chooses labor supply, consumption, saving, and one-time child investment:

$$\begin{aligned} v_t^{3,k}(\Omega_{it}, l) = \max_{a_{t+1}\ge 0,\, c_t\ge 0,\, i_t\ge 0} & \Big\{u(c_t) + \psi_l^k\, 1_{\{l=1\}} + u_k(i_t) + \beta\, \mathbb{E}\big[V_{t+1}(\Omega_{i,t+1}) \mid \Omega_{it}, l, a_{t+1}, j = k\big]\Big\} \\ \text{s.t.} \qquad & \phi_c\big(m_t, 1\big)\, c_t + a_{t+1} = (1 + r)a_t + y_t(\Omega_{it}, l) - i_t, \\ & x_{t+1} = x_t + 1_{\{l=1\}}. \end{aligned}$$

If no birth occurs ($j = 1$) or the woman is an "older" mother without the child present ($j = 3$), investment is absent and the equivalence scale depends only on marital status:

$$\begin{aligned} v_t^{3,j}(\Omega_{it}, l) = \max_{a_{t+1}\ge 0,\, c_t\ge 0} & \Big\{u(c_t) + \psi_l^j\, 1_{\{l=1\}} + \beta\, \mathbb{E}\big[V_{t+1}(\Omega_{i,t+1}) \mid \Omega_{it}, l, a_{t+1}, j\big]\Big\} \\ \text{s.t.} \qquad & \phi_c\big(m_t, 0\big)\, c_t + a_{t+1} = (1 + r)a_t + y_t(\Omega_{it}, l), \\ & x_{t+1} = x_t + 1_{\{l=1\}}. \end{aligned}$$

Contraception and first-birth risk. Only childless women choose contraceptive effort, i.e. when $k_t = 1$ and $t \le T_F$. Let $p_t(\theta_i, e_t, s_t)$ denote the probability of a first birth in period t, decreasing in s_t and depending on age, ability, and education. Then

$$V_t^2(\Omega_{it}) = \max_{s_t\ge 0}\Big\{ - \phi_s\, s_t + p_t(\theta_i, e_t, s_t)\, V_t^{3,k}(\Omega_{it}) + \big(1 - p_t(\theta_i, e_t, s_t)\big)\, V_t^{3,nk}(\Omega_{it})\Big\}.$$

If $k_t \neq 1$ (a first birth already occurred in t or in the past), the household skips contraception:

$$V_t^2(\Omega_{it}) = V_t^{3,ok}(\Omega_{it}).$$

Marriage. If single ($m_t = 0$), the woman meets a potential husband with probability $\mu(e_t, t)$. Conditional on meeting, she compares continuation values under marriage and singlehood. Let $\Omega_{it}(m)$ denote the state with m_t set to $m \in \{0, 1\}$. Then

$$V_t^1(\Omega_{it}) = \begin{cases} \mu(e_t,t)\, \max\bigl\{V_t^2\bigl(\Omega_{it}(1)\bigr),\, V_t^2\bigl(\Omega_{it}(0)\bigr)\bigr\} + \bigl(1-\mu(e_t,t)\bigr)\, V_t^2\bigl(\Omega_{it}(0)\bigr), & \text{if } m_t = 0, \\ V_t^2(\Omega_{it}), & \text{if } m_t = 1, \end{cases}$$

and marriage is absorbing (no divorce).

College. At the end of $t = 1$, teens who complete high school ($d = HSG$) draw a Type-I extreme value shock and choose whether to enroll in college at $t = 2$, $d_C \in \{C, NC\}$. Let $v_2^1(\cdot)$ denote the beginning-of-period value at $t = 2$ given education choice; then

$$V_2^{CD,j}(\Omega_{i2}) = \max_{d_C \in \{C,NC\}} \{v_2^1(\Omega_{i2}; d_C) - \kappa_C(\theta, j) + \sigma_C \varepsilon_2(d_C)\}.$$

Only teens who complete high school face the college-entry decision.

4.3 Preferences, technologies and transfer system

I choose functional forms that are flexible enough to match the joint distribution of fertility timing, schooling, marriage, and labor supply.

Preferences over effective consumption. Utility is CRRA over effective consumption:

$$u(c_t) = \frac{c_t^{1-\rho}}{1-\rho},$$

where ρ is the coefficient of relative risk aversion. Household composition affects the expenditure needed to attain a given c_t. I implement this through an equivalence scale in the budget constraint:

$$\phi_c(m_t, k_t)\, c_t + a_{t+1} = (1+r)a_t + y_t - 1_{\{k_t=2\}}\, i_t,$$

so c_t is what enters utility and $\phi_c(m_t, k_t)c_t$ is the required expenditure. I parameterize

$$\phi_c(m_t, k_t) = 1 + \omega_m\, 1_{\{m_t=1\}} + \omega_{ch}\, 1_{\{k_t=2\}},$$

where $\omega_m \geq 0$ captures additional needs in a two-adult household and $\omega_{ch} \geq 0$ captures additional needs when a child is present in the household (i.e., a birth occurs in the current period under the one-period-child assumption).

Preferences over child quality. If a first birth occurs, parents choose a one-time monetary investment i_t that increases child "quality." Parental altruism enters as utility from child outcomes:

$$u^k(i_t) = \omega_0 + \omega_1\, i_t^{\omega_2},$$

where ω_0 is baseline utility from having a child, ω_1 scales the marginal value of investment, and $\omega_2 \in (0,1)$ imposes diminishing returns and ensures an interior investment choice.

College psych cost College choices are disciplined by a student allowance w_C, tuition TC, and an ability-dependent psychic cost. I model the psychic cost of college attendance as

$$\kappa_c(\theta, k_t) = \frac{\xi_c}{\theta^{\omega_c}} + 1_{\{\text{child present in college}\}}\, \phi_{kbac},$$

and allow continuation (graduate vs. drop out) to be differentially costly when a child is present via an additional cost. High-school continuation/dropout is modeled analogously through a cost wedge that can increase when a birth occurs in the high-school period.

Fertility and contraception. Fertility is stochastic and can be controlled imperfectly through contraceptive effort $s \geq 0$. For a woman who has not yet had a birth, the probability of conceiving in model period t depends on age (through an age-group index g), education e, and effort s, while cognitive ability θ affects how effectively effort reduces conception risk.[5]

[5] Related life-cycle models with imperfect fertility control and contraceptive effort use logit-type mappings for conception risk; see, e.g., Choi (2017); Ejrnæs and Jørgensen (2020); Seshadri and Zhou (2022). The key

The specification is motivated by two empirical regularities. First, "typical use" failure rates for contraceptive methods substantially exceed "perfect use" rates, with the gap driven primarily by inconsistent or incorrect use (Trussell, 2011). Second, this gap varies systematically with socioeconomic characteristics: more educated women and those with higher cognitive ability exhibit lower typical-use failure rates even conditional on method choice (Black et al., 2010; Rosenzweig and Schultz, 1989). These patterns suggest that ability affects not only the quantity of contraceptive effort but also the quality—that is, how effectively a given level of intended control translates into reduced conception risk.

To simplify notation, write $g = g(t)$ and suppress the time index. Let $\lambda_{ge} > 0$ denote the baseline odds of conception for age group g and education e (i.e., risk absent contraceptive effort), and let $\eta_{\theta g} > 0$ capture how ability shifts the effectiveness of effort in that age group. Then the conception probability is

$$p_{ge}(\theta, s) = \Big[\lambda_{\max} \cdot \frac{\lambda_{ge} \exp(-\eta_{\theta g} s)}{1 + \lambda_{ge} \exp(-\eta_{\theta g} s)} \Big]_{\lambda_{\min}}^{\lambda_{\max}}, \tag{1}$$

where $[x]_{\lambda_{\min}}^{\lambda_{\max}} \equiv \min\{\lambda_{\max}, \max\{\lambda_{\min}, x\}\}$ truncates the risk to lie in $[\lambda_{\min}, \lambda_{\max}]$.

This mapping implies $p_{ge}(\theta, s)$ is decreasing in s, with age and education shifting baseline risk through λ_{ge} and ability shifting the marginal effectiveness of effort through $\eta_{\theta g}$.

The parameter $\eta_{\theta g}$ captures a reduced-form wedge in "effective" fertility control. Conceptually, it reflects several mechanisms through which cognitive ability may improve the mapping from intended to realized contraception:

- *Correct and consistent use.* Higher-ability individuals may be more likely to use contraceptive methods correctly (e.g., taking pills at regular intervals, using condoms properly) and consistently (e.g., not skipping doses, not having unprotected intercourse).

- *Planning and anticipation.* Higher-ability individuals may be better at anticipating situations where contraception is needed and preparing accordingly, reducing the incidence of unprotected intercourse.

- *Method switching and persistence.* Higher-ability individuals may be quicker to rec-

distinction in my specification is that ability shifts the effectiveness of effort, not merely its cost or the baseline risk level.

ognize method failure or side effects and switch to more effective methods, or more persistent in using methods with high learning curves.

- *Partner negotiation.* Higher-ability individuals may be more effective at negotiating contraceptive use with partners, particularly for methods requiring partner cooperation.

I do not model these mechanisms separately; instead, $\eta_{\theta g}$ summarizes their combined effect on the effort–risk mapping, and it is consistent with the medical literature documenting large gaps between perfect-use and typical-use failure rates that vary with user characteristics (Black et al., 2010).

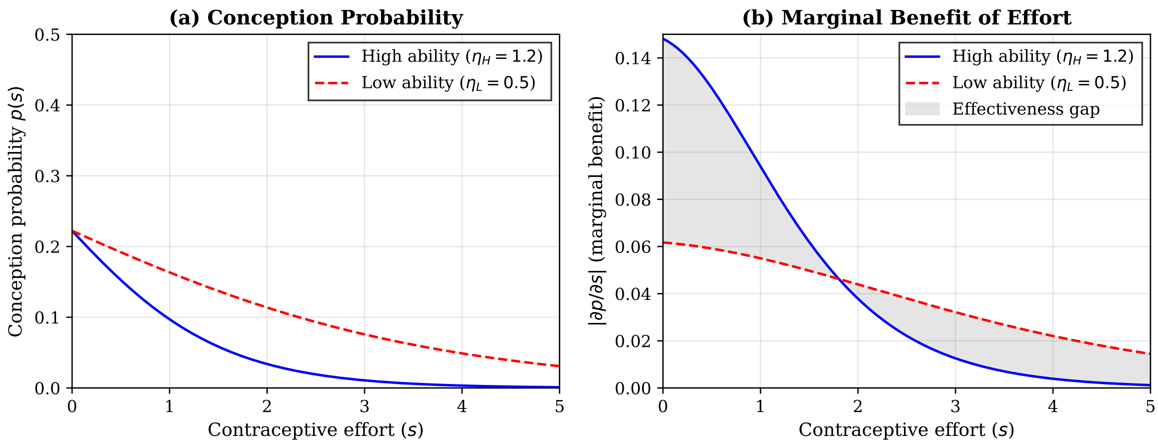
Parameter interpretation and behavioral response. The conception technology separates baseline risk from effort effectiveness. Baseline fecundity varies by education and age through λ_{ge}: holding effort fixed, a higher λ_{ge} raises conception risk at all effort levels. By contrast, $\eta_{\theta g}$ governs how strongly effort reduces conception risk: holding baseline risk fixed, a higher $\eta_{\theta g}$ makes each unit of effort more effective. In the model, changes in λ_{ge} therefore shift the level of pregnancy risk (a "risk shifter"), while changes in $\eta_{\theta g}$ change the slope of the risk–effort relationship (a "technology shifter").

To build intuition, consider two women with the same education and age (and thus the same λ_{ge}) but different cognitive ability. Both face identical baseline conception risk if they exert no effort. However, when both exert the same level of effort s, the high-ability woman achieves a lower conception probability because her effort is more effective ($\eta_{\theta,H} > \eta_{\theta,L}$).

Figure 3 illustrates this mechanism. Panel (a) shows conception probability as a function of effort for two ability types with the same baseline risk λ_{ge}. The high-ability type (solid blue line) achieves lower conception probability at every positive effort level: at any given $s > 0$, the solid curve lies below the dashed curve. Panel (b) shows the marginal benefit of effort—the reduction in conception probability from an additional unit of effort. Here the pattern is more nuanced. At low effort levels, the high-ability type has a higher marginal benefit (the solid curve starts above the dashed curve at $s = 0$). However, the high-ability marginal benefit declines more rapidly, and the two curves cross at intermediate effort levels. Beyond the crossing point, the low-ability type has a higher marginal benefit.

This crossing reflects diminishing returns: high-ability women can achieve very low conception risk with moderate effort, leaving little room for further improvement. Low-ability women, by contrast, still face substantial risk even at moderate effort, so their marginal benefit remains higher at high effort levels. The crossing has important implications for optimal behavior, discussed below.

Figure 3. Conception Technology: Role of Ability-Dependent Effectiveness



Notes: Both panels assume identical baseline conception odds λ_{ge} across ability types. Panel (a): conception probability as a function of contraceptive effort. The high-ability type (solid blue, $\eta_H = 1.2$) achieves lower conception probability than the low-ability type (dashed red, $\eta_L = 0.5$) at any positive effort level. Panel (b): marginal benefit of effort, $|\partial p/\partial s|$. At low effort, the high-ability type has higher marginal benefit; at high effort, the curves cross and the low-ability type has higher marginal benefit. The shaded region shows effort levels where high-ability types have a marginal-benefit advantage.

To impose that higher ability weakly increases the productivity of effort, I restrict $\eta_{\theta g}$ to be weakly increasing in ability quartiles (via nonnegative increments). This restriction is motivated by the empirical literature on contraceptive failure, which documents that typical-use failure rates decline with education and cognitive ability even conditional on method choice (Rosenzweig and Schultz, 1989; Trussell, 2011). Finally, $(\lambda_{\min}, \lambda_{\max})$ bound conception probabilities away from 0 and 1, capturing imperfect control even at high effort and ruling out deterministic fecundity differences across groups.

Comparative statics. Ignoring the outer bounds, the risk function satisfies the following comparative statics:

$$\frac{\partial p_{ge}(\theta, s)}{\partial s} < 0, \qquad \frac{\partial p_{ge}(\theta, s)}{\partial \lambda_{ge}} > 0, \qquad \frac{\partial p_{ge}(\theta, s)}{\partial \eta_{\theta g}} < 0.$$

The first inequality states that effort reduces conception risk. The second states that higher baseline fecundity raises risk at any effort level. The third—the key result—states that higher effectiveness reduces conception risk, holding effort fixed. This third derivative is the source of within-education ability gradients: even if high- and low-ability women within an education group exert identical effort, the high-ability woman achieves lower conception risk.

Moreover, $\eta_{\theta g}$ scales the marginal benefit of effort: $|\partial p/\partial s|$ is increasing in $\eta_{\theta g}$, whereas λ_{ge} primarily shifts risk up or down for a given s. At the bounds, the derivative with respect to effort is zero by construction.

Optimal effort choice. The household chooses effort by equating its marginal cost (proportional to ϕ_s) to its marginal benefit from lowering conception risk, which is proportional to $-\frac{\partial p}{\partial s} \times \left(V^{\text{no child}} - V^{\text{child}}\right)$. The first-order condition is:

$$\phi_s = \left| \frac{\partial p_{ge}(\theta, s)}{\partial s} \right| \times \underbrace{\left(V^{\text{no child}} - V^{\text{child}}\right)}_{\text{value of avoiding birth}}. \tag{2}$$

The left-hand side is the marginal cost of effort. The right-hand side is the marginal benefit: the reduction in conception probability from an additional unit of effort, multiplied by the value of avoiding a birth. Optimal effort equates these two margins.

Ability therefore affects contraception behavior through two distinct channels:

(i) *Effectiveness channel.* Higher $\eta_{\theta g}$ raises $|\partial p/\partial s|$, increasing the marginal benefit of effort at any effort level. This direct effect encourages higher effort.

(ii) *Incentive channel.* Higher ability raises the value of avoiding a birth, $V^{\text{no child}} - V^{\text{child}}$, through better schooling outcomes, higher wages, steeper experience profiles, and improved marriage prospects. This indirect effect also encourages higher effort.

Both channels predict that high-ability women exert more effort and achieve lower conception risk. However, they have different implications for identification. The incentive channel operates through opportunity costs that vary with education and can be disciplined using wage and employment data. The effectiveness channel operates within education groups and generates ability gradients in birth hazards that cannot be explained by opportunity costs alone. Section 5.2 exploits this distinction to separately identify the two channels.

Progressive taxes and transfers. To approximate the U.S. tax-and-transfer system, I adopt the parametric schedule in Daruich and Fernández (2024). Let $\tilde{y}^0$ denote gross annual household income before taxes and transfers (labor earnings, spousal earnings if married, schooling allowances when enrolled, or Social Security in retirement). Disposable annual income is

$$\tilde{y} = \lambda(y^0)^{1-\tau} + T(m_t),$$

so the corresponding net-tax function is $\mathcal{T}(\tilde{y}^0, m_t) = \tilde{y}^0 - \tilde{y}$. Progressivity ($\tau > 0$) reduces the sensitivity of after-tax resources to gross income, while $T(m_t)$ captures a reduced-form transfer floor that varies by marital status.

