The Effect of Cognitive Skills on Fertility Timing*

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Latest Version

Abstract

This paper asks whether standard education- and opportunity-cost mechanisms can explain the steep cognitive-skill gradient in early fertility, and what the answer implies for policies targeting teen childbearing and human-capital accumulation. In the NLSY79, the probability of a first birth by ages 14–17 is 28% in the bottom AFQT quartile versus 3% in the top quartile, and mean age at first birth differs by 5.4 years. I estimate a dynamic life-cycle model in which women jointly choose schooling, labor supply and experience accumulation, marriage, and contraceptive effort under imperfect fertility control. A nested specification that restricts ability to operate only through education, wage profiles, and marriage-market incentives cannot reproduce the observed teen-birth gradient. Matching the data requires a direct role for ability in effective fertility control: higher ability increases the effectiveness of contraceptive effort in reducing conception risk. Counterfactuals imply large effects of improved fertility control: equalizing contraception frictions to those faced by high-ability teens reduces pregnancies before age 18 by 52.7% and increases college attendance by 19.8%; aligning both contraception and schooling opportunities to the high-ability environment raises college attendance by 45.2% and reduces pregnancies before age 18 by 60.0%. Welfare gains from improved fertility control are concentrated among low-ability women.

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1 Introduction

The timing of first birth is a first-order life decision with sizable private and social consequences, with direct implications for schooling completion, early-career labor supply, and lifetime earnings profiles. In the NLSY79 cohort, the ability gradient is stark: the probability of a first birth between ages 14–17 is 28% in the bottom AFQT quartile versus 3% in the top quartile, and mean age at first birth differs by about 5.4 years across these groups. Quasi-experimental evidence indicates that both schooling incentives and fertility-control conditions can shift early fertility: increases in educational attainment reduce teen childbearing (Black et al., 2008), and improvements in contraceptive access and reproductive autonomy reduce early births and facilitate delay (Bailey, 2006; Kearney and Levine, 2009). This paper asks: are these standard education-based mechanisms—operating through schooling attainment, expected wage growth and experience accumulation, and education-related improvements in fertility-risk management—quantitatively sufficient to account for the observed ability gradient in first-birth timing?

Although cognitive ability correlates strongly with schooling and income, those factors do not fully account for the pronounced ability gradient in the timing of first births. Structural life-cycle models leave sizable residual dispersion in first-birth timing even after conditioning on schooling, wage–experience profiles, and marriage/partner formation[1], and the remaining dispersion is systematically related to cognitive skills. Consistent with this finding, reduced-form evidence links skills to fertility behavior: using the NLSY79, Heckman et al. (2006) show that higher cognitive and noncognitive skills reduce teen motherhood and early marriage, and using ALSPAC, Fe et al. (2022) find that greater cognitive skills lower the probability of pregnancy before age 20 and reduce completed fertility. These relationships remain robust to rich sets of covariates, which motivates the question: even if education and labor-market incentives matter on average, can they explain why early fertility is so sharply concentrated among low-AFQT women? A key goal of this paper is to discipline those margins within a forward-looking model that matches fertility, schooling, work, and marriage jointly.

To answer this question, I develop and estimate a structural life-cycle model in which

[1]See, e.g., Bloemen and Kalwij (2001); Francesconi (2002); Heckman and Walker (1990); Keane and Wolpin (2010).

cognitive ability is an early, persistent trait,[2] and in which schooling, labor supply and experience accumulation, marriage formation, fertility, and child investment are jointly determined. I then pose a nested test: restricting ability to affect fertility timing only through education choices, the wage and experience profiles implied by those choices, and marriage-market forces, can the model reproduce the teen first-birth gradient in the data? The model requires an additional wedge: cognitive ability directly shifts effective fertility control by changing how contraceptive effort translates into realized conception risk, allowing me to separate indirect channels operating through education/earnings/marriage from direct channels operating through conception risk. I interpret this "fertility-control" wedge as reduced form: it captures ability-correlated determinants of realized pregnancy risk that are not well proxied by formal schooling or earnings incentives—for example, differences in planning and follow-through, consistency and correctness of use, information processing, and partner negotiation—and that therefore operate beyond the standard opportunity-cost channel.

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 transmission of advantage. It is also directly policy-relevant because leading interventions target precisely the two margins emphasized by the canonical mechanisms: education policies that raise attainment/returns and family-planning policies that expand access to effective contraception. Against this backdrop, a defining feature of recent fertility change in high-income settings is the shift of births away from the teenage years and early twenties toward later ages, with the age at first birth rising and early, often nonmarital childbearing becoming increasingly concentrated among disadvantaged groups (Kearney and Levine, 2015, 2017; Santelli and Melnikas, 2010). Economic explanations for postponement highlight (i) changing incentives in labor and marriage markets—such as higher returns to human capital, steeper wage–experience profiles, and altered matching incentives—which raise the opportunity cost of early childbearing (Caucutt et al., 2002), and (ii) major improvements in reproductive technology and access to effective contraception that reduce unintended early conceptions and facilitate planned delay (Bailey, 2006; Goldin and Katz, 2002; Kearney and

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

Levine, 2009). For policy interpretation, the key distinction is whether observed postponement reflects re-optimization driven by education and labor-market incentives or instead a relaxation of effective fertility-control frictions that disproportionately reduces unintended early births among disadvantaged women. My estimates imply that both margins matter, but that heterogeneity in effective fertility control is quantitatively central for explaining who becomes a teen mother.

Fertility timing matters for both mothers and children. Early childbearing reduces women's educational attainment, flattens wage–experience profiles, lowers labor supply, and reshapes career and family-formation trajectories, and it is associated with worse mental-health outcomes (Adda et al., 2017; Attanasio et al., 2008; Biggs et al., 2017; Black et al., 2008; Eckstein et al., 2019; Foster et al., 2018; Keane and Wolpin, 2010; Levine and Painter, 2003). For children, being born to young or unprepared parents is associated with lower cognitive achievement and human capital, worse life-course outcomes, and lowered intergenerational mobility (Black et al., 2008; Kearney and Levine, 2017, 2011; Miller, 2009; Di Nola et al., 2025; Regalia et al., 2019; Seshadri and Zhou, 2022). At the aggregate level, early nonmarital births are more prevalent in higher-inequality areas, reinforcing inequality over time (Kearney and Levine, 2011; Di Nola et al., 2025; Seshadri and Zhou, 2022). These facts place the determinants of fertility timing at the center of human-capital accumulation and the intergenerational transmission of inequality. They also imply that identifying the mechanisms behind teen childbearing is essential for evaluating the likely effects of policies that expand contraception access or reduce the costs of postsecondary schooling.

Life-cycle models largely attribute differences in fertility timing to education and opportunity costs. Steeper expected wage–experience profiles raise the price of early births (Becker, 1965), and schooling improves fertility-risk management—via planfulness, contraceptive efficacy, and information—thereby reducing unintended early births (Rosenzweig and Schultz, 1989). In these frameworks, cognitive ability matters only indirectly through its effects on schooling and earnings. But cognitive skills may also shift margins that are difficult to proxy with education and wages—such as the precision of expectations, patience and self-control, risk management, and the consistency and effectiveness of contraceptive effort. In my model, this shows up as an ability shifter in effective fertility control: the parameter η governs how cognitive ability shifts the effectiveness of contraceptive effort, i.e., how strongly a given unit of intended effort translates into a lower realized conception probability. Even conditional on education (and thus on the wage profiles that govern opportunity costs), ability captures residual heterogeneity in how intended control translates into realized conception outcomes. If these direct pathways are quantitatively important, attributing the ability–fertility gradient solely to schooling and opportunity costs risks mischaracterizing the relevant policy levers. My estimates support this concern: nested specifications that restrict ability to operate only through schooling and wages cannot reproduce the observed teen-birth gradient, even when contraception costs vary by education; matching the data requires that ability directly raises the effectiveness of contraceptive effort. Thus, the data reject a "schooling-and-wages-only" explanation of the ability gradient in teen childbearing. The point is not that η isolates a biological "technology" of contraception, but that the data require an ability-related wedge beyond formal education and wage-based incentives.