5 Estimation

This section describes the estimation strategy and the identification of the model's key mechanisms. Parameters are disciplined in three steps: (i) a set of externally calibrated parameters, (ii) an earnings process estimated outside the structural model, and (iii) the remaining structural parameters estimated internally using the Simulated Method of Moments. I then discuss how the targeted moments identify the education and opportunity-cost channels separately from ability-driven heterogeneity in effective fertility control.

5.1 Externally Set Parameters and Earnings Process

Externally set parameters. Table 7 reports parameters fixed outside SMM. I discipline (i) preferences and financial conditions using standard values from the structural life-cycle literature, (ii) policy and institutional objects (tuition, taxes, transfers) using established calibrations, and (iii) biological constraints by imposing bounds on conception probabilities that rule out both perfect control and deterministic fecundity.

Table 7. Externally Set Parameters

Parameter	Value	Source / interpretation
Discount factor β_a	0.959 (annual)	Standard annual discount factor (Adda et al., 2017).
Risk aversion ρ	1.98	CRRA curvature (Adda et al., 2017).
Risk-free rate r_a	0.04 (annual)	Annual real return (Adda et al., 2017).
College tuition TC	\$10,200	Annual tuition (2016 \$) (Vandenbroucke, 2023).
Tax parameters (τ, λ)	(0.18, 0.85)	τ controls progressivity and λ pins down average tax levels (Daruich and Fernández, 2024).
Transfer floor $T(m)$	$T_S =$ \$8,634, $T_C =$ \$12,943	Annual transfer floor (2016 \$) for singles vs. couples.
Conception bounds $(\lambda_{\min}, \lambda_{\max})$	(0.05, 0.80)	Bounds ensuring imperfect control and ruling out deterministic fecundity (Trussell, 2004).
Contraception cost ϕ_s	0.001	Normalization.

Notes: Monetary values are in dollars per year (2016 prices). Annual flows are converted to four-year model-period units as described in the text.

Externally estimated earnings process. A key input to the model is the earnings process. I estimate reduced-form earnings profiles in the NLSY79 and use the fitted values to parameterize the model's deterministic component of earnings as a function of observed states. Specifically, I predict annual real wage-and-salary earnings and treat the fitted profiles as the earnings opportunities faced by women and husbands in each model period. Appendix OA.3 provides full details on the estimation sample and specification.

Women's earnings. Let $\widetilde{w}_t^f$ denote predicted annual earnings for women. Earnings depend flexibly on age, education, experience, cognitive-ability quartile, and interactions. To allow earnings to vary systematically with family formation, I also include reduced-form indicators for marriage and nonmarital first birth:

$$\widetilde{w}_t^f = X_t^f \widehat{\beta}^f,$$

where X_t^f includes age and age-squared, education and ability indicators, experience and interactions (education×experience, ability×experience, education×ability), and family-formation indicators.

Husbands' earnings. Husbands' earnings are modeled as a reduced-form function of the wife's observed characteristics and marital status at childbirth (capturing assortative mating and marriage selection):

$$\widetilde{w}_t^h = X_t^h \widehat{\beta}^h,$$

where X_t^h includes age (and a quadratic), the wife's education, and interactions with an indicator for whether the first pregnancy/birth occurs out of wedlock.

5.2 Estimation and Identification

Estimation. I estimate the model by Simulated Method of Moments (SMM). SMM is well-suited for dynamic life-cycle models with discrete choices, unobserved taste shocks, and nonlinear state transitions, and it makes transparent the link between model mechanisms and targeted data moments (Gourieroux et al., 1993; Hansen, 1982; McFadden, 1989; Pakes and Pollard, 1989). I choose parameters Θ to minimize the distance between an empirical moment vector $m^{data} \in \mathbb{R}^{111}$ and its model analogue $m^{sim}(\Theta)$:

$$\widehat{\Theta} = \arg\min_{\Theta} \left(m^{sim}(\Theta) - m^{data}\right)' W \left(m^{sim}(\Theta) - m^{data}\right),$$

where W is diagonal and each moment is scaled by its empirical magnitude to keep the criterion approximately comparable across outcomes (with a small floor to avoid division by zero).

Moment blocks. The 111 targets are organized into blocks aligned with the model mechanisms:

- **Schooling and early fertility:** dropout/attendance/graduation moments conditional on early pregnancy indicators; college attendance by ability quartile.
- **Child investment:** relative investment ratios across schooling states.
- **Fertility timing:** first-birth hazards by age bin $\times$ ability quartile.
- **Contraception:** contraception use by age bin $\times$ education.
- **Marriage:** shares married by age bin $\times$ education.
- **Labor supply:** employment rates by age bin $\times$ education.

All parameters are disciplined by the joint fit across blocks through the model's cross-equation restrictions; the block structure is a guide to the main sources of identifying variation rather than a claim of one-to-one identification. [6]

Identification: separating opportunity costs from fertility control. Cognitive ability affects fertility timing through (i) opportunity costs (schooling, wages, experience accumulation), (ii) marriage-market incentives and spousal resources, and (iii) fertility control. Identification leverages the life-cycle structure: the same latent ability type that matches schooling, labor supply, and marriage outcomes must also rationalize fertility timing, limiting the scope for reallocating fit across margins without degrading non-fertility moments.

Key restrictions and mapping to moments. Identification of the fertility-control channel relies on three restrictions that prevent within-education teen birth gradients from being absorbed elsewhere:

(i) **External earnings environment:** the earnings process is estimated outside the structural SMM step using wage data, so wage–experience profiles by ability are not chosen to improve fertility fit.

(ii) **Disciplined schooling selection:** schooling-cost parameters and education-stage taste-shock scales are disciplined primarily by schooling outcomes (including schooling moments conditional on early fertility), ensuring the model matches the joint distribution of education and ability before attributing residual fertility gradients to fertility control.

(iii) **Within-cell baseline risk:** baseline birth risk $\lambda_h(g, e)$ is common within age–education cells, so within-cell ability gradients in first-birth hazards load on the ability shifter in fertility control rather than on baseline risk differences.

Identifying fertility-control parameters. Conditional on the externally set wage environment and the disciplined schooling/marriage/labor-supply blocks, the fertility technology

[6] Although the model is written in terms of a latent conception risk, the empirical targets are defined on first live births; the estimated "conception technology" should therefore be interpreted as a reduced-form birth-producing hazard that matches birth-based hazards in the data.

parameters are disciplined by the joint behavior of (a) first-birth hazards by age and ability and (b) contraception use by age and education. In the model, $\lambda_h(g, e)$ shifts baseline risk within an age–education cell, ϕ_s shifts the cost of contraceptive effort (and thus average use), and $\eta_{\theta,g}$ shifts the effectiveness with which a given effort level reduces realized risk. The key identifying variation for $\eta_{\theta,g}$ is therefore the residual within-education ability gradient in early birth hazards once schooling, wages, marriage, and average contraception use are pinned down.

Overidentification and specification checks. The model is overidentified: 111 empirical moments discipline 60 estimated structural parameters (with the earnings process estimated externally), implying 51 overidentifying restrictions. Overidentification is used as discipline rather than as a formal test of a single restriction: I assess whether the model matches fertility hazards without degrading contraception, schooling, marriage, and labor-supply moments. I also report a nested specification that shuts down ability heterogeneity in η; the deterioration in the joint fit of within-education hazard gradients provides a check that the fertility-control heterogeneity is doing empirically relevant work rather than substituting for opportunity-cost mechanisms.

6 Results

Four main findings emerge from the estimated model.

First, the model accounts for the sharp ability gradient in early fertility. By age 18, roughly 40% of women in the lowest ability quartile have had a first birth, compared to fewer than 10% in the highest quartile—a fourfold difference. The model matches this gradient while simultaneously fitting education, marriage, labor supply, and contraception profiles (Section 6.1).

Second, this pattern cannot be explained by schooling choices and wage-based opportunity costs alone. Nested specification tests show that restricting contraceptive effectiveness to be equal across ability groups ($\eta = 1$) causes the model to underpredict the ability–fertility gradient by a factor of two to five. Only when effectiveness is allowed to vary by ability does the model match both the steep gradient in birth hazards and the relatively flat gradient in contraception use. This provides direct evidence that ability-dependent fertility control is quantitatively necessary (Section 6.2).

Third, the implied heterogeneity in effective fertility control has large welfare consequences. Giving low-ability women the contraception environment of college graduates is worth 11.2% of lifetime consumption for the bottom ability quartile. The within-education "ability wedge"—the value of equalizing contraceptive effectiveness alone—is worth 5.6% of lifetime consumption for the same group.

Fourth, counterfactual experiments decompose the teen fertility–schooling gradient into selection versus causation. Equalizing fertility control to the high-ability level reduces teen pregnancies by 50% and raises college attendance by 13%—implying that roughly one-quarter to one-third of the fertility–schooling gradient reflects a causal effect of early childbearing on education. The 50% reduction is comparable in magnitude to the 78% reduction observed in the CHOICE Project's LARC intervention, though that estimate likely includes positive selection. Equalizing schooling opportunities has a larger effect on college attendance (+25%) but a smaller effect on teen fertility (−29%), confirming that the two channels—fertility control and opportunity costs—are distinct and complementary (Section 7).

The remainder of this section documents model fit (Section 6.1), presents the nested specification test (Section 6.2), quantifies welfare implications (Section 6.3), and in Section 7 uses the model to decompose the fertility–schooling gradient and evaluate policy counterfactuals.

6.1 Model fit

This section evaluates how well the estimated model matches the targeted moments. The estimation uses 111 moments organized into five blocks: fertility timing by ability, education outcomes, marriage, labor supply, and contraception use. I discuss fit for each block in turn, highlighting where the model succeeds and where it falls short.

Throughout the figures, solid lines with circular markers denote model predictions; dashed lines with square markers denote NLSY79 data moments.

6.1.1 Fertility timing by cognitive ability

Figure 4 (panel (a)) compares the cumulative fraction of women who have had a first birth by age and ability quartile. The model reproduces the sharp ability gradient in the onset of motherhood: by age 18, roughly 40% of women in the lowest ability quartile (Q1) have had a first birth, compared to fewer than 10% in the highest quartile (Q4). This gradient persists through the twenties, with Q1 women reaching near-universal motherhood by age 30 while Q4 women continue accumulating first births into their thirties.

The model captures both the *level* and *timing* of these differences. At ages 14–17 and 18–21, where the ability gradient is steepest and most informative about fertility-control incentives, the model closely tracks the data for all four quartiles. At older ages (30+), the model slightly overpredicts the ability gradient—that is, it predicts somewhat too little convergence across ability groups. This pattern is consistent with the model attributing too much of the fertility-timing difference to persistent effectiveness differences ($\eta_{\theta g}$) rather than to factors that diminish with age.

The tight fit at young ages is particularly important because this is where the ability-dependent effectiveness channel has the most bite. Teen and early-twenties birth hazards are the moments that discipline the $\eta_{\theta g}$ parameters, and the model's ability to match these moments while simultaneously fitting contraception use (discussed below) provides the key identification for the effectiveness channel.

6.1.2 Schooling and child-related outcomes

Table 8 evaluates whether the model captures the joint distribution of schooling attainment and early fertility. The model successfully reproduces several key patterns.

First, the model matches the strong association between teen pregnancy and high school dropout. Among women without a pregnancy by age 14, the dropout rate is 7.0% in the data and 7.1% in the model—an essentially perfect fit. Among those with a pregnancy by age 14, the dropout rate rises to 29% in the data and 44% in the model. The model overpredicts this gap, suggesting it attributes somewhat too much of the dropout–pregnancy association to the causal effect of pregnancy rather than to selection on unobserved characteristics. However, the model correctly captures the qualitative pattern: early pregnancy is strongly associated with school leaving.

Second, the model captures the steep ability gradient in college attendance. In the data, attendance rises monotonically from 11% in Q1 (lowest ability) to 67% in Q4 (highest ability). The model reproduces this gradient: 10.8% for Q1, 32.2% for Q2, 45.8% for Q3, and 48.2% for Q4. The fit is excellent for Q1 and Q3, but the model underpredicts attendance for Q4 (48% vs. 67%). This shortfall is consistent with the model's abstraction from parental resources, financial aid, and credit constraints—factors that covary strongly with measured ability and disproportionately boost college-going for high-ability youth from advantaged backgrounds.

Third, the model reproduces the negative association between pregnancy and college outcomes. College attendance conditional on no pregnancy by age 14 is 41% in the data and 44% in the model; conditional on pregnancy, it falls to 8% in the data and 11% in the model. Similarly, college graduation conditional on attendance and no pregnancy by age 18 is 62% in the data and 84% in the model; conditional on pregnancy, it falls to 26% in both data and model. The model overpredicts graduation for non-pregnant attendees, likely because it does not fully capture dropout for non-pregnancy reasons (financial, academic, or personal). However, it accurately predicts the severe penalty of early pregnancy on college completion.

Child-investment moments are disciplined using external evidence on expenditure gradients from Caucutt and Lochner (2020). The model matches the college-versus-dropout ratio reasonably well (3.3 vs. 4.6 in the data) but overstates the high-school-versus-dropout gradient (2.3 vs. 1.2). This pattern is consistent with compressing heterogeneous child investments into a single child period and with the model's limited treatment of within-education heterogeneity in parenting resources.

6.1.3 Labor-market profiles: participation and experience

Figure 4 (panels (b) and (c)) displays labor-force participation and accumulated work experience by age and education.

Labor-force participation (panel b). The model reproduces the education gradient in participation: college graduates participate at rates of 65–75% during prime working ages, high school graduates at 50–55%, and high school dropouts at 20–30%. The model also captures the life-cycle pattern—rising participation in the twenties, a plateau through the

Table 8. Education Moments: Model vs. Data

	Data	Model		Data	Model
High School Dropout (by Age 14 Pregnancy)			*College Attendance by Ability*		
No pregnancy	0.070	0.071	Ability Q1 (low)	0.110	0.108
Pregnancy	0.290	0.435	Ability Q2	0.250	0.322
			Ability Q3	0.410	0.458
			Ability Q4 (high)	0.670	0.482
College Attendance (by Age 14 Pregnancy)			*College Graduation | Attendance*		
No pregnancy	0.410	0.442	No pregnancy by 18	0.620	0.835
Pregnancy	0.080	0.108	Pregnancy by 18	0.260	0.276
Child Investment Ratio (vs. HSD)					
HS graduate	1.20	2.30			
College graduate	4.60	3.32			

Notes: Data moments from NLSY79. "Pregnancy" indicates first birth occurred by the specified age. Child investment ratios (expenditure on children relative to high school dropouts) from Caucutt and Lochner (2020).

forties, and decline after age 50. The fit is tightest for college graduates; for high school graduates and dropouts, the model slightly underpredicts participation at young ages (before age 25).

Work experience (panel c). Because experience is a state variable that accumulates with labor supply, fitting experience profiles provides an indirect validation of the model's dynamic structure. The model closely tracks experience accumulation for all three education groups: by age 55, college graduates have accumulated roughly 22 years of experience, high school graduates 18–20 years, and dropouts 8–10 years. The slopes are well-matched, indicating that the model correctly captures the rate at which women accumulate experience over the life cycle. This fit is important because experience feeds into wages through the estimated returns to experience, and wages in turn affect the opportunity cost of childbearing.

6.1.4 Marriage: levels and education gradient

Panel (d) displays marriage rates by age and education. The model captures the general life-cycle increase in marriage—rates rise from 40–60% at age 18 to 75–95% by age 38—and reproduces the broad ranking across education groups at young ages.

However, two discrepancies emerge. First, the model *overpredicts* marriage rates for high school dropouts and graduates at older ages: by age 38, the model predicts marriage rates near 90–95% for these groups, compared to 75–85% in the data. Second, the model *underpredicts* marriage for college graduates at all ages: the model shows college graduates with the lowest marriage rates, while the data show convergence (and eventual crossover) by the early thirties.

These patterns suggest that the current specification assigns too little marital surplus to high-education types. The model features perfect assortative matching on education, so college graduates marry college-educated partners. However, marital surplus derives solely from partner earnings and consumption smoothing. The model does not capture non-pecuniary dimensions of partner quality—such as shared values, lifestyle compatibility, or complementarities in home production—that may be higher for college-educated couples. Nor does it capture the insurance value of dual-earner households.

6.1.5 Contraception use: the key fertility-control moment

Panel (e) displays contraception use by age and education. These moments are central to identification: they discipline the fertility-control parameters and—in combination with birth hazards—allow separate identification of baseline risk (λ_{ge}), effort costs (ϕ_s), and ability-dependent effectiveness ($\eta_{\theta g}$).

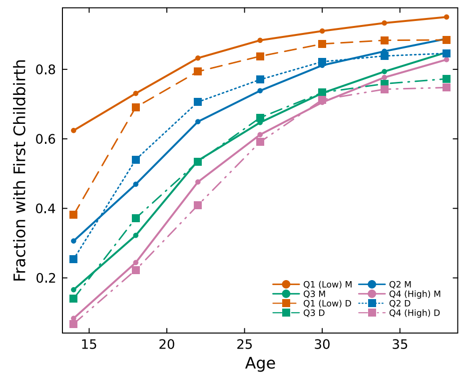
The model matches the education gradient in contraception use: college-educated women report higher use than high school graduates, who in turn report higher use than dropouts. The model also captures the declining age profile—contraception use falls from roughly 80–90% at ages 17–22 to 40–50% by the late thirties—reflecting the transition from fertility postponement to completed fertility.

The fit is tightest for college graduates and high school dropouts. For high school graduates, the model underpredicts contraception use at ages 22–26. Importantly, the model matches the relative ranking across education groups, which is key for identifying education-specific baseline risk λ_{ge}.

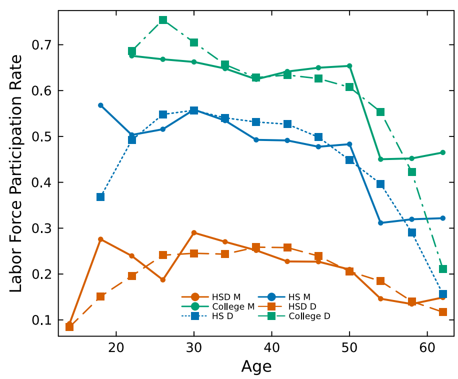
A critical feature of the fit is that the model matches contraception use *and* ability gradients in birth hazards simultaneously. As discussed in Section 6.2, specifications that restrict $\eta = 1$ (no ability-dependent effectiveness) cannot achieve this joint fit: they either match birth hazards and miss contraception use, or vice versa. The full model's ability to fit both margins provides the key empirical support for the effectiveness channel.

Crucially, these limitations are unlikely to affect the paper's central finding. The identification of ability-dependent fertility-control effectiveness relies on within-education ability gradients in birth hazards and contraception use—moments that the model matches well. The marriage and college-completion discrepancies primarily affect the level of opportunity costs for college graduates, not the within-education variation that identifies the effectiveness channel. Moreover, the nested specification test (Section 6.2) shows that restricting $\eta = 1$ dramatically worsens fit on the key fertility-timing moments, confirming that ability-dependent effectiveness is empirically necessary independent of the marriage module's limitations.

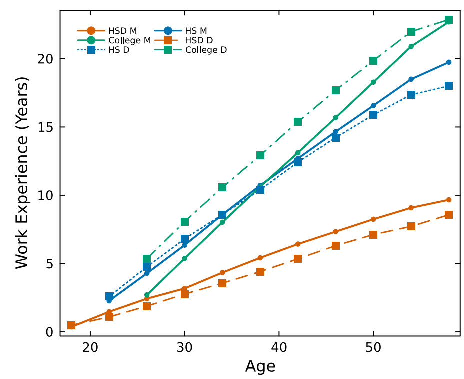
Figure 4. Model Fit: Fertility Timing, Labor Market, Marriage, and Contraception



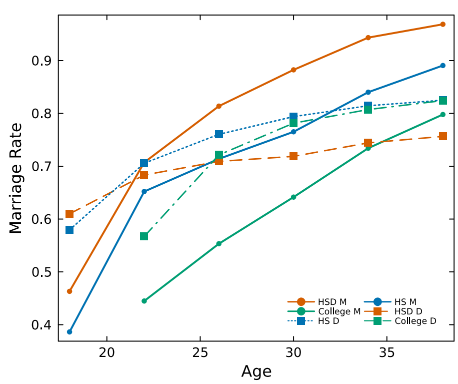
(a) Cumulative first births by age and ability quartile



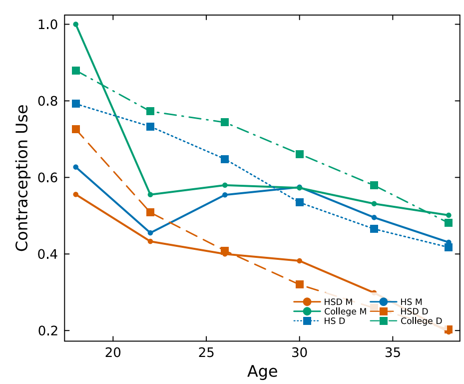
(b) Labor-force participation by education



(c) Accumulated work experience by education



(d) Marriage rates by education



(e) Contraception use by education

Notes: Panel (a) reports the cumulative fraction of women who have had a first birth by each age, separately by AFQT ability quartile (Q1 = lowest, Q4 = highest). Panels (b)–(e) report outcomes by age and completed education (HSD = high school dropout, HS = high school graduate, College = college graduate). Solid lines with circular markers show model predictions; dashed lines with square markers show NLSY79 data moments. "M" denotes model; "D" denotes data.

6.2 Nested Specification Test: Is Ability-Dependent Fertility Control Necessary?

The model allows cognitive ability to affect fertility timing through two channels: (i) opportunity costs, operating through schooling choices and wage profiles, and (ii) fertility-control effectiveness, operating through the parameter $\eta_{\theta g}$ that governs how effort maps into conception risk. A natural question is whether the second channel is empirically necessary, or whether the standard opportunity-cost channel alone can explain the ability gradient in fertility timing.

To address this question, I estimate three nested specifications that progressively relax restrictions on the fertility-control technology:

(1) Baseline (Age only): Baseline conception risk λ_g varies by age group g only, and the effectiveness parameter is normalized to $\eta = 1$ for all individuals. Any ability gradient in fertility timing must arise entirely from differences in schooling choices, wages, and marriage prospects.

(2) Baseline + Education Heterogeneity: Baseline conception risk λ_{ge} varies by age and education, but effectiveness remains $\eta = 1$ for all individuals. Ability gradients can arise from opportunity costs and from sorting into education groups with different baseline risk, but not from within-education differences in how effectively effort reduces conception risk.

(3) Full Model (+ Ability in Effectiveness): Baseline risk λ_{ge} varies by age and education, and the effectiveness parameter $\eta_{\theta g}$ is allowed to vary by ability quartile. This specification allows ability to directly shift how effort translates into reduced conception risk, generating within-education ability gradients in birth hazards even when observed contraception use is similar.

The key restriction in specifications (1) and (2) is $\eta = 1$ for all individuals: a unit of contraceptive effort produces the same reduction in conception risk regardless of cognitive ability. Specification (3) relaxes this restriction, allowing high-ability individuals to achieve greater risk reduction per unit of effort ($\eta_{\theta,H} > \eta_{\theta,L}$). If the opportunity-cost channel alone can explain the data, specifications (1) and (2) should fit the fertility-timing moments as well as (3). If, instead, the data require ability-dependent effectiveness, specification (3) should substantially outperform (1) and (2)—particularly on the within-education ability gradient in birth hazards.

To assess model fit , I use the normalized sum of squared errors (SSE),

$$\mathrm{SSE}(\hat{\vartheta}) = \sum_i \left(\frac{m_i - m_i(\hat{\vartheta})}{m_i} \right)^2,$$

where m_i are empirical moments and $m_i(\hat{\vartheta})$ are their model counterparts under parameter vector $\hat{\vartheta}$. I decompose the total SSE into contributions from each moment block to diagnose which margins drive the fit improvement.

Results. Table 9 reports SSE decompositions across the three specifications. Three patterns emerge.

First, adding education heterogeneity in baseline risk (column 2) yields only modest improvement in total fit (1%) and actually worsens fit on the contraception-use moments (SSE increases from 0.32 to 1.19). This occurs because, with η fixed at 1, the model can only generate ability gradients in birth hazards through differences in baseline risk λ_{ge} across education groups. To match the steep ability gradient in teen births, the model must assign very different baseline risk levels across education groups, which distorts predicted contraception use patterns.

Second, allowing η to vary by ability (column 3) generates a substantial improvement in total fit (32% reduction in SSE relative to baseline). The improvement is broad-based: the pregnancy-and-ability block improves by 35%, the labor-market block improves by 45%, and—crucially—the contraception block returns to baseline fit levels (SSE of 0.31 vs. 0.32). The model can now match both the steep ability gradient in birth hazards and the relatively flat ability gradient in contraception use, because high-ability women achieve lower conception risk through greater effectiveness rather than dramatically higher effort.

Third, the bottom panel of Table 9 reports the model-implied correlation between first-birth probability and ability by age group. The data show a strong negative correlation (approximately −0.26 for ages 14–17 and −0.27 for ages 18–21), indicating that high-ability women are substantially less likely to have a first birth at young ages. With $\eta = 1$ (specifications 1 and 2), the model underpredicts this gradient by a factor of two to five: the implied correlations range from -0.05 to -0.17. Allowing η to vary by ability (specification 3) generates correlations of -0.53 and -0.49, which overpredict the data but capture the correct sign and order of magnitude.

The key finding is that fixing $\eta = 1$—that is, restricting contraceptive effectiveness to be the same across ability groups—prevents the model from matching the observed ability gradient in fertility timing. Specifications (1) and (2) can generate some ability gradient through opportunity costs and education sorting, but the predicted gradient is far too weak. Only when η is allowed to vary by ability can the model match the steep within-education gradient in birth hazards while simultaneously fitting contraception use patterns. This provides direct evidence that ability-dependent fertility-control effectiveness is a quantitatively important channel, distinct from the standard opportunity-cost mechanism.

6.3 Welfare Implications: Consumption-Equivalent Value of Improved Fertility Control

The estimated model reveals large heterogeneity in effective fertility control across education and ability groups. But how consequential are these differences for welfare? To quantify the stakes, I translate the estimated differences in fertility-control frictions into consumption-equivalent units—the permanent proportional increase in lifetime consumption that would make an individual indifferent between her baseline contraception environment and an improved alternative.

This metric has a straightforward interpretation: a consumption equivalent of $\tau\%$ means that access to better fertility control is worth as much as a $\tau\%$ permanent increase in consumption. The calculation holds fixed all other features of the environment (wages, schooling costs, marriage market) and varies only the fertility-control parameters, isolating the welfare value of improved contraception.

Figure 5 reports two counterfactual exercises.

Exercise 1: Equalizing fertility control to the college-graduate level. Panel (a) computes the consumption equivalent of giving each ability group the contraception environ-

Table 9. Nested Specification Test: Model Fit Decomposition

	Specification		
	(1) Baseline ($\eta = 1$)	(2) + Education Het. in λ ($\eta = 1$)	(3) Full Model (+ Ability in η)
Panel A: Sum of Squared Errors by Moment Block			
Total SSE	5.51	5.44	3.76
Pregnancy × Ability	1.44	1.08	0.93
Education outcomes	1.10	0.59	0.79
Marriage	0.38	0.31	0.49
Labor supply	2.27	2.27	1.24
Contraception use	0.32	1.19	0.31
Panel B: Fit Improvement Relative to Baseline (%)			
Total	—	1	32
Pregnancy × Ability	—	25	35
Education outcomes	—	47	28
Marriage	—	18	−28
Labor supply	—	0	45
Contraception use	—	−271	4
Panel C: Corr. of First-Birth Probability with Ability			
Ages 14–17 (*Data:* −0.26)	−0.09	−0.05	−0.53
Ages 18–21 (*Data:* −0.27)	−0.17	−0.17	−0.49
Ages 22–29 (*Data:* −0.07)	−0.13	−0.11	−0.22
Ages 14–29 (*Data:* −0.24)	−0.13	−0.11	−0.22

Notes: Columns (1)–(3) compare three nested specifications. (1) λ varies by age only; $\eta = 1$. (2) λ varies by age and education; $\eta = 1$. (3) λ varies by age and education; η varies by ability quartile. Panel A reports SSE by moment block: $\text{SSE} = \sum_i \left[(m_i - \hat{m}_i)/m_i\right]^2$. Panel B reports $100 \times (1 - \text{SSE}_j/\text{SSE}_1)$ for $j \in \{2, 3\}$; negative values indicate worse fit. Panel C reports the model-implied correlation between first-birth probability and ability quartile; data moments are italicized.

ment faced by college graduates—that is, the baseline conception risk λ_{ge} of college-educated women. This exercise captures the welfare value of eliminating education-related disparities in fertility control.

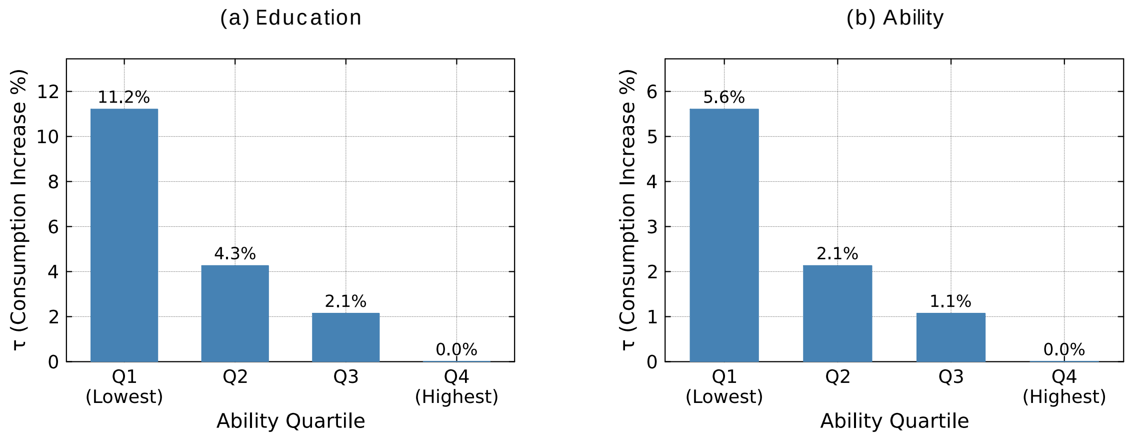
The gains are large and highly concentrated at the bottom of the ability distribution. For women in the lowest ability quartile (Q1), access to the college-graduate contraception environment is worth 11.2% of lifetime consumption. The gains decline sharply with ability: 4.3% for Q2, 2.1% for Q3, and essentially zero for Q4. This pattern reflects two forces. First, low-ability women face the highest baseline conception risk and lowest contraceptive effectiveness, so they benefit most from improved fertility control. Second, low-ability women have the fewest alternative margins for avoiding early childbearing—they are less likely to attend college, have lower wages, and face weaker incentives to delay fertility through the opportunity-cost channel—so direct improvements in fertility control are particularly valuable.

Exercise 2: Equalizing fertility control across ability within education. Panel (b) computes the consumption equivalent of giving each ability group the contraception *effectiveness* ($\eta_{\theta g}$) of the highest ability quartile, holding education-specific baseline risk fixed. This exercise isolates the welfare value of the ability-dependent effectiveness channel identified in Section 6.2.

The implied ability wedge is economically meaningful: a woman in Q1 would require a 5.6% permanent increase in lifetime consumption to be indifferent between her baseline effectiveness and that of a Q4 woman. The corresponding values are 2.1% for Q2 and 1.1% for Q3. These magnitudes are smaller than the education-based wedges in Exercise 1, reflecting that education differences in fertility control operate through multiple channels (baseline risk, effort costs, and effectiveness), while the ability wedge operates through effectiveness alone.

Interpretation. Two takeaways emerge. First, heterogeneity in effective fertility control has substantial welfare consequences, particularly for low-ability women. Second, the ability-dependent effectiveness channel accounts for a meaningful share of the total welfare disparity. Equalizing effectiveness alone is worth roughly half as much as equalizing the full contraception environment, indicating that within-education differences in how effort maps to outcomes are quantitatively important.

These findings have implications for policy design. Interventions that improve access to contraception (reducing effort costs or baseline risk) will generate the largest welfare gains for low-ability women, but the gains will be partially attenuated if these women also face lower effectiveness in using available methods. Complementary investments in contraceptive education, counseling, or access to long-acting reversible methods that reduce the scope for user error may be necessary to fully close the gap.



(a) Equalizing to college-graduate environment

(b) Equalizing effectiveness across ability

Figure 5. Consumption-Equivalent Value of Improved Fertility Control

Notes: Each bar reports the permanent proportional increase in lifetime consumption (τ) that makes an individual indifferent between her baseline contraception environment and an improved alternative. Panel (a): counterfactual gives all women the baseline conception risk and effort costs faced by college graduates, by ability quartile. Panel (b): counterfactual gives all women the contraceptive effectiveness ($\eta_{\theta g}$) of the highest ability quartile (Q4), holding education-specific baseline risk fixed. Q4 is normalized to zero in both panels.

The next section uses the estimated model to decompose selection from causal effects in the teen pregnancy–education relationship and to evaluate targeted policy interventions. A preview of the findings: policies that reduce teen pregnancy rates need not mechanically raise college attainment if the primary barrier for low-ability women is the cost of schooling rather than childbirth per se. However, such policies generate substantial welfare gains through the fertility-timing channel documented here, even when educational attainment is unchanged.

7 Decomposing the Teen Fertility–Schooling Gradient: Selection versus Causation

Teen motherhood is strongly associated with low educational attainment, but this correlation is difficult to interpret causally. Adolescents who become teen mothers differ systematically from their peers along many dimensions—family background, prior achievement, discount rates, and expectations—so naive comparisons may overstate the causal impact of childbearing on education. Consistent with this concern, Hotz et al. (2005) use miscarriages as an instrument and find limited long-run effects of teen births on completed schooling. Similarly, Levine and Painter (2003) use propensity-score matching and conclude that a substantial share of the raw association reflects selection rather than causation, though meaningful negative effects on college attendance remain.

This paper takes a different approach. Rather than attempting to identify a single "causal effect of teen childbearing," I use the estimated structural model to decompose the teen fertility–schooling gradient into distinct channels and ask: when we observe that early childbearers have low educational attainment, how much reflects barriers to effective fertility control versus how much reflects low returns to schooling that both depress education and raise early fertility?

This decomposition matters for policy. If the gradient is primarily driven by fertility-control frictions, then improving access to contraception should reduce teen births and raise schooling through the channel documented in Section 6.3. If instead the gradient reflects low schooling returns, then contraception interventions may reduce teen births without substantially affecting educational attainment—and the appropriate policy response is to address the underlying barriers to education directly.