Using this framework, we would look into policy counterfactuals that lower the effective cost of avoiding conception versus interventions that shift schooling incentives and returns. In the model, improved fertility control primarily reduces unintended early births and yields the largest welfare gains for disadvantaged (low-ability) women, while changes in schooling opportunities mainly operate through educational attainment and longer-run labor-market outcomes.

This paper makes four contributions. First, it documents a set of stylized facts on cognitive ability and fertility timing in the NLSY79 that jointly discipline schooling, work, marriage, and contraceptive-related behaviors. [3] Second, it estimates a structural life-cycle model in which the canonical opportunity-cost channels (schooling and wage growth) are nested within a framework that also allows cognitive ability to affect the effectiveness of contraceptive effort. The estimated model matches the difference in teen birth hazards across ability groups and the attenuation of this gradient with age. Third, the counterfactuals show that the direct "fertility-control" channel is quantitatively central: equalizing contra-

[3] While the empirical literature has long established that cognitive skills predict schooling and wages (e.g., Neal and Johnson, 1996), and also correlate with a range of "social behaviors," including early fertility (e.g., Heckman et al., 2006), existing evidence is typically organized margin-by-margin. My contribution is to quantify these gradients jointly—in common age bins and within a single cohort—so that they can discipline a unified life-cycle model of fertility timing.

ception frictions to those faced by high-ability teens reduces pregnancies before age 18 by 52.7% (35.1% before age 22) and increases college attendance by 19.8%, while aligning both contraception and schooling opportunities raises college attendance by 45.2% and reduces pregnancies before age 18 by 60.0%. Fourth, a cohort decomposition of the 1990s decline in teen pregnancies indicates that improved schooling opportunities explain an important additional share, and changes in contraception access explain only a small fraction of the cohort gap.

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. My framework 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; my 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.[4] In this tradition, Heckman et al. (2006) show that higher cognitive and noncognitive skills reduce risky behaviors, includ-

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

ing teen pregnancy and early marriage, while Fe et al. (2022) links childhood cognition to adult behaviors and outcomes, including lower fertility in young adulthood. My 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 my 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.

3 Empirical Evidence

This section documents the relationship between cognitive skills and fertility using the National Longitudinal Survey of Youth 1979 (NLSY79), the same cohort used for model estimation. I first 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. In the analysis, ability enters as within-cohort AFQT quartiles. 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.

3.2.1 Cognitive Skills and Age at First Childbirth

Panel (A) of Table 1 reports conditional first-birth hazards by age bin and cognitive-skill quartile. Each cell is computed among women who are childless at the beginning of the age bin, so differences across ability groups reflect the timing of entry into motherhood. 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 summary fertility outcomes by quartile: mean age at first birth (standard deviation in parentheses), the fraction married at first pregnancy, the share with at least one child by age 40, and completed fertility (total number of children).

Table 1. Fertility Timing and Outcomes by Ability Quartile

	Ability Quartile			
Age / Outcome	**1**	**2**	**3**	**4**
(A) First-birth probability by age (live birth)				
14–17	28%	16%	9%	3%

18–21	49%	38%	25%	16%
22–29	54%	53%	46%	45%
(B) Age at First-birth and Number of Children				
Age at First Child	20.14	21.66	23.45	25.56
	(4.66)	(5.07)	(5.49)	(5.38)
Married at First Pregnancy	0.38	0.56	0.72	0.84
	(0.49)	(0.50)	(0.45)	(0.36)
At least one child at 40	0.87	0.82	0.74	0.72
	(0.33)	(0.38)	(0.44)	(0.45)
Total Number of Children	2.37	1.89	1.58	1.55
	(1.57)	(1.34)	(1.27)	(1.28)

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 age-at-first-birth (mean, s.d. in parentheses), the share married at first pregnancy, the share with at least one child by age 40, and the total number of children.

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 shrinks 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), are less likely to have had a birth by age 40 (0.72 vs. 0.87), and have lower completed fertility on average (1.55 vs. 2.37).

3.2.2 Ability and Education

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. These patterns suggest that education is an important link between cognitive skills and fertility timing. 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. 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

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.[5]

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

[5]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.

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.

These patterns are descriptive and reflect joint determination of schooling and fertility. 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. Because both channels operate simultaneously and are correlated with cognitive skills, a dynamic framework is needed to disentangle selection from causal mechanisms.

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). [6]

In the NLSY79, I summarize two descriptive 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/OOW fertility, but also selection on background characteristics, marriage-market conditions, and preferences.

[6] 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	**Education Outcome** HS Dropout	HS Graduate	College Graduate
(A) First Pregnancy			
14–17	77%	87%	92%
18–21	71%	85%	87%
22–29	64%	75%	85%
(B) No Premarital Pregnancy			
All ages	84%	84%	83%

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. "Ever married" 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, among premarital first pregnancies, ever-marriage rates increase steeply with education and are lower for earlier pregnancies. For example, among high-school graduates with a premarital first pregnancy, the probability of ever marrying declines from 87% (ages 14–17) to 75% (ages 22–29). Second, for women with no premarital pregnancy, ever-marriage rates are high and nearly flat across education groups (83–84%). Taken together, the table indicates that premarital fertility is associated with both a lower likelihood of transitioning into marriage among the least educated and meaningful heterogeneity in marriage outcomes by pregnancy timing.

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 mother's completed education, age at first pregnancy, and OOW status, conditional on marriage. In most education groups and age bins, women with an OOW first pregnancy marry lower-earning husbands on average (the HS-dropout, ages 14–17 cell is a small exception with a negligible difference). The implied spousal-earnings differential is largest for high-school graduates (up to about \$11,000 per year), more modest for college graduates (up to about \$8,000), and smaller for high-school dropouts (around \$2,000).

These marriage and spouse-earnings gradients by pregnancy timing and education motivate modeling partnership formation and household income jointly with fertility timing, as they shape the incentives to delay first birth and to invest in schooling.

3.2.5 Education and Labor Market Outcomes

Motivated by Adda et al. (2017), this subsection documents how fertility intersects with women's labor-market careers across the cognitive-ability distribution, highlighting the opportunity cost of time out of work. 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 are increasing in ability at all ages, with the gradient steepening over the lifecycle. 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).

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%). This implies that foregone experience early in the career is especially costly for high-ability women.

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. The stronger attachment at higher ability amplifies the cost of career interruptions.

Panel D reports average wage growth by ability, which increases monotonically across quartiles (2.69%, 3.12%, 3.53%, 4.33%). This pattern is consistent with faster human-capital accumulation at the top of the ability distribution.

Panel E summarizes labor-market dynamics around the first birth. Following maternity-related gaps, mean log wage growth is 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). Thus, high-ability mothers both take longer breaks and face a larger opportunity cost of doing so because their returns to experience are steeper.