7.1 Counterfactual Design

I conduct three counterfactual experiments that isolate specific channels by equalizing ability-related margins while holding other features of the environment fixed:

1. **Equalize fertility-control environment:** all women the contraception parameters (baseline risk λ_{ge}, effectiveness $\eta_{\theta g}$, and effort costs ϕ_s) of the highest-ability group, holding fixed college costs and wage profiles. This experiment asks: how much of the fertility–schooling gradient would close if low-ability women faced the same fertility-control technology as high-ability women?

2. **Equalize schooling and earnings opportunities:** Give all women the college cost schedule and wage profile of the highest-ability group, holding fixed the fertility-control environment. This experiment asks: how much would teen fertility fall if low-ability women faced the same returns to education and labor market opportunities as high-ability women?

Table 10. Counterfactual Experiments: Decomposing the Fertility–Schooling Gradient

	(1) Equalize Fertility Control	(2) Equalize Education/Wages	(3) Equalize Both
Percentage Change Relative to Baseline			
College attendance	+13.2%	+24.7%	+33.3%
Pregnancies by age 18	−50.0%	−29.3%	−57.2%
Pregnancies by age 22	−35.5%	−21.4%	−42.1%

Notes: Each column reports percentage changes in outcomes relative to the baseline economy. Column (1): all women receive the fertility-control parameters (baseline risk λ_{ge}, effectiveness $\eta_{\theta g}$, effort costs ϕ_s) of the highest-ability quartile. Column (2): all women receive the college cost schedule and wage profile of the highest-ability quartile. Column (3): all women receive both the fertility-control parameters and the education/wage parameters of the highest-ability quartile. "Pregnancies by age X" refers to the cumulative fraction of women who have had a first birth by age X.

3. **Equalize both margins:** Simultaneously equalize fertility control, college costs, and wage profiles. This experiment captures the total effect and allows assessment of complementarities between channels.

7.2 Results

Table 10 reports percentage changes in key outcomes relative to the baseline economy.

Fertility-control frictions are a first-order driver of early fertility. Column 1 shows that equalizing the fertility-control environment to the high-ability level reduces pregnancies by age 18 by 50.0% and pregnancies by age 22 by 35.5%. These are large effects: half of teen pregnancies in the baseline economy would not occur if low-ability women had access to the same effective fertility control as their high-ability peers. This finding corroborates the welfare results in Section 6.3 and confirms that ability-dependent effectiveness is quantitatively important for early fertility outcomes.

Improved fertility control generates meaningful spillovers to education. The same counterfactual (Column 1) increases college attendance by 13.2% relative to baseline. This spillover arises endogenously: when early pregnancies are avoided, women who would otherwise have dropped out or foregone college now find it optimal to continue their education. The mechanism operates through the career-cost channel—avoiding early childbirth preserves the option to accumulate human capital and experience—and through the direct effect of not having child-rearing responsibilities during the college years.

Schooling opportunities affect education more than fertility. Column 2 isolates the education-and-earnings channel. Equalizing college costs and wage profiles to the high-ability level increases college attendance by 24.7%—nearly twice the effect of equalizing fertility control alone. However, the effect on early fertility is more modest: pregnancies by age 18 fall by 29.3% and by age 22 by 21.4%. Better schooling incentives raise college-going substantially because they increase the return to investing in education. They also reduce early fertility, but the effect is smaller because the opportunity-cost channel operates indirectly: higher returns to schooling must first translate into greater effort to avoid pregnancy, which then reduces birth hazards.

Complementarities. Column 3 combines both channels. When fertility control and schooling opportunities are simultaneously equalized, college attendance rises by 33.3%, pregnancies by age 18 fall by 57.2%, and pregnancies by age 22 fall by 42.1%. Notably, the combined effects are less than additive for fertility outcomes but more than additive for college attendance. The intuition is as follows: both channels reduce early fertility, but they operate through partially overlapping populations—women who would avoid pregnancy under either intervention alone cannot avoid it "twice." For college attendance, however, the channels are complementary: reducing early pregnancies increases the pool of women who could benefit from improved schooling opportunities, while improved schooling opportunities raise the value of avoiding early births.

7.3 Policy Implications

These counterfactuals have three implications for policy design.

First, interventions that improve access to effective fertility control—such as subsidized long-acting reversible contraceptives (LARCs), improved sex education, or expanded access to family planning services—can generate large reductions in teen pregnancy. The 50% reduction in pregnancies by age 18 under the fertility-control counterfactual is comparable in order of magnitude to the effects documented in evaluations of LARC programs: the Contraceptive CHOICE Project found that teen pregnancy rates among participants were roughly 78% lower than national rates for sexually experienced teens (Secura et al., 2014).

A caveat is warranted when comparing these magnitudes. The LARC evaluations are not randomized experiments: women who enroll in programs offering free contraception may be more motivated to avoid pregnancy than the general population, so the estimated program effects likely reflect both the true causal effect of LARCs and positive selection into take-up. My counterfactual, by contrast, holds preferences fixed and varies only the fertility-control technology, isolating the technology channel. That my estimate (50%) is smaller than the CHOICE Project's (78%) is consistent with this interpretation: the CHOICE estimate includes positive selection, while mine does not. Despite these methodological differences, the comparison is informative because LARCs operate through the same mechanism my model emphasizes: they largely eliminate the scope for user error by providing contraception that does not require daily compliance or correct use. In the language of my model, LARCs raise η—the effectiveness with which effort translates into reduced conception risk—toward its upper bound. The CHOICE Project's dramatic reductions in unintended pregnancy thus provide external validation that the effectiveness channel is quantitatively important, even if the precise magnitudes are not directly comparable.

Second, reducing teen pregnancy does generate meaningful increases in educational attainment, but the spillover is partial. The 13.2% increase in college attendance under the fertility-control counterfactual implies that roughly one-quarter to one-third of the fertility–schooling gradient reflects a causal effect of childbearing on education. The remainder reflects selection: women who become teen mothers would have had lower educational attainment even absent the pregnancy, because they face higher schooling costs and lower returns.

Third, the most effective strategy for jointly improving fertility and education outcomes is to address both margins simultaneously. Policies that only target fertility control will reduce teen births substantially but leave underlying educational barriers in place. Policies that only improve schooling opportunities will raise attainment but have limited effects on early fertility. Bundled interventions—for example, comprehensive programs that combine contraception access with educational support, mentoring, or college preparation—have the potential to achieve the largest joint gains.

8 Conclusion

This paper asks whether the standard economic channels emphasized in life-cycle models—schooling choices and wage-based opportunity costs—can explain why women with higher cognitive skills delay first births, and it quantifies the policy-relevant mechanisms behind the large skill gradient in teen childbearing. In a nationally representative U.S. cohort, the data show a steep negative relationship between adolescent cognitive skill and early fertility that attenuates with age: low-skill women are much more likely to enter motherhood as teenagers, while high-skill women predominantly postpone first births into later ages. These facts coexist with strong skill gradients in schooling attainment, marriage, and completed fertility, motivating a framework in which these outcomes are jointly determined.

To interpret these patterns, I develop and estimate a dynamic model in which young women make decisions over schooling, marriage, fertility, labor supply, and contraceptive effort. A central feature is a fertility-control technology in which age and education shift baseline conception risk, while cognitive ability shifts the productivity of contraceptive effort. The model is estimated by the simulated method of moments to jointly match fertility timing by ability, education outcomes, marriage profiles, labor supply, and contraception use. This joint discipline is crucial: it forces the model to reconcile the teen-birth gradient with observed differences in schooling, work, marriage, and contraceptive behavior, rather than loading the entire pattern onto an unconstrained reduced-form shifter.

The estimated model delivers three main conclusions. First, it accounts for the sharp ability gradient in teen first-birth hazards and the subsequent attenuation of this gradient with age, consistent with postponement among higher-ability women. Second, the model shows that opportunity costs alone cannot rationalize the data: nested fit comparisons indicate that allowing cognitive ability to directly shift fertility control is necessary to match the joint set of moments. Third, differences in effective fertility control are economically meaningful in welfare terms, with gains from improved contraception access concentrated among low-ability women.

The paper's main contribution to the structural fertility literature is the introduction and identification of ability-dependent contraceptive effectiveness as a distinct channel shaping fertility timing. While prior work has modeled imperfect fertility control (Choi, 2017; Ejrnæs and Jørgensen, 2020) and documented reduced-form associations between cognitive skills and fertility outcomes (Fe et al., 2022; Heckman et al., 2006), the model allows cognitive ability to directly shift the productivity of contraceptive effort conditional on education. The nested specification test demonstrates that this channel is empirically necessary: restricting contraceptive effectiveness to be equal across ability groups causes the model to underpredict the ability–fertility gradient by a factor of two to five, while simultaneously degrading fit on contraception use patterns. Only when effectiveness is allowed to vary by ability can the model match both the steep gradient in birth hazards and the relatively flat gradient in contraception use.

The counterfactuals clarify which margin is quantitatively central for the teen fertility–schooling gradient. When all women face the contraception environment of the highest-ability group, the model predicts large reductions in early fertility: pregnancies before age 18 fall by 50.0% and pregnancies before age 22 fall by 35.5%. College attendance rises by 13.2%, indicating that lowering early pregnancy risk can generate meaningful schooling responses. In contrast, equalizing college costs and wage profiles to the highest-ability group raises college attendance by 24.7% but produces comparatively modest declines in early fertility (29.3% before age 18). The largest joint improvements arise when both margins move together: equalizing both contraception and schooling opportunities increases college attendance by 33.3% while reducing pregnancies before age 18 by 57.2% and before age 22 by 42.1%. These results imply two policy lessons. First, policies that reduce fertility-control frictions can generate large declines in teen pregnancies, but educational gains may be limited if schooling costs and returns remain unchanged. Second, policies that improve schooling incentives without addressing fertility control deliver large increases in college-going but only modest reductions in early pregnancies.

The welfare analysis quantifies the stakes of heterogeneity in effective fertility control. Giving low-ability women the contraception environment of college graduates is worth 11.2% of lifetime consumption for the bottom ability quartile. The within-education ability wedge—the value of equalizing contraceptive effectiveness alone—is worth 5.6% of lifetime consumption. These magnitudes suggest that policies reducing user-dependent variation in contraceptive failure rates—such as subsidizing long-acting reversible contraceptives (LARCs) that minimize scope for user error—may generate substantial welfare gains concentrated among disadvantaged women. The 50% reduction in teen pregnancies predicted under the fertility-control counterfactual is comparable in magnitude to the 78% reduction documented in the Contraceptive CHOICE Project's LARC intervention (Secura et al., 2014), though that estimate likely includes positive selection into take-up. This comparison provides external validation that the effectiveness channel is quantitatively important.

Overall, the paper contributes a quantified mechanism linking cognitive skills to fertility timing through heterogeneity in effective fertility control, disciplined by a model that matches fertility, schooling, marriage, labor supply, and contraception profiles jointly. The findings imply that interventions that lower contraception frictions can deliver large reductions in early fertility and sizable welfare gains for disadvantaged women, while sustained improvements in educational attainment are most likely when policies also strengthen schooling incentives and returns.

References

Adda, Jérôme, Christian Dustmann, and Katrien Stevens, "The career costs of children," *Journal of Political Economy*, 2017, *125* (2), 293–337.

Almlund, Mathilde, Angela L. Duckworth, James J. Heckman, and Tim Kautz, "Personality Psychology and Economics," in Eric A. Hanushek, Stephen Machin, and Ludger Woessmann, eds., *Handbook of the Economics of Education*, Vol. 4, Elsevier, 2011, pp. 1–181.

Amador, Diego, "The Consequences of Abortion and Contraception Policies on Young Women's Reproductive Choices, Schooling and Labor Supply," Technical Report 2017-43, Universidad de los Andes, Facultad de Economía, CEDE June 2017.

Attanasio, Orazio, Hamish Low, and Virginia Sánchez-Marcos, "Explaining changes in female labor supply in a life-cycle model," *American Economic Review*, 2008, *98* (4), 1517–1552.

Bailey, Martha J., "More Power to the Pill: The Impact of Contraceptive Freedom on Women's Life Cycle Labor Supply," *Quarterly Journal of Economics*, 2006, *121* (1), 289–320.

Bailey, Martha J, Vanessa Wanner Lang, Alexa Prettyman, Iris Vrioni, Lea J Bart, Daniel Eisenberg, Paula Fomby, Jennifer Barber, and Vanessa Dalton, "How Costs Limit Contraceptive Use among Low-Income Women in the U.S.: A Randomized Control Trial," Working Paper 31397, National Bureau of Economic Research June 2023.

Becker, Gary S, "An economic analysis of fertility," in "Demographic and economic change in developed countries," Columbia University Press, 1960, pp. 209–240.

_ , *A treatise on the family: Enlarged edition*, Harvard university press, 1991.

_ **and H Gregg Lewis**, "On the interaction between the quantity and quality of children," *Journal of political Economy*, 1973, *81* (2, Part 2), S279–S288.

Ben-Porath, Yoram, "Fertility response to child mortality: micro data from Israel," *Journal of Political Economy*, 1976, *84* (4, Part 2), S163–S178.

Black, Kirsten I, Surabhi Gupta, Andrew Rassi, and Ali Kubba, "Why do women experience untimed pregnancies? A review of contraceptive failure rates," *Best Practice & Research Clinical Obstetrics & Gynaecology*, 2010, *24* (4), 443–455.

Bronars, Stephen G and Jeff Grogger, "The economic consequences of unwed motherhood: Using twin births as a natural experiment," *The American Economic Review*, 1994, pp. 1141–1156.

Caucutt, Elizabeth M and Lance Lochner, "Early and late human capital investments, borrowing constraints, and the family," *Journal of Political Economy*, 2020, *128* (3), 1065–1147.

Caucutt, Elizabeth M., Nezih Guner, and John A. Knowles, "Why Do Women Wait? Matching, Wage Inequality, and the Incentives for Fertility Delay," *Review of Economic Dynamics*, 2002, *5* (4), 815–855.

Choi, Sekyu, "Fertility risk in the life cycle," *International economic review*, 2017, *58* (1), 237–259.

Cunha, Flavio and James J. Heckman, "The Technology of Skill Formation," *American Economic Review*, 2007, *97* (2), 31–47.

Daruich, Diego and Raquel Fernández, "Universal basic income: A dynamic assessment," *American Economic Review*, 2024, *114* (1), 38–88.

der Klaauw, Wilbert Van, "Female labour supply and marital status decisions: A life-cycle model," *The Review of Economic Studies*, 1996, *63* (2), 199–235.

Ejrnæs, Mette and Thomas H. Jørgensen, "Family Planning in a Life-Cycle Model with Income Risk," *Journal of Applied Econometrics*, 2020, *35* (5), 567–586.

Fe, Eduardo, David Gill, and Victoria Prowse, "Cognitive skills, strategic sophistication, and life outcomes," *Journal of Political Economy*, 2022, *130* (10), 2643–2704.

Fort, Margherita, Nicole Schneeweis, and Rudolf Winter-Ebmer, "Is Education Always Reducing Fertility? Evidence from Compulsory Schooling Reforms," *Economic Journal*, 2016, *126* (595), 1823–1855.

Francesconi, Marco, "A Joint Dynamic Model of Fertility and Work of Married Women," *Journal of Labor Economics*, 2002, *20* (2), 336–380.

Goldin, Claudia and Lawrence F Katz, "The power of the pill: Oral contraceptives and women's career and marriage decisions," *Journal of political Economy*, 2002, *110* (4), 730–770.

Gourieroux, Christian, Alain Monfort, and Eric Renault, "Indirect Inference," *Journal of Applied Econometrics*, 1993, *8* (S), S85–S118.

Hansen, Lars Peter, "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 1982, *50* (4), 1029–1054.

Heckman, James J. and James R. Walker, "The Relationship between Wages and Income and the Timing and Spacing of Births: Evidence from Swedish Longitudinal Data," *Econometrica*, 1990, *58* (6), 1411–1441.

Heckman, James J and Stefano Mosso, "The economics of human development and social mobility," *Annu. Rev. Econ.*, 2014, *6* (1), 689–733.

_ , Jora Stixrud, and Sergio Urzua, "The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior," *Journal of Labor economics*, 2006, *24* (3), 411–482.

Hotz, V. Joseph and Robert A. Miller, "An Empirical Analysis of Life Cycle Fertility and Female Labor Supply," *Econometrica*, 1988, *56* (1), 91–118.

Hotz, V Joseph, Susan Williams McElroy, and Seth G Sanders, "Teenage childbearing and its life cycle consequences exploiting a natural experiment," *Journal of Human Resources*, 2005, *40* (3), 683–715.

Iskhakov, Fedor, Thomas H Jørgensen, John Rust, and Bertel Schjerning, "The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks," *Quantitative Economics*, 2017, *8* (2), 317–365.

Keane, Michael P and Kenneth I Wolpin, "The role of labor and marriage markets, preference heterogeneity, and the welfare system in the life cycle decisions of black, hispanic, and white women," *International Economic Review*, 2010, *51* (3), 851–892.

Kearney, Melissa S and Phillip B Levine, "Subsidized contraception, fertility, and sexual behavior," *The review of Economics and Statistics*, 2009, *91* (1), 137–151.