The wage and experience profiles by ability discipline the model's earnings opportunities (levels and growth) and the returns to experience; in turn, these objects pin down the opportunity-cost component of fertility timing. The next section asks whether these opportunity-cost forces are quantitatively sufficient to explain the ability gradient in first-birth timing, or whether an additional direct role for cognitive skills—through fertility control—is required.

Table 6. Descriptive Statistics by Ability: Labor Market Outcomes

Ability Quartile	**1**	**2**	**3**	**4**
(A) Wage				
Wage at age 20	19688	21554	22811	23042
	(8072)	(7596)	(8247)	(8775)
Wage at age 25	23954	27850	32250	38412
	(9891)	(12814)	(14502)	(16979)
Wage at age 30	27778	33689	38978	49126
	(16573)	(16776)	(17618)	(28089)
Wage at age 40	30382	40112	46392	65713
	(14564)	(22798)	(26790)	(52591)
(B) Return to Experience				
Log wage growth at potential experience 5 years	24%	35%	45%	57%

Continued on next page

Table 6 (continued)

Ability Quartile	**1**	**2**	**3**	**4**
	(48%)	(50%)	(51%)	(58%)
Log wage growth at potential experience 10 years	39%	52%	65%	78%
	(53%)	(51%)	(55%)	(64%)
Log wage growth at potential experience 15 years	47%	61%	75%	90%
	(53%)	(54%)	(56%)	(68%)
(C) Experience by Age				
Average work experience at age 25	1.85	3.20	3.85	3.99
	(2.33)	(2.62)	(2.60)	(2.38)
Average work experience at age 30	3.60	6.04	7.20	7.51
	(3.77)	(3.92)	(3.79)	(3.39)
Average work experience at age 40	7.94	12.65	14.64	14.44
	(6.90)	(6.17)	(6.00)	(5.89)
(D) Wage Growth				
Avg. log growth rate	2.69%	3.12%	3.53%	4.33%
	(30.22%)	(30.26%)	(29.80%)	(32.26%)
(E) Pregnancy Labor Gap and Wage Growth				
Log wage growth 1-year gap	0.02	-0.01	0.00	0.04
	(0.41)	(0.45)	(0.48)	(0.53)
Log wage growth 3-year gap	-0.02	-0.03	0.05	0.05
	(0.45)	(0.51)	(0.58)	(0.66)
Log wage growth 5-year gap	-0.01	-0.12	0.02	0.07
	(0.56)	(0.48)	(0.53)	(0.56)
Time out of labor force after 1 child (years)	0.31	0.50	0.56	0.60
	(0.36)	(0.40)	(0.42)	(0.44)

Continued on next page

Table 6 (continued)

Ability Quartile	**1**	**2**	**3**	**4**

Notes: Means by ability quartile; standard deviations in parentheses. "Work" (and thus "experience") is defined at the year level as averaging ≥ 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. Ability quartiles are defined as in the main text.

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-year. Women enter the model at age 14 with cognitive ability θ and initial assets $a_1 = 0$. They remain fertile through ages 14–37 ($t \leq T_F = 6$) and can work through 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 a single-adult unit, and after marriage it is a two-adult unit that pools income and chooses jointly. Marriage is absorbing.

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 are assets; $\theta_i \in \{1, 2, 3, 4\}$ is ability quartile; $e_t \in \{HSD, HS, C\}$ is education status/attainment; x_t is accumulated labor-market experience; $m_t \in \{0, 1\}$ is marital status; $k_t \in \{1, 2, 3\}$ records child status (never had a birth / birth in t / birth in the past); and m_k records marital status at childbirth (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 OA.1 and Figure OA.2 summarize the period mapping and within-period sequencing.

4.2 Preferences, budget constraint, and key technologies

Preferences. Per-period utility is defined over consumption with CRRA utility $u(c_t)$ and includes (i) a work disutility (through the discrete labor choice), (ii) a cost of contraception effort in fertile periods, and (iii) utility from child investment when a birth occurs. Discrete choices are subject to i.i.d. Type-I extreme value taste shocks [7]

Budget constraint and experience accumulation. Let $\tilde{y}_t^0(\Omega_{it}, l_t)$ denote gross non-asset income (female earnings when working plus spousal earnings when married). Disposable resources are given by a parsimonious tax-and-transfer mapping

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

[7]Online Appendix OA.2.1 provides the full set of choice-specific value functions and shock aggregation.

following Daruich and Fernández (2024). The within-period budget constraint is

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

and experience evolves according to $x_{t+1} = x_t + \mathbf{1}\{l_t = 1\}$.

Fertility risk and contraception. In fertile periods, childless women choose effort $s_t \geq 0$ at cost $\phi_s s_t$. A first birth occurs with probability

$$p_t(\theta_i, e_t, s_t),$$

which is decreasing in s_t and depends on age, education, and ability. Ability can affect fertility timing through standard channels (education, wages, experience, and marriage) and, in the full model, through the effectiveness of contraception effort in reducing conception risk. More details about the functional form of $p_t(\cdot)$ are in Subsection 5.1.

Marriage. Single women meet a potential husband with probability $\mu(e_t)$ and decide whether to marry; marriage is absorbing. Spousal earnings are modeled as a reduced-form function of the woman's characteristics.

4.3 Household problem and nested specifications

Let $V_t(\Omega_{it})$ denote the ex-ante value at the start of period t, before the realization of i.i.d. taste shocks that rationalize discrete choices (e.g., work, schooling continuation, college entry, marriage acceptance). The choice set $\mathcal{D}(\Omega_{it})$ collects the discrete alternatives that are feasible in state Ω_{it} at t (which depends on life stage, marital status, and child status). For each discrete alternative $d_t \in \mathcal{D}(\Omega_{it})$, the household then chooses —consumption c_t, next-period assets a_{t+1}, labor supply l_t when relevant, contraceptive effort s_t when fertile and childless, and child investment i_t when a birth occurs—subject to the period budget constraint and the relevant laws of motion for experience, education, and family states. I denote by $\Gamma(\Omega_{it}, d_t)$ the corresponding feasibility set for continuous controls given (Ω_{it}, d_t).

Formally, the ex-ante value aggregates over the Type-I extreme value shocks $\varepsilon_t(d)$ that enter additively in the discrete alternatives:

$$V_t(\Omega_{it}) = \mathbb{E}_\varepsilon\left[\max_{d_t\in\mathcal{D}(\Omega_{it})}\Big\{v_t(\Omega_{it},d_t)+\varepsilon_t(d_t)\Big\}\right],$$
$$v_t(\Omega_{it},d_t) = \max_{\{c_t,a_{t+1},l_t,s_t,i_t\}\in\Gamma(\Omega_{it},d_t)}\Big\{u(c_t)+\beta\,\mathbb{E}[V_{t+1}(\Omega_{i,t+1})\mid \Omega_{it},d_t,c_t,a_{t+1},l_t,s_t,i_t]\Big\}.$$

The first line defines V_t as the expected maximum over feasible discrete alternatives, where the expectation is taken over the vector of taste shocks $\{\varepsilon_t(d)\}_{d\in\mathcal{D}(\Omega_{it})}$. The second line defines $v_t(\Omega_{it},d_t)$ as the choice-specific (shock-free) value associated with discrete option d_t, obtained by optimally selecting continuous controls from $\Gamma(\Omega_{it},d_t)$. The inner expectation in the continuation value integrates over the next-period uncertainty implied by the model (e.g., meeting and marriage opportunities when single, stochastic conception when fertile and childless, and any other exogenous transitions), producing the next-period state $\Omega_{i,t+1}$ via the laws of motion.

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:

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

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:

$$v_t^{3,j}(\Omega_{it}, l) = \max_{a_{t+1}\geq 0,\, c_t \geq 0} \Big\{ u(c_t) + \psi_l^j\, 1_{\{l=1\}} + \beta\, \mathbb{E}\big[V_{t+1}(\Omega_{i,t+1}) \mid \Omega_{it}, l, a_{t+1}, j\big] \Big\}$$

$$\text{s.t.} \qquad \phi_c\big(m_t, 0\big)\, c_t + a_{t+1} = (1+r)a_t + y_t(\Omega_{it}, l),$$

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

Nested specifications. To isolate mechanisms, I estimate nested versions of the model that restrict the channels through which ability affects fertility timing. In the education/opportunity-cost baseline, ability affects fertility only through schooling choices, wage and experience profiles, and marriage-market incentives. In the full model, ability also shifts effective fertility control by changing how contraception effort maps into conception risk. 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.

4.4 Solution method

In post-fertile working ages, I solve the discrete–continuous labor/savings problem using DC-EGM (Iskhakov et al., 2017). In fertile ages and schooling periods, I solve by value-function iteration with grid search over savings. Online Appendix OA.2.9 reports the full computational algorithm and implementation details.

5 Functional Forms, Targets, and Identification

This section specifies the model's key functional forms, summarizes how parameters are set or estimated, and clarifies how the SMM targets identify the mechanisms of interest. I first present the preference, fertility-control, schooling, labor-supply, marriage, and fiscal mappings that govern decisions. I then describe the three-layer parameterization (externally set parameters, an externally estimated earnings process, and internally estimated structural parameters). Finally, I lay out the identification logic that separates education/opportunity-cost channels from heterogeneity in effective fertility control by ability.

5.1 Functional Forms and Parametrization

I choose functional forms that are flexible enough to match the joint distribution of fertility timing, schooling, marriage, and labor supply, while maintaining a transparent mapping between parameters and mechanisms (fertility control, career incentives, schooling costs, and parental altruism). The parameterization combines (i) externally set parameters disciplined by the literature and institutional objects, (ii) an earnings process estimated outside the model and treated as an input, and (iii) remaining parameters estimated internally by Simulated Method of Moments (SMM). Conditional on the first two layers, I estimate the remaining 55 parameters by SMM, matching 111 empirical targets. The model is therefore overidentified, so parameters are disciplined by the joint fit across moment blocks rather than by any single statistic.

Preferences and 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).

Child quality and parental altruism. 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.

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 the age-group index $g(t)$), education e, and effort s, while cognitive ability θ affects how effectively effort translates into pregnancy prevention. I model conception risk using a logit-style mapping from effort to the probability of no conception, scaled and bounded to allow for imperfect control and baseline fecundity differences.[8]

Let $\lambda_h(g, e)$ denote baseline conception risk (absent effort) for age group $g = g(t)$ and education e, and let $g(t) \in \{1, 2, 3\}$ index broad age groups (e.g., $g = 1$ for ages 14–22, $g = 2$ for 22–30, $g = 3$ for 30–38). Define

$$\pi(t, \theta, e, s) = \frac{1}{1 + \lambda_h(g(t), e) \exp\bigl(-\eta_{\theta, g(t)}\, s\bigr)},$$

$$\bar{p}(t, \theta, e, s) = 1 - \pi(t, \theta, e, s) = \frac{\lambda_h(g(t), e) \exp\bigl(-\eta_{\theta, g(t)}\, s\bigr)}{1 + \lambda_h(g(t), e) \exp\bigl(-\eta_{\theta, g(t)}\, s\bigr)},$$

$$p(t, \theta, e, s) = \min\Bigl\{\lambda_{\max},\ \max\bigl\{\lambda_{\min},\ \lambda_{\max}\, \bar{p}(t, \theta, e, s)\bigr\}\Bigr\}.$$

Here $\pi(t, \theta, e, s)$ is the probability of no conception, $\bar{p}(t, \theta, e, s)$ is the unbounded conception probability implied by the logit mapping, and $p(t, \theta, e, s)$ is the bounded conception probability used in the model. This guarantees $p(\cdot) \in [\lambda_{\min}, \lambda_{\max}]$ and $p(\cdot)$ decreasing in s. Age and education shift baseline risk through $\lambda_h(g, e)$, while ability shifts the effectiveness of contraceptive effort through $\eta_{\theta,g}$.

Parameter interpretation and behavioral response. Baseline fecundity varies by education and age through $\lambda_h(g, e)$. The parameters $\eta_{\theta,g}$ govern how contraceptive effort trans-

[8] 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).

lates into pregnancy prevention by scaling how strongly a marginal increase in effort reduces conception risk, allowing this semi-elasticity to vary by ability type θ and age group g. To impose that higher ability weakly increases the productivity of effort, I parameterize $\eta_{\theta,g}$ monotonically across ability quartiles via increments $\delta_{q,g} \geq 0$; for example, $\eta_{1,g} = 1$ and $\eta_{q,g} = 1 + \sum_{k=2}^{q} \delta_{k,g}$ for $q = 2, 3, 4$. 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.

Ignoring the outer bounds, the marginal effect of effort is

$$\frac{\partial p(t, \theta, e, s)}{\partial s} = -\lambda_{\max}\, \eta_{\theta,g(t)}\, \frac{\lambda_h(g(t), e) \exp\bigl(-\eta_{\theta,g(t)} s\bigr)}{\bigl(1 + \lambda_h(g(t), e) \exp\bigl(-\eta_{\theta,g(t)} s\bigr)\bigr)^2}.$$

Thus, $\eta_{\theta,g(t)}$ directly scales the marginal effectiveness of effort (at the bounds, $\partial p/\partial s = 0$ by construction). In the household's optimality condition for s, the marginal cost of effort (proportional to ϕ_s) is equated to the marginal benefit from reducing the conception probability, which is proportional to $-\frac{\partial p}{\partial s} \times \bigl(V^{\text{no child}} - V^{\text{child}}\bigr)$. Ability therefore affects contraception behavior both mechanically, by changing the productivity of effort via $\eta_{\theta,g}$, and indirectly, because ability shifts the value gap between the "child" and "no child" states through schooling, wages, experience, and marriage.

Marriage market. A single woman meets a potential husband with probability $\mu(e)$. I parameterize $\mu(e)$ parsimoniously with three education-specific parameters.

Labor supply. Work disutility varies by education and age. I allow (i) education-by-age variation in the baseline work disutility ψ_l (three age bins $\times$ three education groups), and (ii) an additional disutility from working when a child is present, ψ_{lk}, varying by education.

Schooling decisions: high school and college. 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.

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

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

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.

5.2 Externally Set Parameters and Earnings Process

Time and units. One model period corresponds to four years. When objects are naturally annual (earnings, taxes/transfers, tuition, Social Security), I compute the annual object first and then aggregate to the four-year model period. [9]

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.

[9] In particular, if y_t^a is annual disposable income, model-period resources entering the budget constraint are $y_t = 4y_t^a$. Preference and return parameters are converted as $\beta = \beta_a^4$ and $r = (1 + r_a)^4 - 1$.

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/partners in each model period.

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. Appendix OA.3 provides full details on the estimation sample and specification.