_ and _ , "Why is the teen birth rate in the United States so high and why does it matter?," *Journal of Economic Perspectives*, 2012, *26* (2), 141–166.

Kearney, Melissa S. and Phillip B. Levine, "Investigating Recent Trends in the U.S. Teen Birth Rate," *Journal of Health Economics*, 2015, *41*, 15–29.

Levine, David I and Gary Painter, "The schooling costs of teenage out-of-wedlock childbearing: Analysis with a within-school propensity-score-matching estimator," *Review of Economics and Statistics*, 2003, *85* (4), 884–900.

McCrary, Justin and Heather Royer, "The Effect of Female Education on Fertility and Infant Health: Evidence from School Entry Policies Using Exact Date of Birth," *American Economic Review*, 2011, *101* (1), 158–195.

McFadden, Daniel, "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration," *Econometrica*, 1989, *57* (5), 995–1026.

Musick, Kelly, Paula England, Sarah Edgington, and Nicole Kangas, "Education differences in intended and unintended fertility," *Social Forces*, 2009, *88* (2), 543–572.

Pakes, Ariel and David Pollard, "Simulation and the Asymptotics of Optimization Estimators," *Econometrica*, 1989, *57* (5), 1027–1057.

Regalia, Ferdinando, José-Víctor Ríos-Rull, and Jacob Short, "What Accounts for the Increase in the Number of Single Households?," 2019. Manuscript.

Rosenzweig, Mark R and T Paul Schultz, "Schooling, information and nonmarket productivity: contraceptive use and its effectiveness," *International Economic Review*, 1989, pp. 457–477.

Secura, Gina M, Tessa Madden, Colleen McNicholas, Jennifer Mullersman, Christina M Buckel, Qiuhong Zhao, and Jeffrey F Peipert, "Provision of no-cost, long-acting contraception and teenage pregnancy," *New England Journal of Medicine*, 2014, *371* (14), 1316–1323.

Seshadri, Ananth and Anson Zhou, "Intergenerational mobility begins before birth," *Journal of Monetary Economics*, 2022.

Sheran, Michelle, "The career and family choices of women: A dynamic analysis of labor force participation, schooling, marriage, and fertility decisions," *Review of Economic Dynamics*, 2007, *10* (3), 367–399.

Trussell, James, "Contraceptive failure in the United States," *Contraception*, 2004, *70* (2), 89–96.

_ , "Contraceptive failure in the United States," *Contraception*, 2011, *83* (5), 397–404.

Vandenbroucke, Guillaume, "The return on investing in a college education," *The Federal Reserve Bank of St. Louis, https://www. stlouisfed. org/publications/regional-economist/2023/mar/return-investing-college-education*, 2023, pp. 379–400.

Willis, Robert J., "A New Approach to the Economic Theory of Fertility Behavior," *Journal of Political Economy*, 1973, *81* (2, Part 2), S14–S64.

Wolpin, Kenneth I, "An estimable dynamic stochastic model of fertility and child mortality," *Journal of Political economy*, 1984, *92* (5), 852–874.

Online Appendix (Not for Publication)

OA.1 Data Cleaning and Variable Construction

This appendix documents the data cleaning and construction of the variables used in the paper.

OA.1.1 Data source and cohort coverage

The NLSY79 follows a nationally representative cohort of individuals born 1957–1964 who were ages 14–22 at the first interview in 1979. Interviews are annual from 1979–1994 and biennial thereafter, with rich topical modules covering schooling, labor market outcomes, family formation, and fertility.

OA.1.2 Panel structure and alignment to model time

I construct an annual panel indexed by individual i and calendar year t and compute age at interview as:

$$\text{Age}_{it} = t - \text{BirthYear}_i.$$

In NLSY79, birth year is inferred from the respondent's age in the baseline year and then used to back out age in all years when age is missing.

Because the structural model uses four-year periods starting at age 14, I map annual observations into four-year "age bins":

$$\text{AgeBin}_{it} = 14 + 4\left\lfloor \frac{\text{Age}_{it} - 14}{4} \right\rfloor,$$

so that the bins are 14–17, 18–21, 22–25, $\ldots$. When a model object is defined at the period level (e.g., employment, experience, fertility hazard), I aggregate annual measures within the bin using consistent rules described below.

OA.1.3 Global cleaning conventions and special codes

NLSY variables commonly use negative values to encode nonresponse and survey routing (e.g., refusal, don't know, valid skip, non-interview). I apply the following conventions before constructing analysis variables:

1. **Invalid / nonresponse codes:** values < 0 are treated as missing unless they have a structural interpretation in the paper (e.g., "no spouse" for spouse income).
2. **Structural zeros:** variables that are economically meaningful zeros (e.g., spouse income when no partner is present) are explicitly set to 0 rather than missing, and retained in household aggregates.
3. **Deflation:** nominal dollar amounts are converted to real 2016 dollars using CPI-based deflators merged by calendar year.

OA.1.4 Cognitive ability

I use the AFQT measure available in the NLSY79 created score files. Observations with invalid AFQT codes (negative values) are dropped. I then form within-cohort quartiles of the AFQT distribution ($q \in \{1, 2, 3, 4\}$), which is the ability measure used throughout the empirical moments and wage estimation.

OA.1.5 Education

Education is measured as highest grade completed and mapped into three mutually exclusive groups:

$$\text{HSD} : < 12, \quad \text{HSG} : \ 12 \leq \text{HGC} < 16, \quad \text{COL} : \ \text{HGC} \geq 16.$$

In NLSY79, I use the individual-specific maximum of reported grade completed over the panel to reduce spurious year-to-year reporting noise.

Additionally, I construct an indicator for college attendance between ages 18 and 22, defined as

$$1 \{\exists\, t \text{ s.t. } 18 \leq \text{Age}_{it} \leq 22 \text{ and } \text{HGC}_{it} > 12\},$$

i.e., it equals one if the respondent reports completing more than 12 years of schooling at any interview conducted when she is ages 18–22, and zero otherwise.

OA.1.6 Fertility and pregnancy histories

First birth timing. I use the created child-birth-date variables for the first child (month/year) to define:

$$\text{AgeAtFirstBirth}_i = \text{BirthYearChild1}_i - \text{BirthYear}_i,$$

and I set $\text{AgeAtFirstBirth}_i = 99$ for women with no recorded birth in the observation window.

Wantedness and contraception. To discipline moments on pregnancy intentions and contraceptive behavior, I construct pregnancy-level indicators using the fertility and contraception modules and then aggregate them to the model's age bins.

(i) Wantedness. For each pregnancy p of woman i, let $\text{Wanted}_{ip} \in \{0, 1\}$ indicate whether the respondent reports that the pregnancy was wanted at the time of conception.[7]

(ii) Contraception at conception. For each pregnancy p, define

$$\text{NoContraception}_{ip} \equiv 1\{\text{no contraceptive method at the time of conception}\},$$

where "contraceptive method" includes any reported method (e.g., pill, condom, IUD, rhythm-withdrawal, etc.). Invalid/non-response codes are set to missing.

Mapping to the model. The model features a period-level contraception choice that applies to women who are *at risk* of conception. Accordingly, the targeted moments are constructed as at-risk non-use rates:

$$\Pr(\text{NoContraception}_{it} = 1 \mid \text{AtRisk}_{it} = 1,\ \text{age bin } b,\ \theta_i,\ \text{Educ}_{it}),$$

where $\text{AtRisk}_{it} = 1$ indicates that the woman is fertile and has not yet had a first birth. In the model, $\text{AtRisk}_{it} = 1$ corresponds to periods in which the household is in the fertile stage and first birth has not yet occurred, so the model-implied moments are computed over the same at-risk set.

[7] When the survey distinguishes *mistimed* from *unwanted* pregnancies, I code $\text{Wanted}_{ip} = 0$ for both categories and report robustness separating the two. Responses coded as "don't know", "refused", or survey skips are treated as missing.

OA.1.7 Marriage and partner outcomes

Marital status. Marital status is defined annually using marriage start/end dates. I construct:

$$\text{Married}_{it} = 1\{t \in [\text{MarriageStart}_i, \text{MarriageEnd}_i)\},$$

treating an open-ended marriage (missing end date with a valid start date) as ongoing.

Partner earnings and work. Partner wage-and-salary income is taken from spouse/partner earnings modules when available. "No spouse" codes are set to 0; invalid negative codes are dropped. Partner weeks worked and hours worked are used for partner employment definitions in the wage-process estimation below.

OA.1.8 Labor market outcomes: hours, earnings, employment, experience

Annual hours. Annual hours are constructed from the Work History / Weekly files, producing (i) total annual hours and (ii) annual weeks worked. The weekly labor-force status and wage measures in NLSY79 are documented in the topical guides.

Annual earnings. I use annual wage-and-salary income (respondent and spouse/partner) and deflate to 2016 dollars.

Interpolation and internal consistency checks. Because annual earnings can exhibit missingness and occasional spurious zeros in years with positive hours, I implement two consistency checks before estimation and aggregation: (1) set annual earnings to 0 when annual hours are 0; (2) treat earnings as missing in "very low hours" years when earnings are recorded as zero, and linearly interpolate earnings over time within individual (only across years with valid neighboring information). This step is designed to reduce measurement-error spikes while preserving low earnings when corroborated by low hours.

Employment and experience. A woman-year is classified as employed if it satisfies: (i) at least 26 weeks worked; (ii) average weekly hours > 20; and (iii) real annual wage-and-salary income at least \$10,500 (2016 dollars). I then define annual experience as $\text{ExpYear}_{it} = 1\{\text{employed}\}$ and cumulative experience as $\text{CumExp}_{it} = \sum_{\tau \le t} \text{ExpYear}_{i\tau}$.

OA.2 The Model

OA.2.1 Environment, timing, and state space

Time is discrete in four-year periods. I index periods by $t \in \{1, \ldots, T\}$, with decisions made for $t = 1, \ldots, T-1$ and terminal period $T = 17$ (age 78), in which agents consume all remaining resources and die. Fertility is feasible through ages 14–37, i.e. through $t \leq T_F = 6$. Women can work through age 61 and are retired from age 62 onward. Each woman can have at most one child, and the child resides with the household for *one* period only (four years). Hence, child investment is a one-time choice made in the birth period.

Life-cycle mapping and within-period timing. Figure 1 maps periods to ages, while Figure 2 summarizes within-period sequencing in fertile working ages.

State variables. Let V_t^ℓ denote the value function in period t and within-period sub-stage $\ell \in \{1, 2, 3\}$ (for non-fertile and retirement periods, there is a single stage and I suppress ℓ when convenient). The household state at the beginning of period t is

$$\Omega_{it} = \{a_t, \theta_i, e_t, x_t, m_t, k_t, m_k\},$$

where:

- a_t are assets;
- $\theta_i \in \{1, 2, 3, 4\}$ is cognitive-ability quartile;
- $e_t \in \{HSD, HS, C\}$ is education status/attainment;
- x_t is accumulated labor-market experience (in four-year units);
- $m_t \in \{0, 1\}$ is marital status;
- $k_t \in \{1, 2, 3\}$ is child-status: $k_t = 1$ never had a birth up to t; $k_t = 2$ a first birth occurs in period t (a child is present in t); $k_t = 3$ had a birth in an earlier period (mother, but child not present in t);
- $m_k \in \{0, 1\}$ records marital status at childbirth (relevant only if $k_t \neq 1$).

Controls. Choice variables are next-period assets $a_{t+1} \in [0, \bar{a}]$, consumption $c_t \geq 0$, female labor supply $l_t \in \{0, 1\}$,[8] child investment $i_t \geq 0$ (only if $k_t = 2$), and contraceptive effort $s_t \geq 0$ (only in fertile periods when $k_t = 1$).

OA.2.2 Income, taxes/transfers, equivalence scales, and experience

Disposable resources. Gross annual household non-asset income is denoted $\tilde{y}_t^0(\Omega_{it}, l_t)$ and includes female earnings when working and spousal earnings when married. Disposable annual income is mapped from gross income using a parsimonious approximation to the U.S. tax-and-transfer system:

$$y_t^a(\Omega_{it}, l_t) = \lambda\big(\tilde{y}_t^0(\Omega_{it}, l_t)\big)^{1-\tau} + T(m_t),$$

following Daruich and Fernández (2024). Model-period resources aggregate annual resources:

$$y_t(\Omega_{it}, l_t) = 4\, y_t^a(\Omega_{it}, l_t).$$

Budget constraint. The within-period budget constraint is

$$\phi_c\big(m_t, 1\{k_t = 2\}\big)\, c_t + a_{t+1} = (1 + r)a_t + y_t(\Omega_{it}, l_t) - 1\{k_t = 2\}\, i_t,$$

where $\phi_c(\cdot)$ is an equivalence scale that depends on household composition (marital status and whether a newborn is present).

Experience accumulation. Experience evolves according to

$$x_{t+1} = x_t + 1\{l_t = 1\}.$$

OA.2.3 Discrete choices and taste shocks

Several stages feature discrete choices (e.g. labor supply, schooling continuation, college entry). Discrete alternatives are subject to i.i.d. Type-I extreme value taste shocks. For a generic discrete choice $d \in \mathcal{D}$ with shocks $\varepsilon_t(d)$ and scale $\sigma_{\mathcal{D}}$, define the choice-specific value

[8] I follow Attanasio et al. (2008) in modeling female labor supply.

net of shocks $v_t(\Omega, d)$. The ex-ante value is

$$V_t(\Omega) = \mathbb{E}_\varepsilon\Big[\max_{d\in\mathcal{D}}\{v_t(\Omega, d) + \sigma_{\mathcal{D}}\varepsilon_t(d)\}\Big] = \gamma\sigma_{\mathcal{D}} + \sigma_{\mathcal{D}}\log\sum_{d\in\mathcal{D}}\exp\Big(\tfrac{v_t(\Omega,d)}{\sigma_{\mathcal{D}}}\Big),$$

where γ is the Euler–Mascheroni constant.

OA.2.4 Retired households (ages 62–77; $t = 13$–16)

From age 62 onward, the household is retired: female labor supply is fixed at zero and there are no schooling, fertility, marriage, or child-investment decisions. The only intertemporal choice is savings. Households receive Social Security benefits that depend on education and marital status. Let $ss_t(e_t)$ denote the woman's own benefit and $ss_t^h(e_t, m_k)$ denote the additional spousal benefit received when married.

For $t = 13, \ldots, 16$, the retirement problem is

$$V_t(\Omega_{it}) = \max_{a_{t+1}\geq 0,\, c_t\geq 0}\Big\{u(c_t) + \beta V_{t+1}(\Omega_{i,t+1})\Big\},$$
$$\phi_c(m_t)\, c_t + a_{t+1} = (1+r)a_t + y_t,$$

where gross annual non-asset income is

$$\tilde{y}_t^0 = ss_t(e_t) + 1_{\{m_t=1\}}\, ss_t^h(e_t, m_k),$$

and $y_t = 4\, y_t^a$ is disposable model-period income computed using the tax/transfer mapping in subsection OA.2.2. At the terminal period $t = T = 17$, agents consume all remaining resources and die.

OA.2.5 Working, non-fertile households (ages 38–61; $t = 7$–12)

After age 37 ($t \geq 7$), fertility risk is absent and no child is present under the one-period-child assumption. The household chooses whether the woman works, $l_t \in \{0, 1\}$, and chooses consumption and next-period assets. At the beginning of period t, the household draws taste shocks $\{\varepsilon_t(0), \varepsilon_t(1)\}$ for labor supply. Let $v_t(\Omega_{it}, l)$ denote the choice-specific value net of shocks. The ex-ante value is

$$V_t(\Omega_{it}) = \mathbb{E}_\varepsilon\Big[\max_{l\in\{0,1\}}\{v_t(\Omega_{it},l)+\sigma_l\varepsilon_t(l)\}\Big].$$

Conditional on l, the choice-specific problem is

$$\begin{aligned} v_t(\Omega_{it},l) = \max_{a_{t+1}\geq 0,\, c_t\geq 0} &\big\{u(c_t)+\psi_l\,1_{\{l=1\}}+\beta\,\mathbb{E}\big[V_{t+1}(\Omega_{i,t+1})\mid \Omega_{it},l,a_{t+1}\big]\big\} \\ \text{s.t.} \qquad &\phi_c(m_t)\,c_t + a_{t+1} = (1+r)a_t + y_t(\Omega_{it},l), \\ &x_{t+1} = x_t + 1_{\{l=1\}}, \end{aligned}$$

where gross annual household income is

$$\tilde{y}_t^0(\Omega_{it},l) = 1_{\{l=1\}}\,w(\Omega_{it}) + 1_{\{m_t=1\}}\,w^h(\Omega_{it}),$$

and disposable model-period resources are

$$y_t(\Omega_{it},l) = 4\left[\lambda\big(\tilde{y}_t^0(\Omega_{it},l)\big)^{1-\tau}+T(m_t)\right].$$

Here $w(\Omega_{it})$ denotes the woman's wage as a function of education and experience (and other state variables). Spousal labor income, $w^h(\Omega_{it})$, is received only when married.[9]

OA.2.6 Young adult (ages 22–37; $t = 3$–6)

In young adulthood, schooling is complete (e_t fixed) and marriage-market and fertility risk are active until $t = T_F = 6$. Within each period $t \leq T_F$, decisions and uncertainty are ordered in three sub-stages.