Household disposable income in model units. Outside school, annual pre-tax household income is the sum of female earnings when she works and spousal earnings when married:

$$\tilde{y}^0_{t,a}(\Omega_{it}, l_t) = 1_{\{l_t=1\}}\, w^f_{t,a}(\Omega_{it}) + 1_{\{m_t=1\}}\, w^h_{t,a}(\Omega_{it}),$$

where the subscript a denotes annual units. Disposable annual income is $\tilde{y}_{t,a} = \lambda(\tilde{y}^0_{t,a})^{1-\tau} + T(m_t)$, and model-period resources entering the budget constraint are $y_t(\Omega_{it}, l_t) = 4\,\tilde{y}_{t,a}(\Omega_{it}, l_t)$. In school periods, gross income is replaced by the schooling allowance net of direct schooling costs; the same tax/transfer mapping is applied to obtain disposable resources.

5.3 Estimation and Identification

Estimation. Let $m^{data} \in \mathbb{R}^{111}$ denote the empirical moment vector and $m^{sim}(\Theta)$ the model-implied counterpart for parameter vector Θ. I estimate Θ by minimizing a weighted distance between $m^{sim}(\Theta)$ and m^{data}:

$$\widehat{\Theta} = \arg\min_{\Theta} \sum_{q=1}^{111} w_q \left(\frac{m_q^{sim}(\Theta) - m_q^{data}}{m_q^{sim}(\Theta) + 0.01} \right)^2,$$

with uniform weights $w_q \equiv 1$. The small constant avoids division by zero when a simulated moment is near zero.

Moment blocks. The 111 SMM targets are grouped into blocks that map to the model's mechanisms:

- **Schooling and early fertility.** HS dropout by pregnancy-at-14 status; college attendance by pregnancy-at-14 status; college graduation by pregnancy-at-18 status; college attendance by ability quartile.

- **Child investment.** Relative investment ratios (HS/HSD and College/HSD).
- **Fertility timing.** First-birth probabilities by ability quartile × age.
- **Marriage.** Fraction married by education × age.
- **Labor supply.** Working rates by education × age.
- **Contraception.** Contraception use by education × age.

This organization is useful for identification because it clarifies which moments are most informative about each mechanism, while all parameters are ultimately pinned down by the joint fit across blocks through the model's cross-equation restrictions. In particular, the schooling, labor-supply, and marriage moments discipline opportunity costs and selection, while the fertility-timing and contraception moments discipline the conception technology and fertility-control parameters.[10]

Identification: separating opportunity costs from fertility control. A central identification challenge is that cognitive ability affects fertility timing through multiple channels. Ability shapes schooling choices and, through the externally estimated earnings process, the wage and experience profiles that determine the opportunity cost of childbearing; it also affects marriage-market incentives through selection into marriage and spousal resources. The model additionally allows an ability shifter in fertility control that changes the mapping from contraceptive effort into realized conception risk. The identification strategy disciplines the schooling and opportunity-cost environment outside the fertility block, so that the model cannot match the ability gradient in birth hazards solely by reallocating fit through education selection or wages.

Following Low and Meghir (2017), I build identification on the mapping between mechanisms and moments, exploiting cross-equation restrictions implied by the life-cycle structure and using overidentifying restrictions for specification discipline. The model is overidentified (111 moments for 55 structural parameters, with the earnings process estimated externally), so inference comes from the joint fit across margins rather than any single target.

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

Disciplining the opportunity-cost environment outside the fertility block. I first discipline the economic objects that govern the return to delaying fertility. Earnings opportunities are parameterized using an externally estimated earnings process that depends flexibly on age, education, experience, and ability (Appendix OA.3), anchoring the opportunity-cost channel with earnings that are not chosen within the structural model. Given this earnings environment, labor-supply disutility parameters are pinned down by employment profiles by education and age, and marriage meeting parameters are pinned down by marriage profiles by education and age.

Identifying schooling selection. Because ability strongly predicts educational attainment, it is crucial to match the joint distribution of ability and education before attributing remaining ability gradients in fertility to fertility-control parameters. I therefore target college attendance by ability quartile and schooling outcomes conditional on early fertility (dropout/attendance/graduation by pregnancy-at-14/18). These moments discipline schooling costs and education-stage taste-shock scales, limiting the extent to which the model can generate ability gradients in fertility timing purely through endogenous sorting into education.

Identifying fertility-control parameters. Conditional on the disciplined earnings environment and schooling selection, the fertility-technology parameters $\{\lambda_h(\cdot), \eta(\cdot), \phi_s\}$ are identified by the joint behavior of (i) first-birth hazards by age bin and ability quartile and (ii) contraception use by age and education. Here $\lambda_h(g, e)$ governs baseline age–education conception risk absent effort, ϕ_s governs the marginal cost of effort and hence the overall level of use, and $\eta_{\theta,g}$ governs how effectively effort lowers conception risk by ability. Conditional on wages, schooling, labor supply, and marriage, within-education differences in birth hazards discipline $\eta_{\theta,g}$: given common costs ϕ_s and a fixed baseline $\lambda_h(g, e)$, the model can match large early ability gradients only if effort is more effective for higher-ability women.

Interpretation: an ability wedge beyond education. The ability shifter η is a reduced-form wedge in effective fertility control: it captures ability-correlated determinants of realized pregnancy risk that operate within education groups (and thus conditional on the associated wage profiles and opportunity costs) and are not separately measured in the data. This includes heterogeneity in correct and consistent use, planning, partner negotiation, and related behaviors that affect the mapping from intended control into realized conception outcomes. In nested specifications that shut down η, the model is forced to fit within-education ability gradients in birth timing using only baseline-risk and opportunity-cost components, which worsens the joint fit of the fertility and contraception moments.

Table 8. Estimation Targets and Main Sources of Identification (SMM)

Moment block	#	Ages	Empirical targets	Parameters primarily disciplined
Schooling and early fertility	10	14–21	(i) HS dropout by pregnancy at age 14; (ii) college attendance by pregnancy at age 14; (iii) college graduation by pregnancy at age 18; (iv) college attendance by ability quartile.	HS/college cost wedges (e.g. κ_{HS}, $\kappa_c(\cdot)$, $\kappa_{k,C}$), schooling taste-shock scales $(\sigma_{HS}, \sigma_C, \sigma_{cd}, \sigma_{cg})$.
Child investment	2	birth period	Relative child investment ratios across schooling states (HS/HSD and C/HSD).	Child-quality curvature/scale (ω_1, ω_2).
Fertility timing	28	14–37	First-birth (or birth-hazard) rates by ability quartile × age bin.	Fertility technology and effort costs: $\lambda_h(g, e)$, $\eta_{\theta,g}$.
Contraception	18	14–37	Contraception use by education × age bin.	Fertility technology and effort costs: $\lambda_h(g, e)$, $\eta_{\theta,g}$, ϕ_s.
Marriage	17	22–37	Share married by education × age bin.	Meeting probabilities $\mu(e)$ (and interaction with the externally estimated spousal earnings process).
Labor supply	36	14–61	Work rates by education × age bin.	Work disutility by age×education (ψ_l), work–child interaction (ψ_{lk}), and shock scale (σ_l).

Notes: The model is overidentified: 111 empirical targets discipline 55 structural parameters (with the earnings process estimated externally). Moment blocks mirror the key mechanisms in the model (schooling costs, fertility control, marriage, labor supply, and parental investment).

6 Results

Three findings emerge from the estimated model. First, the model accounts for the sharp ability gradient in early fertility—teen first-pregnancy hazards are an order of magnitude larger in the bottom than in the top ability quartile—and for the fact that this gradient attenuates with age because higher-ability women primarily postpone rather than avoid motherhood. Second, this pattern cannot be rationalized by schooling choices and wage-based opportunity costs alone: nested fit comparisons show that allowing cognitive ability to directly shift the fertility-control technology delivers a sizable improvement in overall fit (Table 10) while preserving the model's ability to match education, marriage, labor supply, and contraception profiles jointly. Third, the implied heterogeneity in effective fertility control is economically large. In consumption-equivalent terms, policies that reduce contraception frictions generate welfare gains measured in several percent of lifetime consumption, and the estimated "ability wedge" corresponds to very large permanent consumption changes (Figure 2).

The remainder of the section documents model fit and then quantifies how opportunity costs and ability-driven fertility control shape fertility timing, translating these mechanisms into welfare measures across education and ability groups.

6.1 Model fit

I organize fit around the main empirical relationships the paper targets: (i) fertility timing by ability, (ii) schooling and child-related outcomes, and (iii) marriage, contraception use, and labor-market profiles. In the figures, solid lines denote model-implied moments and markers denote their empirical counterparts in the NLSY79.

6.1.1 Fertility timing by cognitive ability

Figure 1 (panel (a)) compares first-pregnancy hazards by age bin and ability quartile, conditional on being childless at the beginning of each bin. The model reproduces the key non-monotonic pattern emphasized in the paper: higher-ability women exhibit lower teen and college-age pregnancy rates and a shift of first births into later ages. The fit is tight for ages 14–17 and 18–21, where the ability gradient is steepest and most informative about fertility control.

6.1.2 Schooling and child-related outcomes

Table 9 evaluates whether the model captures the joint distribution of schooling attainment and early fertility. The model matches the concentration of teen childbearing among low-ability women and reproduces that early pregnancy is associated with worse educational outcomes. A main shortcoming is that the model underpredicts college attendance for the top ability quartile, consistent with abstracting from parental resources and financial constraints that covary strongly with measured ability in the data.

I discipline child-investment differences across education groups using external evidence on expenditure gradients. The resulting child-investment moments line up closely for the college-versus-dropout comparison, while the model overstates the high-school-versus-dropout gradient, consistent with compressing child-related expenditures into a single child period.

Table 9. Education Moments: Model Fit

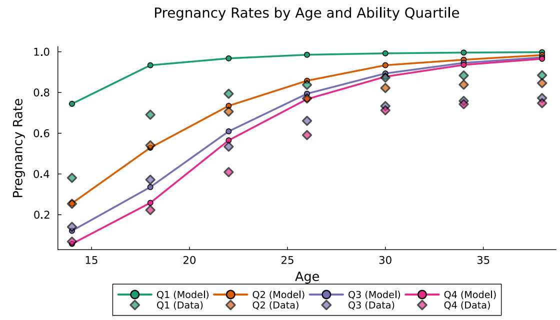
Moment	**Data**	**Model**
High School Dropout (Age 14)		
HS Dropout (No Pregnancy)	0.070	0.104
HS Dropout (Pregnancy)	0.290	0.553
College Attendance		
College Attend (No Pregnancy at 14)	0.410	0.447
College Attend (Pregnancy at 14)	0.080	0.097
College Attend (Ability Q1)	0.110	0.132
College Attend (Ability Q2)	0.250	0.347
College Attend (Ability Q3)	0.410	0.439
College Attend (Ability Q4)	0.670	0.460
College Graduation (Given Attendance)		
College Grad (No Pregnancy at 18)	0.620	0.995
College Grad (Pregnancy at 18)	0.260	0.290
Child Investment (Relative to HSD)		
Child Inv: HS/HSD Ratio	1.20	2.29
Child Inv: College/HSD Ratio	4.60	3.20

Notes: Data moments from NLSY79. Child investment ratios from Caucutt and Lochner (2020).

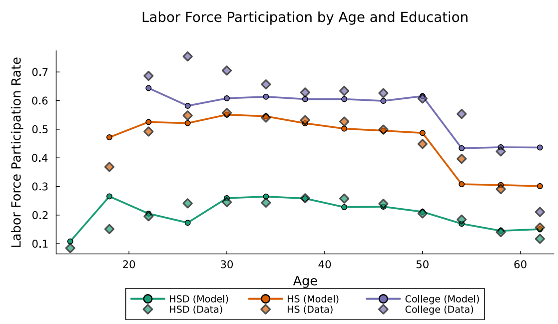
6.1.3 Labor-market profiles, marriage, and contraception

Figure 1 (panels (b)–(e)) summarizes model fit along four life-cycle margins by education: labor-force participation, accumulated experience, marriage, and contraception use. The model tracks the average labor-market profiles and reproduces the ranking by education group. Because experience is a state variable and wages depend on experience, this fit provides an indirect validation of the dynamic career-cost channel: childbirth-induced interruptions reduce experience accumulation and feed back into wages over the remainder of the working life. The figure also shows that the model matches the broad life-cycle shapes of marriage and contraception use and reproduces the positive education gradient in contraception take-up. In the model, contraception use is an endogenous policy outcome—women choose contraceptive effort to trade off its contemporaneous utility/resource cost against the expected value of avoiding a conception—and the simulated take-up moments discipline the level and education-profile of fertility-control. A remaining discrepancy is that the model underpredicts marriage among college graduates, indicating that the current specification assigns too little surplus from marriage for high-education types (e.g., through partner earnings, match quality, or the insurance value of marriage).

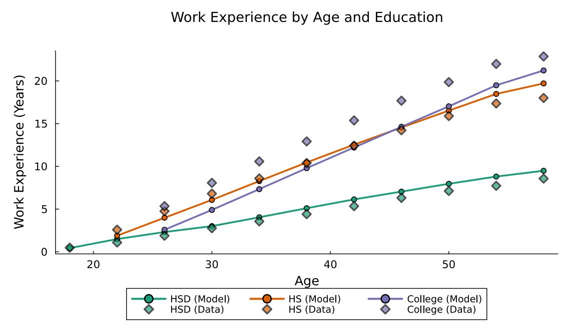
Figure 1. Model fit: fertility timing, labor-market profiles, marriage, and contraception



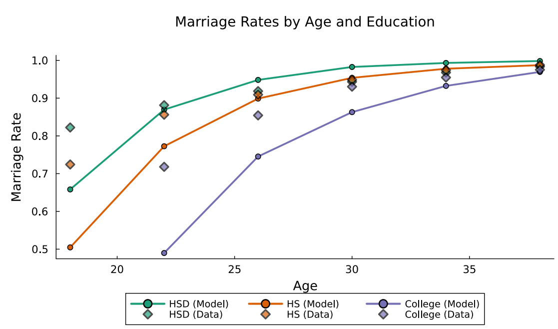
(a) Pregnancy rates by age and cognitive ability quartile



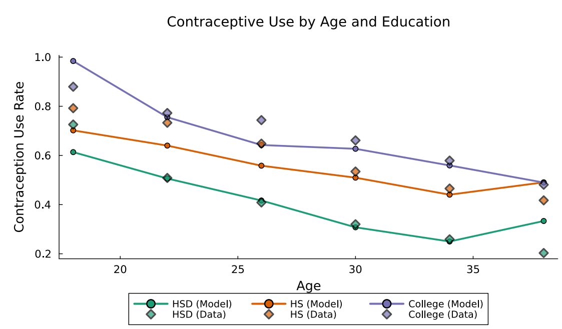
(b) Labor force participation



(c) Average work experience



(d) Marriage rates



(e) Contraception use

Notes: Panel (a) reports the fraction experiencing a first pregnancy by age bin and ability quartile, conditional on being childless at the beginning of the bin. Panels (b)–(e) report outcomes by age and education. Solid lines show model predictions; markers show NLSY79 moments.