Sub-stage 3: labor supply, consumption–saving, and child investment. Let $j \in \{k, nk, ok\}$ index the fertility/child-status outcome in period t: $j = k$ if a first birth occurs in t (so $k_t = 2$), $j = nk$ if no birth occurs and the woman remains childless ($k_t = 1$), and $j = ok$ if the woman had a child in a previous period ($k_t = 3$). Conditional on (Ω_{it}, j), the household

[9] I model the husband's earnings as a reduced-form function of the woman's observed characteristics, as in Adda et al. (2017); Van der Klaauw (1996); Sheran (2007).

chooses female labor supply, consumption, and savings; and chooses child investment only when $j = k$. The choice-specific value function net of taste shocks is

$$v_t^{3,j}(\Omega_{it}, l) = \max_{a_{t+1}\geq 0,\, c_t \geq 0,\, i_t \geq 0} \Big\{ u(c_t) + \psi_l^j \, 1_{\{l=1\}} + 1_{\{j=k\}} \, u_k(i_t) + \beta V_{t+1}^1(\Omega_{i,t+1}) \Big\}$$

$$\text{s.t.} \qquad \phi_c\big(m_t, 1_{\{j=k\}}\big) \, c_t + a_{t+1} = (1+r)a_t + y_t(\Omega_{it}, l) - 1_{\{j=k\}} \, i_t,$$

$$x_{t+1} = x_t + 1_{\{l=1\}}.$$

Investment enters only if a birth occurs ($j = k$). Because the child lives for one period only, this is the only period in which parents choose i_t.

Sub-stage 2: contraception and first-birth risk. Only childless women choose contraceptive effort, i.e. when $k_t = 1$ and $t \leq T_F$. Let $p_t(\theta_i, e_t, s_t)$ denote the probability of a first birth in period t, decreasing in s_t and depending on age, ability, and education. Then

$$V_t^2(\Omega_{it}) = \max_{s_t \geq 0} \Big\{ -\phi_s \, s_t + p_t(\theta_i, e_t, s_t) \, V_t^{3,k}(\Omega_{it}) + \big(1 - p_t(\theta_i, e_t, s_t)\big) \, V_t^{3,nk}(\Omega_{it}) \Big\}.$$

If $k_t \neq 1$ (a first birth already occurred in t or in the past), the household skips contraception:

$$V_t^2(\Omega_{it}) = V_t^{3,ok}(\Omega_{it}).$$

Sub-stage 1: marriage. If single ($m_t = 0$), the woman meets a potential husband with probability $\mu(e_t, t)$. Conditional on meeting, she compares continuation values under marriage and singlehood. Let $\Omega_{it}(m)$ denote the state with m_t set to $m \in \{0, 1\}$. Then

$$V_t^1(\Omega_{it}) = \begin{cases} \mu(e_t, t) \, \max\big\{V_t^2\big(\Omega_{it}(1)\big), \, V_t^2\big(\Omega_{it}(0)\big)\big\} + \big(1 - \mu(e_t, t)\big) \, V_t^2\big(\Omega_{it}(0)\big), & \text{if } m_t = 0, \\ V_t^2(\Omega_{it}), & \text{if } m_t = 1, \end{cases}$$

and marriage is absorbing (no divorce).

Never having a child. In the last fertile period $t = T_F = 6$, I include a reduced-form utility shifter for remaining childless to match the observed mass of women who never have children:

$$V_6^{3,nk}(\Omega_{i6}) + 1_{\{k_6=1\}}\, \mu_0(e_6).$$

OA.2.7 College age (ages 18–21; $t = 2$)

Period $t = 2$ corresponds to ages 18–21 and is the point at which women can be in one of two education tracks.

- **Non-college track.** Women who do not enroll in college at $t = 2$ are already in the post-school environment: they participate in the labor market, face marriage-market risk if single, and (since they are still fertile and childless) choose contraception. Thus, at $t = 2$ they follow the same within-period timing as in young adulthood.

- **College track.** Women who enroll in college at $t = 2$ do *not* work during this period. Instead, they receive a student allowance w_C and pay direct schooling costs TC. After observing the fertility outcome, they decide whether to remain in college (continue and graduate) or to drop out and enter the labor market in this period as a high school graduate. Having a child while enrolled in college raises the (psychic) cost of continuing by $\kappa_{k,C}$.

The remainder of this subsection describes the college track.

Sub-stage 3: consumption–saving and (if a birth occurs) child investment. Let $j \in \{k, nk\}$ denote the fertility outcome in $t = 2$. Conditional on the education decision $d \in \{G, CD\}$ from sub-stage 2 (continue/graduate vs. drop out), the within-period problem differs because college students do not work in this period ($l_2 = 0$), while college dropouts choose labor supply as high-school graduates.

For $d = G$ (continue and graduate), the household solves

$$\begin{aligned} v_2^{3,j}(\Omega_{i2}; G) = & \max_{a_3 \geq 0,\, c_2 \geq 0,\, i_2 \geq 0} \Big\{ u(c_2) + 1_{\{j=k\}}\, u_k(i_2) - 1_{\{j=k\}}\, \kappa_{k,C} + \beta V_3^1(\Omega_{i3}) \Big\} \\ \text{s.t.} \quad & \phi_c(m_2, 1_{\{j=k\}})\, c_2 + a_3 = (1+r)a_2 + (w_C - TC) - 1_{\{j=k\}}\, i_2. \end{aligned}$$

For $d = CD$ (drop out and work as HS graduate), the household chooses labor supply

$l_2 \in \{0,1\}$ and solves

$$v_2^{3,j}(\Omega_{i2}; CD) = \max_{l_2\in\{0,1\},\, a_3\geq 0,\, c_2\geq 0,\, i_2\geq 0} \Big\{ u(c_2) + \psi_l^j \, 1_{\{l_2=1\}} + 1_{\{j=k\}} \, u_k(i_2) + \beta V_3^1(\Omega_{i3}) \Big\}$$

$$\text{s.t.} \qquad \phi_c(m_2, 1_{\{j=k\}}) \, c_2 + a_3 = (1+r)a_2 + y_2(\Omega_{i2}, l_2) - 1_{\{j=k\}} \, i_2,$$

$$x_3 = x_2 + 1_{\{l_2=1\}}.$$

In the dropout branch, disposable non-asset income is

$$y_2(\Omega_{i2}, l_2) = 4\left[\lambda\big(\tilde{y}_2^0(\Omega_{i2}, l_2)\big)^{1-\tau} + T(m_2)\right], \qquad \tilde{y}_2^0(\Omega_{i2}, l_2) = 1_{\{l_2=1\}} \, w(\Omega_{i2}),$$

while in the college-student branch disposable resources are given directly by the student allowance net of direct schooling costs, $w_C - TC$.[10]

Sub-stage 2: continue college vs. drop out. After observing j, college women choose $d \in \{G, CD\}$ with Type-I extreme value shocks. To match observed college dropout, the model includes a graduation-specific cost that is incurred only upon completion. Let ϕ_G denote this graduation cost. Then

$$V_2^{2,j}(\Omega_{i2}) = \max_{d\in\{G,CD\}} \Big\{ v_2^{3,j}(\Omega_{i2}; d) - 1_{\{d=G\}} \, \phi_G + \sigma_{CD}\varepsilon_2(d) \Big\}.$$

Sub-stage 1: contraception. At the start of $t=2$, childless women in the college track choose s_2:

$$V_2^1(\Omega_{i2}) = \max_{s_2\geq 0} \Big\{ -\phi_s s_2 + p_2(\theta_i, e_2, s_2) V_2^{2,k}(\Omega_{i2}) + \big(1 - p_2(\theta_i, e_2, s_2)\big) V_2^{2,nk}(\Omega_{i2}) \Big\}.$$

OA.2.8 Teen (ages 14–17; $t=1$)

At $t=1$, all women are in high school. The within-period timing is: (i) contraception, (ii) after observing fertility, continue high school vs. drop out, and (iii) consumption–saving (and child investment if a birth occurs). Teens who remain in school receive an allowance

[10] In school periods, the student allowance w_C (net of direct schooling costs TC) is treated as non-taxable transfer-like resources in the model and therefore enters the budget constraint directly. The tax/transfer mapping is applied to labor-market income when working.

w_{HS} in sub-stage 3; dropouts enter the labor market immediately and begin accumulating experience.

Sub-stage 3: consumption–saving, child investment, and college entry at $t = 2$. Let $j \in \{k, nk\}$ denote the fertility outcome in $t = 1$. Conditional on the schooling decision $d \in \{HSG, HSD\}$ (stay and complete HS vs. drop out) from sub-stage 2, teens solve

$$
\begin{aligned}
v_1^{3,j}(\Omega_{i1}; d) = \max_{a_2 \geq 0,\, c_1 \geq 0,\, i_1 \geq 0} & \Big\{ u(c_1) + 1_{\{j=k\}} u_k(i_1) - 1_{\{d=\text{HSG}\}} 1_{\{j=k\}} \kappa_{\text{HS}} \\
& + \beta \Big[1_{\{d=\text{HSG}\}} V_2^{CD,j}(\Omega_{i2}) + 1_{\{d=\text{HSD}\}} V_2^1(\Omega_{i2}) \Big] \Big\} \\
\text{s.t.} \qquad & \phi_c(m_1, 1_{\{j=k\}})\, c_1 + a_2 = (1+r)a_1 + y_1(\Omega_{i1}; d) - 1_{\{j=k\}}\, i_1, \\
& x_2 = x_1 + 1_{\{d=\text{HSD}\}}.
\end{aligned}
$$

Resources satisfy $y_1(\Omega_{i1}; d) = w_{HS}$ if $d = \text{HSG}$, while if $d = \text{HSD}$ the teen works as a dropout and

$$
y_1(\Omega_{i1}; \text{HSD}) = 4 \left[\lambda \big(\tilde{y}_1^0(\Omega_{i1}) \big)^{1-\tau} + T(m_1) \right], \qquad \tilde{y}_1^0(\Omega_{i1}) = w(\Omega_{i1}).
$$

At the end of $t = 1$, teens who complete high school ($d = \text{HSG}$) draw a Type-I extreme value shock and choose whether to enroll in college at $t = 2$, $d_C \in \{C, NC\}$. Let $v_2^1(\cdot)$ denote the beginning-of-period value at $t = 2$ given education choice; then

$$
V_2^{CD,j}(\Omega_{i2}) = \max_{d_C \in \{C, NC\}} \{ v_2^1(\Omega_{i2}; d_C) - \kappa_C(\theta, j) + \sigma_C \varepsilon_2(d_C) \}.
$$

Only teens who complete high school face the college-entry decision.

Sub-stage 2: continue high school vs. drop out. After observing j, teens choose $d \in \{HSG, HSD\}$ with Type-I extreme value shocks:

$$
V_1^{2,j}(\Omega_{i1}) = \max_{d \in \{HSG, HSD\}} \{ v_1^{3,j}(\Omega_{i1}; d) + \sigma_{HS} \varepsilon_1(d) \}.
$$

Sub-stage 1: contraception. At the start of $t = 1$, teens choose s_1:

$$
V_1^1(\Omega_{i1}) = \max_{s_1 \geq 0} \Big\{ -\phi_s s_1 + p_1(\theta_i, e_1, s_1) V_1^{2,k}(\Omega_{i1}) + \big(1 - p_1(\theta_i, e_1, s_1)\big) V_1^{2,nk}(\Omega_{i1}) \Big\}.
$$

OA.3 Wage Process Estimation

This appendix describes how I estimate the wage profiles used to parameterize earnings opportunities in the structural model. The goal is to recover flexible conditional mean earnings profiles by age, education, cognitive ability, and experience, separately for women and (when relevant) husbands/partners.

OA.3.1 Wage measures and estimation samples

Women. Let w_{it} denote real annual wage-and-salary income (2016 dollars). The wage estimation sample includes woman-years that meet the employment definition in Appendix OA.1 (minimum weeks worked, minimum hours, and minimum annual earnings). The dependent variable is in levels (annual dollars), consistent with how the model is parameterized.

Husbands/partners. Let w_{it}^m denote partner annual wage-and-salary income (2016 dollars) and let Age_{it}^m denote the partner's age. The husband/partner wage estimation sample is restricted to years in which the woman is married and partner earnings exceed the same annual earnings threshold used for women. In the husband regressions, education is the woman's education, denoted $\text{Educ}_i^f \in \{\text{HSD}, \text{HSG}, \text{COL}\}$, matching the table panel "Wife's education."

OA.3.2 Baseline specification: women

I estimate:

$$\begin{aligned}
w_{it} &= \alpha_t + \beta_1 \text{Age}_{it}^f + \beta_2 \left(\text{Age}_{it}^f\right)^2 + \rho\,\text{CumExp}_{it} \\
&\quad + \sum_{e\in\{\text{HSG,COL}\}} \left(\gamma_e + \delta_e\,\text{CumExp}_{it}\right) 1\{\text{Educ}_i^f = e\} \\
&\quad + \sum_{q=2}^{4} \left(\gamma_q + \delta_q\,\text{CumExp}_{it}\right) 1\{\text{Ability}_i = q\} \\
&\quad + \sum_{e\in\{\text{HSG,COL}\}} \sum_{q=2}^{4} \left(\gamma_{eq} + \delta_{eq}\,\text{CumExp}_{it}\right) 1\{\text{Educ}_i^f = e\}\, 1\{\text{Ability}_i = q\} + \varepsilon_{it}.
\end{aligned} \tag{3}$$

where α_t are calendar-year fixed effects. The interaction structure $\text{CumExp} \times \text{Educ}^f \times \text{Ability}$ allows returns to experience to vary flexibly across education and cognitive-ability quartiles.

OA.3.3 Baseline specification: husbands/partners

For husbands/partners I estimate:

$$
\begin{aligned}
w_{it}^m \; = \; & \alpha_t^m + \theta_{\text{HSG}}\, 1\{\text{Educ}_i^f = \text{HSG}\} \\
& + \theta_{\text{COL}}\, 1\{\text{Educ}_i^f = \text{COL}\} + \beta_1^m \text{Age}_{it}^m + \beta_2^m \, (\text{Age}_{it}^m)^2 \\
& + \sum_{e \in \{\text{HSG,COL}\}} \left(\beta_{1e}^m \text{Age}_{it}^m + \beta_{2e}^m \, (\text{Age}_{it}^m)^2 \right) 1\{\text{Educ}_i^f = e\} \\
& + \lambda^m \, 1\{\text{MarryBeforeBirth}_i = 1\} + \sum_{e \in \{\text{HSG,COL}\}} \kappa_e^m \, 1\{\text{Educ}_i^f = e\}\, 1\{\text{MarryBeforeBirth}_i = 1\} + u_{it}.
\end{aligned}
\tag{4}
$$

with year fixed effects α_t^m and an indicator $1\{\text{MarryBeforeBirth}_i = 1\}$ capturing systematic differences in spouse earnings associated with marrying prior to first birth.

OA.3.4 Estimated parameters

Appendix Table OA.1. Women's Earnings Process Estimates

	Annual wage (2016\$)
Experience	
Cumulative work experience	953^{***}
	(33)
Education (baseline: HS dropout)	
HS graduate	1164^{***}
	(393)
College graduate	2291^{**}
	(904)
Education × experience	
HS graduate × experience	228^{***}
	(35)
College graduate × experience	916^{***}
	(77)
Ability quartiles (baseline: Q1)	
Ability Q2	1414^{**}
	(564)

Continued on next page

Table OA.1 continued

	Annual wage (2016$)
Ability Q3	1202
	(963)
Ability Q4	3078*
	(1710)
Ability × experience	
Q2 × experience	-29
	(55)
Q3 × experience	257***
	(78)
Q4 × experience	-170*
	(89)
Education × ability	
HS grad × Q2	-50
	(632)
HS grad × Q3	1801*
	(1008)
HS grad × Q4	428
	(1743)
College grad × Q2	6572***
	(1186)
College grad × Q3	6423***
	(1388)
College grad × Q4	6990***
	(1951)
Education × ability × experience	
HS grad × Q2 × exp	134**
	(60)
HS grad × Q3 × exp	-87
	(82)
HS grad × Q4 × exp	540***
	(93)
College grad × Q2 × exp	-254**
	(100)
College grad × Q3 × exp	-12
	(115)
College grad × Q4 × exp	748***
	(120)
Age profile	
Age at interview	1444***
	(118)
Age at interview^2	-22***
	(2)
Constant	-7617***

Continued on next page

Table OA.1 continued

	Annual wage (2016$)
	(1987)
Observations	94156
Adjusted R^2	0.292

Notes: Robust SE in parentheses; year FE included. Baselines: HS dropout and ability Q1. Coefficients and SE are rounded to the nearest dollar; R^2 is reported with decimals. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table OA.2. Husband/Partner Earnings Process Estimates

	Annual wage (2016$)
Wife's education (baseline: HS dropout)	
HS graduate	-28089***
	(7298)
College graduate	-106082***
	(11760)
Marriage timing (baseline: first marriage after first birth)	
First marriage before first birth (=1)	79
	(1301)
Education × marriage timing	
HS grad × (marriage before birth)	13913***
	(1414)
College grad × (marriage before birth)	15275***
	(2563)
Age profile	
Age at interview	794
	(498)
HS grad × age	1149***
	(427)
College grad × age	5490***
	(668)
Age at interview^2	0
	(8)
HS grad × age^2	-7
	(6)
College grad × age^2	-48***
	(9)
Constant	12431
	(7908)
Observations	37728
Adjusted R^2	0.159

Notes: Robust SE in parentheses; year FE included. Baselines: HS dropout and "first marriage after first birth." Coefficients and SE are rounded to the nearest dollar; R^2 is reported with decimals. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

OA.3.5 Retirement income process

The NLSY wage-and-salary measures do not capture the older-age components of retirement resources (Social Security benefits, employer pensions, and other transfers) because the survey population has not reached that age.