6.2 Why ability must enter fertility control: mechanism and identification evidence

A central question is whether the ability gradient in fertility timing can be explained solely through standard channels—schooling choices and wage-based opportunity costs—or whether the data require ability to directly shift fertility-control technology. To assess this, I estimate nested model variants and evaluate their fit using the normalized sum of squared errors (SSE),

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

where m_i are empirical moments and $m_i(\hat{\vartheta})$ are their model counterparts under parameter vector $\hat{\vartheta}$.

Table 10 reports SSE decompositions. Moving from an age-only fertility-control specification to education-dependent fertility control improves fit, but the improvement is limited and uneven across blocks. Allowing fertility control to depend on both education and ability generates a substantial additional improvement and aligns fit across the pregnancy/ability, education, and marriage blocks. The key interpretation is that the ability gradient in fertility timing is not simply a byproduct of schooling and wages: matching the data requires an additional margin that operates through pregnancy risk conditional on effort.

Table 10. Decomposing the Model Fit

	(1)	(2)	(3)
	Baseline	Baseline	Baseline
		+ Educ. Het.	+ Educ. Het.
			+ Ab. Cont.
Total SSE	5.51	5.44	3.76
Pregnancies and Ability Moments SSE	1.44	1.08	0.93
Education Moments SSE	1.10	0.59	0.79
Marital Moments SSE	0.38	0.31	0.49
Labor Market Participation SSE	2.27	2.27	1.24
Contraception Use SSE	0.32	1.19	0.31
Fit Improvement $\left(1-\frac{\text{SSE}_i}{\text{SSE}_1}\right)$	+ Educ. Het.	+ Ab. Cont.	
Total Fit		1%	32%
Pregnancies and Ability Moments		25%	35%
Education Moments		47%	28%
Marital Moments		18%	-28%
Labor Market Participation		0%	45%
Contraception Use		-271%	4%
Corr(P_{14-17}, Ability) Data=-0.26	-0.09	-0.05	-0.53
Corr(P_{18-21}, Ability) Data=-0.27	-0.17	-0.17	-0.49
Corr(P_{22-29}, Ability) Data=-0.07	-0.13	-0.11	-0.22
Corr(P_{14-29}, Ability) Data=-0.24	-0.13	-0.11	-0.22

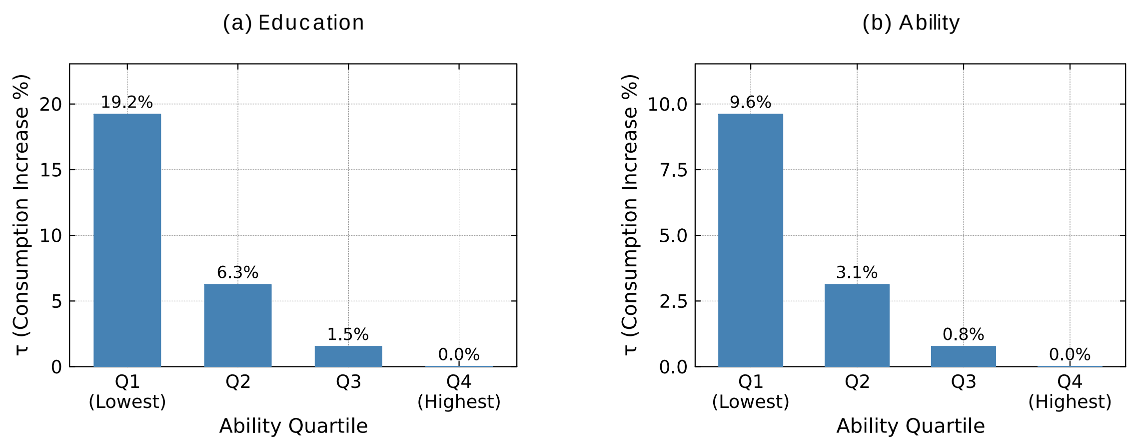
Notes: "Fit improvement" is computed relative to the baseline specification in column (1) as $1-\text{SSE}_i/\text{SSE}_1$ for $i \in \{2,3\}$. Thus the entries in "+ Educ. Het." and "+ Ab. Cont." both use the same baseline reference; marginal gains from moving from (2) to (3) are obtained by comparing the SSE levels in columns (2) and (3) directly.

6.3 Welfare interpretation: contraception wedges in consumption-equivalent units

Finally, I translate estimated differences in fertility-control frictions into consumption equivalent units. I compute the permanent proportional change in lifetime effective consumption that makes an individual indifferent between her estimated contraception environment and an alternative contraception environment.

Figure 2 reports two exercises. First, equalizing the contraception environment across education groups to the level faced by college graduates yields sizable welfare gains that are highly concentrated among low-ability women. The implied consumption-equivalent increases are 19.2% for ability Q1, 6.3% for Q2, 1.5% for Q3, and essentially zero for Q4. This pattern indicates that education-related differences in effective fertility control matter primarily for women at the bottom of the ability distribution.

Second, the implied ability wedge is also economically meaningful but smaller than the education-based wedge in the previous exercise. A low-ability teenager would require a 9.6% permanent increase in lifetime consumption to be indifferent between her baseline contraception environment and the environment faced by a high-ability teenager; the corresponding values are 3.1% for Q2 and 0.8% for Q3 (with Q4 normalized to zero). Overall, the welfare evidence reinforces that heterogeneity in effective fertility control is most consequential for low-ability women.



(a) Education counterfactual

(b) Ability counterfactual

Figure 2. Consumption-equivalent value of improved fertility control

Notes: Left panel: lifetime consumption equivalent of giving all women the contraception environment of college graduates. Right panel: lifetime consumption equivalent for a low-ability teen of achieving the pregnancy risk of a high-ability teen.

The next section uses the estimated model to disentangle selection from causal effects in the teen pregnancy–education relationship and to evaluate counterfactual reductions in contraception frictions. The key message is that policies that reduce teen pregnancies 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 can have large effects on early fertility and welfare.

7 Do Teen Pregnancies Lead to Lower Academic Performance or Vice-versa?

Single motherhood and teen childbearing are central policy concerns, but interpreting the strong negative correlation between early fertility and schooling is complicated by selection. Adolescents who become teen mothers differ from their peers along observed and unobserved dimensions (family background, prior achievement, 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 within-school propensity score matching and conclude that a substantial share of the raw association between teen childbearing and low educational attainment reflects selection rather than causation, while still finding meaningful negative effects on college attendance.

I use the model to evaluate whether early pregnancies primarily depress schooling (a "childbearing-to-schooling" channel) or whether low expected schooling opportunities primarily increase early fertility (a "schooling-to-fertility" channel). To do so, I conduct three counterfactual experiments in which I equalize specific ability-related margins while holding the remaining environment fixed:

1. **High ability for contraception:** all women face the contraception cost schedule of the top-ability group, holding fixed college costs and wage profiles.

2. **High ability for education and wages:** all women face the college cost and wage profile of the top-ability group, holding fixed contraception costs.

3. **High ability for contraception, education, and wages:** all women face the top-ability schedules for contraception, college costs, and wages.

Table 11 reports the results. Column 1 shows that equalizing contraception costs produces a large decline in early fertility: pregnancies by age 18 fall by 52.7% and pregnancies by age 22 fall by 35.1%. College attendance rises by 19.8% relative to baseline, a sizable increase that indicates a meaningful schooling response when early pregnancies are reduced. Column 2 isolates the education-and-earnings channel. Equalizing college costs and wage profiles strengthens schooling incentives and increases college attendance by 18.3% relative to baseline. However, its effect on early fertility is comparatively modest: pregnancies by age 18 fall by 9.1% and pregnancies by age 22 fall by 6.8%. Thus, improving schooling opportunities alone generates a substantial proportional increase in college-going but only limited reductions in early pregnancies.