To ensure computational tractability, I model retirement income in reduced form as an education-specific replacement rate applied to pre-retirement earnings capacity, separately for women and husbands/partners.

Let T_R denote the first retirement period (the last N_{retired} model periods). For each education group $e \in \{\text{HSD,HSG,COL}\}$, I compute a baseline pre-retirement earnings level as the average predicted annual labor income in the final working period,

$$\bar{w}_e \equiv \mathbb{E}[\widehat{w}_{it} \mid \text{Educ}_i = e,\ t = T_R - 1]\,, \qquad \bar{w}_e^m \equiv \mathbb{E}[\widehat{w}_{it}^m \mid \text{Educ}_i = e,\ t = T_R - 1]\,,$$

where expectations are taken over the model state distribution in that period (ability, accumulated experience, and other discrete states relevant for the wage grids).

In retirement periods $t \geq T_R$, labor income is replaced by a deterministic benefit level:

$$w_e^R = \phi_e\,\bar{w}_e, \qquad (w^m)_e^R = \phi_e\,\bar{w}_e^m,$$

held constant over all retirement ages.

Social Security replacement rates. To discipline retirement income in the model, I calibrate education-specific replacement rates using Social Security Administration Office of the Chief Actuary replacement-rate statistics (first-year retired-worker benefits as a percent of wage-indexed career-average earnings). The model does not implement the statutory benefit formula (AIME/PIA) directly; instead, I use these statistics to discipline education-specific multipliers ϕ_e in a reduced-form retirement-income rule. In particular, ϕ_e should be interpreted as a replacement rate relative to late-career earnings in the model, proxied by $\bar{w}_e$, rather than literally relative to wage-indexed career-average earnings.[11]

OA.3.6 Model inputs and aggregation to four-year periods

The estimated coefficients from the above regressions are used to generate predicted annual earnings paths by (age, education, ability quartile, cumulative experience). In the model, each period corresponds to four years; I therefore interpret the predicted annual earnings at the period's representative age (the start-of-bin age) as the period-specific annual earnings opportunity, and update cumulative experience using the model-consistent experience accumulation rule.

For retirement periods, I do not predict the wage regressions. Instead, I replace labor earnings with an education-specific deterministic retirement-income level constructed from the pre-retirement predicted wage arrays, as described in Appendix OA.3.5.

OA.4 Model Fit

OA.4.1 Targeted Moments

This appendix presents a detailed comparison between the empirical moments used to calibrate the model and their corresponding model-generated counterparts. The estimation procedure employs the Simulated Method of Moments (SMM), which minimizes the weighted distance between 111 empirical moments from the NLSY79 data and their model analogues.

The targeted moments are organized into six categories: (i) schooling and early fertility decisions, (ii) child investment, (iii) fertility timing by ability, (iv) marriage patterns by education, (v) labor force participation by education, and (vi) contraception use by education. This comprehensive set of moments disciplines the model's ability to jointly capture the key life-cycle patterns that characterize women's decisions regarding education, fertility, marriage, labor supply, and family planning.

Tables OA.3–OA.8 report the data moments and model moments for each targeted statistic. The model achieves a reasonable fit across all moment categories, capturing both the

[11] Because $\bar{w}_e$ is a proxy for earnings capacity at the end of the working life rather than AIME, the mapping from the SSA tables into ϕ_e is an approximation that preserves the education gradient in replacement rates while maintaining a parsimonious retirement-income process.

levels and the heterogeneity across education and ability groups.

Appendix Table OA.3. Model Fit: Schooling, Early Fertility, and Child Investment

Moment	Data	Model	Moment	Data	Model
Panel A: High School Dropout by Pregnancy Status at Age 14					
No pregnancy at 14	0.070	0.063	Pregnancy at 14	0.290	0.458
Panel B: College Attendance by Pregnancy Status at Age 14					
No pregnancy at 14	0.410	0.471	Pregnancy at 14	0.080	0.088
Panel C: College Attendance by Ability Quartile at Age 18					
Quartile 1 (lowest)	0.110	0.112	Quartile 2	0.250	0.345
Quartile 3	0.410	0.472	Quartile 4 (highest)	0.670	0.504
Panel D: College Graduation by Pregnancy Status at Age 18					
No pregnancy at 18	0.620	0.987	Pregnancy at 18	0.260	0.240
Panel E: Relative Child Investment by Education					
HS Graduate / HS Dropout	1.200	2.330	College Graduate / HS Dropout	4.600	3.696

Notes: Data moments are computed from the NLSY79. Child investment ratios are based on estimates from Caucutt and Lochner (2020).

Appendix Table OA.5. Model Fit: Fraction with Children by Ability Quartile and Age

	Quartile 1		Quartile 2		Quartile 3		Quartile 4	
Age	Data	Model	Data	Model	Data	Model	Data	Model
14	0.381	0.744	0.254	0.256	0.140	0.121	0.068	0.057
18	0.691	0.934	0.540	0.529	0.372	0.336	0.223	0.258
22	0.794	0.967	0.706	0.735	0.534	0.609	0.409	0.565
26	0.838	0.985	0.770	0.858	0.661	0.794	0.591	0.767
30	0.873	0.992	0.822	0.934	0.733	0.893	0.713	0.878
34	0.884	0.996	0.838	0.961	0.759	0.945	0.743	0.936
38	0.885	0.998	0.846	0.984	0.773	0.972	0.748	0.965

Notes: Data moments are computed from the NLSY79. Ability quartiles are based on AFQT scores. Quartile 1 is the lowest ability group and Quartile 4 is the highest.

Appendix Table OA.6. Model Fit: Fraction Married by Education and Age

	HS Dropout		HS Graduate		College Graduate	
Age	Data	Model	Data	Model	Data	Model
18	0.633	0.658	0.394	0.505	—	—
22	0.822	0.870	0.724	0.773	0.446	0.490
26	0.881	0.948	0.856	0.899	0.718	0.745
30	0.918	0.983	0.909	0.954	0.854	0.863
34	0.943	0.993	0.949	0.978	0.930	0.932
38	0.968	0.998	0.974	0.987	0.955	0.969

Notes: Data moments are computed from the NLSY79. College graduates enter the marriage market at age 22.

Appendix Table OA.7. Model Fit: Labor Force Participation by Education and Age

	HS Dropout		HS Graduate		College Graduate	
Age	Data	Model	Data	Model	Data	Model
14	0.084	0.108	—	—	—	—
18	0.151	0.265	0.368	0.472	—	—
22	0.196	0.205	0.492	0.525	0.686	0.644
26	0.241	0.173	0.548	0.521	0.754	0.582
30	0.245	0.259	0.557	0.551	0.705	0.608
34	0.243	0.265	0.541	0.545	0.657	0.614
38	0.259	0.258	0.532	0.521	0.628	0.605
42	0.258	0.228	0.527	0.502	0.634	0.605
46	0.239	0.229	0.499	0.495	0.626	0.599
50	0.206	0.211	0.448	0.487	0.607	0.616
54	0.184	0.170	0.397	0.308	0.554	0.434
58	0.140	0.145	0.291	0.305	0.422	0.437
62	0.117	0.151	0.157	0.301	0.211	0.436

Notes: Data moments are computed from the NLSY79. HS dropouts can work from age 14, HS graduates from age 18, and college graduates from age 22.

Appendix Table OA.8. Model Fit: Contraception Use by Education and Age

	HS Dropout		HS Graduate		College Graduate	
Age	Data	Model	Data	Model	Data	Model
18	0.726	0.614	0.792	0.702	0.880	0.984
22	0.508	0.506	0.733	0.640	0.773	0.756
26	0.409	0.417	0.648	0.558	0.744	0.642
30	0.320	0.308	0.535	0.510	0.661	0.627
34	0.259	0.250	0.465	0.440	0.579	0.559
38	0.203	0.333	0.417	0.491	0.481	0.490

Notes: Data moments are computed from the NLSY79. Contraception use is measured among sexually active women who are not currently pregnant.

OA.5 Estimated Structural Parameters

This appendix reports the structural parameters estimated by Simulated Method of Moments (SMM) in the main estimation sample. Parameters are grouped to match the model blocks in the text: (i) the fertility-risk technology, which combines baseline conception odds $\lambda_h(g,e)$ with ability- and age-specific effort productivity $\eta_{\theta,g}$; (ii) the marriage market, summarized by education-specific meeting probabilities $\mu(e)$; (iii) schooling/college cost shifters (including additional costs when a child is present); (iv) labor-supply preference shifters; and (v) discrete-choice shock scales.

Appendix Table OA.9. Estimated Structural Parameters

Parameter	**Estimate**	**Parameter**	**Estimate**
Baseline conception odds by age group and education $\lambda_h(g,e)$			
$\lambda_h(g{=}14–22, e{=}\text{HSD})$	5.0060	$\lambda_h(g{=}14–22, e{=}\text{HS})$	2.5305
$\lambda_h(g{=}14–22, e{=}\text{College})$	5.6717	$\lambda_h(g{=}22–30, e{=}\text{HSD})$	3.6768
$\lambda_h(g{=}22–30, e{=}\text{HS})$	0.9868	$\lambda_h(g{=}22–30, e{=}\text{College})$	6.0935
$\lambda_h(g{=}30–38, e{=}\text{HSD})$	1.8960	$\lambda_h(g{=}30–38, e{=}\text{HS})$	0.0747

Continued on next page

Table OA.9 (continued): Estimated Structural Parameters

Parameter	**Estimate**	**Parameter**	**Estimate**
$\lambda_h(g{=}30\text{–}38, e{=}\text{College})$	4.3309		
Effort effectiveness (ability-specific increments) $\eta_{\theta,g}$			
$\eta_{\theta=2,g=14\text{–}22}$ increment	0.5596	$\eta_{\theta=3,g=14\text{–}22}$ increment	1.0588
$\eta_{\theta=4,g=14\text{–}22}$ increment	1.4836	$\eta_{\theta=2,g=22\text{–}30}$ increment	1.3559
$\eta_{\theta=3,g=22\text{–}30}$ increment	1.1874	$\eta_{\theta=4,g=22\text{–}30}$ increment	0.0643
$\eta_{\theta=2,g=30\text{–}38}$ increment	1.2492	$\eta_{\theta=3,g=30\text{–}38}$ increment	1.0089
$\eta_{\theta=4,g=30\text{–}38}$ increment	1.4708		
Marriage market: meeting probabilities $\mu(e)$			
$\mu(e{=}\text{HSD})$	0.6372	$\mu(e{=}\text{HS})$	0.5498
$\mu(e{=}\text{College})$	0.5109		
Schooling/college incentives and child-related schooling-cost shifters			
HS allowance	40.1299	College allowance	73.1557
ϕ_k^{HSD} (child-present schooling-cost shifter)	-0.3004	ϕ_k^{HS} (child-present schooling-cost shifter)	-0.4905
ϕ_k^{BA} (child-present college-cost shifter)	-0.4662	ξ_{cf} (psychic/cognitive college-cost component)	-0.4591
Labor-supply preference shifters			
ψ_ℓ HSD, ages 14–26	-0.0224	ψ_ℓ HSD, ages 30–50	-0.0149
ψ_ℓ HSD, ages 54–62	-0.0173	ψ_ℓ HS, ages 14–26	-0.0055
ψ_ℓ HS, ages 30–50	-0.0042	ψ_ℓ HS, ages 54–62	-0.0116
ψ_ℓ College, ages 14–26	-0.0002	ψ_ℓ College, ages 30–50	-0.0001
ψ_ℓ College, ages 54–62	-0.0071	$\psi_{\ell k}$ education 1	-0.5430
$\psi_{\ell k}$ education 2	-1.2873	$\psi_{\ell k}$ education 3	-0.0545
ϕ_{nk} education 1	0.2500	ϕ_{nk} education 2	0.2711
ϕ_{nk} education 3	0.2699		
Shock standard deviations (discrete-choice scales and other shocks)			
σ_ℓ labor supply shock scale	0.0091	σ_{cd} child-related shock component	0.3550
σ_{cg} child-related shock component	0.2144	σ_{cgh} child-related shock component	0.0857

Continued on next page

Table OA.9 (continued): Estimated Structural Parameters

Parameter	Estimate	Parameter	Estimate

Notes: "HSD," "HS," and "College" denote education groups as defined in the data section. Age ranges refer to model age groups $g(t)$. Baseline conception parameters $\lambda_h(g, e)$ enter the logit mapping for conception risk as the odds term (risk at $s = 0$), while $\eta_{\theta,g}$ scales how strongly contraceptive effort s reduces conception risk for ability type θ in age group g. The parameters $\mu(e, t)$ govern marriage opportunities (meeting rates) by education. The parameters ϕ_k^e shift schooling/college costs when a child is present in the corresponding education stage, and ξ_{cf} enters the psychic/cognitive cost component of college.

OA.5.1 State space, grids, and timing

Time is discrete in four-year periods, indexed by $t = 1, \dots, T$. The mapping from period to age is $\text{age}_t = 10 + 4t$, so $t = 1$ corresponds to age 14.

The individual state is

$$s_t \equiv (a_t, \theta, e_t, x_t, m_t, mk_t, k_t, t),$$

where a_t is assets at the beginning of t, θ is cognitive ability type (discrete), e_t is education (dropout / HS / college), x_t is experience (discrete, accumulated when working), m_t is marital status (single/married), mk_t is an indicator for whether the first birth occurred out of marriage, and k_t is child status. In the implementation, $k_t \in \{1, 2, 3\}$ corresponds to: no child; newborn in the current period; and older child in later periods.

The continuous state a_t is discretized on an exogenous grid $\mathcal{A} = \{a^1, \dots, a^{N_a}\}$ with cubic spacing:

$$a_j = a_{\min} + (a_{\max} - a_{\min}) \cdot (j/N_a)^3, \quad j = 0, \dots, N_a.$$

This concentrates grid points near the borrowing constraint where policy functions are steepest. Policy functions are stored on $\mathcal{A}$ and evaluated off-grid by linear interpolation in simulation.

Within-period timing and sub-stages. The code solves a three-substage problem within each fertile working period:

1. **Stage 3:** Given marital status and realized fertility outcome (child/no child), the household chooses labor $l_t \in \{0, 1\}$, savings a_{t+1}, consumption c_t, and (if a newborn arrives) child investment i_t.

2. **Stage 2:** Prior to the fertility realization, the household chooses contraception effort s_t which governs pregnancy probability; the stage-2 value integrates stage-3 values over the birth realization.

3. **Stage 1:** If single and eligible to meet, the household draws a meeting opportunity and chooses whether to marry; the stage-1 value integrates the stage-2 value over meeting opportunities and the marriage decision rule.

OA.5.2 Household problem and key first-order conditions

Preferences are CRRA in consumption, $u(c) = c^{1-\rho}/(1-\rho)$, where ρ is the coefficient of relative risk aversion for the woman. Per-adult-equivalent consumption is implemented via an equivalence-scale denominator

$$\mathrm{den}(m_t, k_t) = 1 + \mathbf{1}\{m_t = \text{married}\}\phi_{ca} + \mathbf{1}\{k_t = 2\}\phi_{ck}.$$

Thus, the child-related equivalence-scale term ϕ_{ck} enters the budget constraint only in the birth period($k_t = 2$), consistent with the "one-period child in the household" assumption. After the birth period, the state moves from $k_t = 2$ to $k_{t+1} = 3$ (child has left the household), so that $\mathbf{1}\{k_{t+1} = 2\} = 0$ in all subsequent periods.

Let y_t denote disposable (post-tax/post-transfer) income in period t (four-year total). Gross income is transformed by a progressive tax-transfer function:

$$y_t = \tau(\text{gross}_t, m_t) = \lambda \cdot \text{gross}_t^{1-\tau} + T_{m_t},$$

where $\tau = 0.18$ is the progressivity parameter, $\lambda = 0.85$ is the scale parameter, and T_m is the guaranteed minimum income (\$8.606 thousand for singles, \$12.898 thousand for couples, yearly in 2016 dollars).

The stage-3 budget constraint is

$$c_t \cdot \mathrm{den}(m_t, k_t) + i_t + a_{t+1} = (1+r)a_t + y_t.$$

Child investment subproblem (stage 3, newborn only). When $k_t = 2$ (newborn in period t), child investment enters the continuation value through

$$V_k(i_t) = \omega_0 + \omega_1 i_t^{\omega_2}, \quad \omega_2 < 1.$$

The household's problem is

$$\max_{c_t, i_t} \quad u(c_t) + V_k(i_t) + \beta V_{t+1}(a_{t+1}) \quad \text{s.t.} \quad c_t \cdot \mathrm{den}(m_t, k_t) + i_t + a_{t+1} = (1+r)a_t + y_t.$$

The first-order condition equates marginal utility per dollar:

$$\frac{u'(c_t)}{\mathrm{den}(m_t, k_t)} = V_k'(i_t) \quad \iff \quad c_t^{-\rho} = \mathrm{den}(m_t, k_t)\, \omega_1 \omega_2\, i_t^{\omega_2 - 1}.$$

Solution method. Given a_{t+1}, the budget constraint implies $c_t \cdot \mathrm{den} + i_t = \text{available}$, where $\text{available} \equiv (1+r)a_t + y_t - a_{t+1}$. Substituting into the FOC yields a single equation in i_t. The code solves this via *bisection* on $i_t \in [10^{-6}, 0.9999 \times \text{available}]$:

1. Compute $c_t(i_t) = (\text{available} - i_t)/\text{den}$.

2. Evaluate FOC residual: $r(i_t) = c_t(i_t)^{-\rho} - \mathrm{den}(m_t, k_t)\, \omega_1 \omega_2\, i_t^{\omega_2 - 1}$.

3. Update bracket: if $r(i_t) < 0$, increase i_t (consumption too high); else decrease.

4. Terminate when $|r(i_t)| < 10^{-10}$ or bracket width $< 10^{-10}$ (max 50 iterations).

The solution is unique because $r(i_t)$ is strictly increasing in i_t: $c_t(i_t)$ is decreasing in i_t, so $u'(c_t(i_t))$ rises, while $V_k'(i_t)$ falls when $\omega_2 < 1$.
Solution method. Given a_{t+1}, the budget constraint implies $c_t \cdot \mathrm{den} + i_t = \text{available}$, where $\text{available} \equiv (1+r)a_t + y_t - a_{t+1}$. Substituting into the FOC yields a single equation in i_t. The code solves this via *bisection* on $i_t \in [10^{-6}, 0.9999 \times \text{available}]$:

1. Compute $c_t(i_t) = (\text{available} - i_t)/\text{den}$.

2. Evaluate FOC residual: $r(i_t) = c_t(i_t)^{-\rho} - \omega_1 \omega_2 \, i_t^{\omega_2 - 1}$.

3. Update bracket: if $r(i_t) < 0$, increase i_t (consumption too high); else decrease.

4. Terminate when $|r(i_t)| < 10^{-10}$ or bracket width $< 10^{-10}$ (max 50 iterations).

The solution is unique because $c_t(i_t)$ is decreasing in i_t (budget constraint) and $V_k'(i_t)$ is decreasing in i_t ($\omega_2 < 1$), so $u'(c_t)$ is increasing and $V_k'(i_t)$ is decreasing, guaranteeing a single crossing. The upper bound on investment is determined by the budget constraint.

Contraception choice (stage 2). Let $p_t(s_t)$ be the pregnancy probability. Given stage-3 values with and without a birth, $(V_t^{\text{birth}}, V_t^{\text{nobirth}})$, the stage-2 objective is

$$V_t^{(2)} = p_t(s_t) \, V_t^{\text{birth}} + \big(1 - p_t(s_t)\big) V_t^{\text{nobirth}} - \phi_s s_t,$$

with an interior FOC $p_t'(s_t) \, (V_t^{\text{birth}} - V_t^{\text{nobirth}}) = \phi_s$. The code uses a closed-form solution for s_t under the implemented $p_t(s)$ specification.

Labor choice with taste shocks. In periods solved by DC-EGM, the labor decision has i.i.d. type-I extreme value taste shocks with scale $\sigma_l(e)$, implying an inclusive value (log-sum) aggregator and a logit work probability:

$$\begin{aligned} V_t &= \sigma_l(e) \log\Big(\exp(V_{t,l=0}/\sigma_l(e)) + \exp(V_{t,l=1}/\sigma_l(e)) \Big), \\ P_t(l=1) &= \frac{\exp(V_{t,1}/\sigma_l(e))}{\exp(V_{t,0}/\sigma_l(e)) + \exp(V_{t,1}/\sigma_l(e))}. \end{aligned}$$

OA.5.3 Solution algorithm (backward induction)

This section documents the solver `VFI_P_DCEGM` in `vfi_dcegm.jl`. The algorithm proceeds by backward induction, but uses different numerical routines depending on age.

Overview. Let T_R be the number of retired periods, and let T_{NF} denote the number of working periods after fertility ends. The code partitions the horizon into: (i) retirement ($t > T - T_R$), solved by EGM; (ii) non-fertile working ages ($T - T_R - T_{NF} < t \le T - T_R$), solved by DC-EGM; (iii) fertile ages ($t \leq T - T_R - T_{NF}$), solved by VFI with grid search (plus analytical or one-dimensional inner problems for i_t and s_t).

Algorithm 1 (Retirement, EGM). In retirement, labor is absent and the problem is a standard consumption-saving model with a borrowing constraint. The EGM step for each discrete state (θ, e, m, mk, k) is:

1. Fix the exogenous grid for next-period assets $\mathcal{A} = \{a'\}$.

2. For each $a' \in \mathcal{A}$, compute expected marginal utility next period using the already-solved consumption policy $c_{t+1}(\cdot)$, and invert the Euler equation

$$u'(c_t(a')) = \beta(1+r)\,\mathbb{E}[u'(c_{t+1}(a'))]$$

to obtain $c_t(a')$.

3. Use the budget constraint to map $(a', c_t(a'))$ into the endogenous current asset level $a_t(a')$.

4. Interpolate from the endogenous grid back to the exogenous grid, impose the borrowing constraint, and store $c_t(a)$, $a_{t+1}(a)$, and $V_t(a)$.

Algorithm 2 (Non-fertile working ages, DC-EGM). In working ages after fertility ends ($t \in \{T - T_R - T_{NF} + 1, \ldots, T - T_R\}$), the household chooses labor $l_t \in \{0, 1\}$ and savings. Because labor is discrete and shocks are extreme value, the continuation value involves an inclusive value and choice probabilities. The code implements DC-EGM following Iskhakov et al. (2017), Algorithm 1.

For each period t (going backward) and each discrete state (θ, e, x, m, mk, k):

1. Choice-specific EGM step. For each current labor choice $l_t \in \{0, 1\}$:

   (a) Compute disposable income $y_t(l_t) = \tau(\text{gross}(l_t), m)$ where $\tau(\cdot)$ is the progressive tax-transfer function.

   (b) For each $a' \in \mathcal{A}$ (exogenous next-period asset grid), compute expected marginal utility at $t+1$:

$$\mathbb{E}_t[u'(c_{t+1})] = \sum_{l'=0}^{1} P_{t+1}(l'=1 \mid a') \cdot u'(c_{t+1,l'}(a')),$$

where $P_{t+1}(l'=1 \mid a')$ is the work probability from the previous iteration (logit).

(c) Invert the Euler equation to obtain consumption on the endogenous grid:

$$c_{t,l_t}(a') = \big[\beta(1+r)\,\mathbb{E}_t[u'(c_{t+1})]\big]^{-1/\rho}.$$

(d) Map to endogenous current assets using the budget constraint:

$$a_{t,l_t}(a') = \frac{c_{t,l_t}(a') \cdot \mathrm{den}(m,k) + a' - y_t(l_t)}{1+r}.$$

(e) Construct the choice-specific value on the endogenous grid:

$$V_{t,l_t}\big(a_{t,l_t}(a')\big) = u(c_{t,l_t}(a')) + \mathbf{1}\{l_t = 1\}\psi_l(t,e) + \beta\, V_{t+1}(a').$$

2. *Upper envelope.* The endogenous grid $(a_{t,l}, c_{t,l}, V_{t,l})$ may be non-monotonic when labor decisions change discontinuously. Apply the upper-envelope method:

   (a) Sort by endogenous assets $a_{t,l}$.

   (b) Check monotonicity: if $a_{t,l,j+1} \geq a_{t,l,j} - 10^{-10}$ for all j, use direct interpolation.

   (c) Otherwise, for each exogenous grid point $a \in \mathcal{A}$, compute $V_t(a) = \max_j V_{t,l}(\mathrm{segment}_j(a))$ over all segments.

3. *Credit constraint region.* For $a < \min(\{a_{t,l}(a')\})$, set $c_t = (a(1+r) + y_t - \underline{a})/\mathrm{den}$ and $a_{t+1} = \underline{a}$.

4. *Logit aggregation.* Aggregate choice-specific values with Type-I EV taste shocks (scale $\sigma_l(e)$):

$$V_t(a) = \sigma_l(e)\log\big(\exp(V_{t,0}(a)/\sigma_l) + \exp(V_{t,1}(a)/\sigma_l)\big),$$
$$P_t(l=1 \mid a) = \frac{\exp(V_{t,1}(a)/\sigma_l)}{\exp(V_{t,0}(a)/\sigma_l) + \exp(V_{t,1}(a)/\sigma_l)}.$$

Algorithm 3 (Fertile ages and schooling, VFI with grid search). In fertile ages (and in early schooling periods), the code switches to grid-search VFI because the within-period structure (meeting/marriage, contraception and pregnancy risk, newborn investment, schooling decisions, and experience dynamics) generates non-convexities and additional discrete margins that are not well suited for DC-EGM.

For each fertile period t (going backward) and each discrete state (θ, e, x, m, mk, k):

1. *Stage 3 (given marital and fertility outcome).* For each labor choice $l_t \in \{0, 1\}$, the code searches over $a_{t+1} \in \mathcal{A}$ and computes implied consumption from the budget. If $k_t = 2$ (newborn), it solves (c_t, i_t) jointly using the FOC (bisection method described above) for each candidate a_{t+1}. It stores the maximizing a_{t+1}, c_t, i_t and the resulting choice-specific value.

2. *Labor aggregation.* For each state, it aggregates across l_t using the log-sum formula with scale $\sigma_l(e)$.

3. *Stage 2 (contraception and pregnancy risk).* For states with no child ($k_t = 1$), it computes V_t^{birth} and V_t^{nobirth} from stage 3 and solves for optimal contraception analytically. It then forms the expected value integrating over the realized birth.

4. *Stage 1 (meeting and marriage).* For eligible singles, it applies the meeting probability $\mu_{t,e}$ and compares the stage-2 value under marriage versus remaining single, generating the marriage policy and the beginning-of-period value.

5. *Schooling decisions.* In the first periods, it solves high-school continuation and college attendance/continuation decisions using choice-specific value comparisons with extreme-value taste shocks.

Numerical details. (i) Grid search is accelerated by breaking when consumption turns negative and by exploiting local monotonicity in a'. (ii) The child-investment inner problem uses bisection with tolerance 10^{-10} and maximum 50 iterations. (iii) All consumption values are floored at 10^{-10} before utility evaluation to prevent numerical overflow.

Convergence and numerical tolerances. The solver employs the following numerical tolerances:

- *Consumption positivity:* $c_t \geq 10^{-10}$ (machine epsilon floor)
- *Child investment FOC:* Bisection terminates when $|u'(c_t) - V_k'(i_t)| < 10^{-10}$ or bracket width $< 10^{-10}$ (maximum 50 iterations)
- *Upper envelope:* Segments are considered monotonic if $a_{t,j+1} - a_{t,j} > -10^{-10}$
- *Interpolation:* Weights clamped to $[0,1]$ using $w = \min(\max(w,0),1)$
- *Logit aggregation:* Uses log-sum-exp trick to prevent overflow: $\log(\sum_j \exp(x_j)) = x_{\max} + \log(\sum_j \exp(x_j - x_{\max}))$

OA.5.4 Forward simulation

The function `simulationF` takes the policy objects produced by `VFI_P_DCEGM` and simulates N life histories. It uses pre-drawn uniform random variables for fertility, meeting, and labor choices to ensure reproducibility across parameter vectors. In early periods, schooling continuation and college continuation/dropout are stage-3 policies that are indexed by the realized fertility outcome $j \in \{k, nk\}$; accordingly, these schooling rules are evaluated after the fertility draw and conditional on the realized j (see Section 4 and Appendix OA.5.3).

Algorithm 4 (Simulation). For each simulated woman $i = 1, \ldots, N$:

1. Initialize $(a_1, \theta, e_1, x_1, m_1, mk_1, k_1)$ and store deterministic objects (age mapping, IDs).
2. For $t = 1, \ldots, T$:
   (a) Evaluate policy functions at the current asset level by linear interpolation on $\mathcal{A}$.
   (b) If eligible and single, realize a meeting draw and apply the marriage decision rule (sub-stage 1).
   (c) If in fertile ages and without a child, apply the contraception policy, compute $p_t(s_t)$, and realize conception with the fertility draw (sub-stage 2), obtaining $j \in \{k, nk\}$.

(d) Apply schooling decisions in early periods using the stage-3 policy rules conditional on the realized j (high-school continuation, college attendance/continuation/dropout).

(e) Realize labor supply using $P_t(l = 1)$ and the labor draw. Update experience deterministically when working.

(f) Given realized discrete outcomes, update assets using the savings policy; store consumption, income, and other outcomes.

3. After simulating all individuals, compute model moments from simulated histories.

OA.5.5 Calibration (SMM) and optimization

Target moments and loss function. Let $m^{\text{data}} \in \mathbb{R}^{111}$ denote the vector of empirical moments and $m(\vartheta) \in \mathbb{R}^{111}$ the simulated moments under parameter vector ϑ. The SMM loss function is

$$\mathcal{L}(\vartheta) = \sum_{j=1}^{111} w_j \left(\frac{m_j(\vartheta) - m_j^{\text{data}}}{m_j(\vartheta) + 0.01} \right)^2,$$

where all weights $w_j = 1$ (equal weighting). The additive constant 0.01 in the denominator prevents division by zero for near-zero moments and scales the loss to be approximately unit-free. This formulation emphasizes *percentage fit* rather than absolute deviations, which is appropriate given the wide range of moment magnitudes (e.g., pregnancy rates $\sim$ 0.05–0.30 vs. college attendance $\sim$ 0.10–0.70).

Algorithm 5 (SMM objective evaluation). Given a candidate parameter vector ϑ:

1. Map ϑ into model objects (e.g., the conception technology parameters, labor preference/taste-shock scales, meeting probabilities, and child-investment parameters).

2. Solve the model to obtain value and policy functions (Algorithm 1–3).

3. Simulate outcomes (Algorithm 4).

4. Compute $m(\vartheta)$ from simulated histories and return $\mathcal{L}(\vartheta)$.

Global optimization and parallelization. The file `calibration_hpc.jl` runs a global search using differential evolution through `BlackBoxOptim.jl` (variant: `de_rand_1_bin`). The algorithm operates as follows:

1. Initialize 47 parallel workers, each with a perturbed starting parameter vector.
2. Each worker runs an independent differential evolution search with population size 10–15.
3. Terminate when all workers complete their allocated time budget (7 days per worker) or when the loss improvement falls below 10^{-6} for 1000 consecutive evaluations.

OA.5.6 Computational performance and implementation

Hardware and software. Estimation was performed on a high-performance computing cluster with Intel Xeon Gold 6248R processors (48 cores per node, 3.0 GHz base frequency). The code is implemented in Julia 1.9.3, leveraging multithreading for EGM/DC-EGM steps and distributed parallelism for calibration. Key packages: `Interpolations.jl` (v0.14), `BlackBoxOptim.jl` (v0.6), `Distributed.jl` (standard library).

Solution time. A single model solution at the estimated parameters requires:

- *VFI (backward induction):* ∼15–20 seconds (30 asset grid points)
- *Simulation (10,000 agents):* ∼8–12 seconds
- *Total (solve + simulate + moments):* ∼25–35 seconds per parameter vector

Calibration runtime. The SMM estimation uses differential evolution (`de_rand_1_bin`) with 47 parallel workers, each running independent searches from perturbed starting values. Total calibration time: approximately 8064 CPU-hours (168 hours wall-clock time with 48 cores). The algorithm evaluates approximately 420,0000 parameter vectors before convergence.

Grid density and accuracy. The baseline specification uses $N_a = 30$ asset grid points with cubic spacing: $a_j \propto j^3$ to concentrate points near the borrowing constraint. Robustness checks with $N_a = 50$ yield moment differences $< 0.5\%$ for all targeted statistics, confirming numerical convergence. Child investment is solved analytically via the first-order condition (bisection with tolerance 10^{-10}), avoiding discretization error.

Numerical stability. To ensure stability: (i) All consumption values are floored at 10^{-10} before utility evaluation. (ii) Logit aggregation uses the log-sum-exp trick: $\log(\sum_j \exp(x_j)) = x_{\max} + \log(\sum_j \exp(x_j - x_{\max}))$ to prevent overflow. (iii) Interpolation weights are clamped to $[0, 1]$. (iv) The bisection algorithm for child investment uses robust bracketing with explicit checks for corner solutions.

Computational requirements.

- *Minimal replication:* Single model solution requires < 1 minute on a standard laptop (4 cores, 16GB RAM)
- *Full estimation:* Requires HPC access (48+ cores recommended); wall-clock time 168 hours wall-clock.
- *Memory:* Peak usage ∼8GB per worker (solution), ∼2GB (simulation)

Random number generation. All stochastic elements (simulation draws for fertility, marriage, labor, education) use pre-generated uniform random variables with fixed seed (4546), ensuring exact replicability across parameter vectors. This design ensures that changes in moments reflect only parameter changes, not simulation noise. Calibration uses pseudo-random perturbations for initial parameter values (seed set per worker ID).

Software dependencies. Core packages with versions: `Parameters.jl` (0.12), `Interpolations.jl` (0.14), `BlackBoxOptim.jl` (0.6), `Distributed.jl` (standard library), `DataFrames.jl` (1.5), `Distributions.jl` (0.25), `CSV.jl` (0.10). Full environment specified in `Project.toml` in the replication package.