Column 3 combines both channels. When contraception costs and schooling opportunities are simultaneously equalized, the model delivers a large increase in college attendance (+45.2% relative to baseline) together with sizeable reductions in early fertility (pregnancies by age 18 fall by 60.0%, and by age 22 fall by 41.5%). Overall, the counterfactuals imply that (i) contraception costs are the first-order driver of early fertility outcomes, while (ii) sizable improvements in educational attainment require policies that directly affect the costs and returns to schooling, and (iii) the strongest joint improvements arise when both margins move together.

Table 11. Counterfactual Results

	High Ability Contraception	**High Ability Education/Wages**	**High Ability Both**
College Attendance (pct. change)	+19.8%	+18.3%	+45.2%
Pregnancies Before 18 (pct. change)	-52.7%	-9.1%	-60.0%
Pregnancies Before 22 (pct. change)	-35.1%	-6.8%	-41.5%

Notes: All rows report percentage changes relative to the baseline economy. The three counterfactuals (i) equalize contraception costs, (ii) equalize college costs and wage profiles, and (iii) equalize both sets of margins.

8 The Decline in Teen Pregnancies During the 1990s

Between 1990 and 2005, teen births in the United States declined sharply (about 32%) (Santelli and Melnikas, 2010). To discipline the mechanisms behind this change, I re-estimate the model using the NLSY97 cohort (women born 1980–1984), who were teenagers during the 1990s and entered adulthood in the early 2000s, and I compare the estimated environment to the NLSY79 benchmark. Relative to NLSY79, the NLSY97 estimates imply (i) a lower effective cost of fertility control at young ages (consistent with much higher contraceptive use by age 18) and (ii) substantially improved schooling opportunities, reflected in large increases in college attendance throughout the cognitive-skill distribution.

Table 12 summarizes the key cross-cohort shifts in the moments targeted in estimation. Three patterns stand out. First, early childbearing declines in every ability quartile, but the relative disparity by skill widens: the ratio of first-birth risk at age 18 for Q1 versus Q4 rises from 5.62 to 9.66. Second, college attendance increases markedly, especially among lower-ability women (e.g., Q1 rises by 23 pp and Q2 by 41 pp), and even conditional on early pregnancy at age 14 college attendance rises by 19 pp. Third, contraceptive use at age 18 rises strongly across education groups (by 11–20 pp), consistent with a substantial cross-cohort improvement in effective fertility control.

Table 12. Comparison of Calibration Moments: NLSY79 vs. NLSY97

Moment	**NLSY79**	**NLSY97**	**Change**
Educational Outcomes			
HS dropout rate (no pregnancy at 14)	0.070	0.060	-0.010
HS dropout rate (pregnancy at 14)	0.290	0.370	+0.080
College attendance (no pregnancy at 14)	0.410	0.660	+0.250
College attendance (pregnancy at 14)	0.080	0.270	+0.190
College attendance, Q1 ability	0.110	0.340	+0.230
College attendance, Q2 ability	0.250	0.660	+0.410
College attendance, Q3 ability	0.410	0.760	+0.350
College attendance, Q4 ability	0.670	0.780	+0.110
College graduation (no pregnancy)	0.620	0.670	+0.050
College graduation (pregnancy)	0.260	0.200	-0.060
Teen Pregnancy			
Pregnancy ratio Q1/Q4 at age 18	5.62	9.66	+4.04
Teen Pregnancy by Ability			
Fraction with child at 18, Q1	0.381	0.307	-0.074
Fraction with child at 18, Q2	0.254	0.166	-0.088
Fraction with child at 18, Q3	0.140	0.099	-0.041
Fraction with child at 18, Q4	0.068	0.032	-0.036
Fraction with child at 22, Q1	0.691	0.607	-0.084
Fraction with child at 22, Q2	0.540	0.437	-0.104
Fraction with child at 22, Q3	0.372	0.272	-0.100
Fraction with child at 22, Q4	0.223	0.138	-0.085
Marriage			
Married at 22, HSD	0.822	0.823	+0.001
Married at 22, HS	0.724	0.710	-0.014
Married at 22, College	0.446	0.508	+0.062
Married at 30, HSD	0.918	0.965	+0.047
Married at 30, HS	0.909	0.943	+0.033

Continued on next page

Table 12 (continued): Comparison of Calibration Moments: NLSY79 vs. NLSY97

Moment	**NLSY79**	**NLSY97**	**Change**
Married at 30, College	0.854	0.902	+0.048
Labor Force Participation			
Working at 22, HSD	0.196	0.199	+0.003
Working at 22, HS	0.492	0.433	-0.059
Working at 22, College	0.686	0.445	-0.241
Working at 30, HSD	0.245	0.308	+0.062
Working at 30, HS	0.557	0.512	-0.045
Working at 30, College	0.705	0.705	-0.000
Contraception			
Using contraception at 18, HSD	0.726	0.928	+0.203
Using contraception at 18, HS	0.792	0.956	+0.164
Using contraception at 18, College	0.880	0.991	+0.111

Notes: Moments are computed from the NLSY79 and NLSY97 samples used in estimation. "Change" is NLSY97 minus NLSY79.

To estimate the model in NLSY97, I keep fixed the preference and parameters set externally, re-estimate the income process, and target the same set of moments used in the previous sections. Appendix OA.5 provides details on the NLSY97 estimation results.

8.1 Cohort decomposition

To quantify which mechanisms account for the cohort differences, I partition parameters into six blocks—wages, child utility, college costs, contraception technology, labor disutility, and residual factors—and decompose the change in outcomes using a Shapley-value decomposition (an order-invariant attribution rule that averages marginal effects over all possible orderings of block replacements).[11]

Table 13 reports the Shapley contributions in percentage points (pp) and as shares of the total cohort gap. Shares can be negative or exceed 100% because some mechanisms offset others; by construction, the contributions sum exactly to the total cohort change.

[11] In the code implementation, the Shapley weight on a coalition marginal contribution is proportional to $|S|!(n-|S|-1)!/n!$ and the contribution of block i is the weighted average of $v(S \cup \{i\}) - v(S)$ across all coalitions $S \subseteq N \setminus \{i\}$.

The decomposition implies three substantive lessons. First, the residual block labeled *Other Factors* explains the largest share of the decline in teen childbearing (-32.05 pp; 156.9% of the gap) and a large share of the rise in college attendance (+15.53 pp; 167.3%). In this partition, *Other Factors* bundles changes outside wages, college costs, contraception technology, and labor disutility (including meeting probabilities and remaining preference/technology parameters), so the result indicates that cross-cohort shifts in these residual margins are quantitatively central for matching the joint change in fertility and schooling.

Second, improved schooling opportunities play an important role: the *College Cost* block accounts for -9.13 pp (44.7%) of the decline in teen childbearing and +8.50 pp (91.6%) of the increase in college attendance, consistent with a strong schooling-opportunity channel that both raises college-going and increases the incentive to avoid early births.

Third, some blocks move outcomes in the opposite direction and therefore offset the main forces above. In particular, *Child Utility* increases teen childbearing (+20.98 pp) and reduces college attendance (-12.55 pp), implying that cohort shifts captured by that block work against the observed trends. The *Wage Process* and *Labor Disutility* blocks are quantitatively smaller and also include offsetting effects.

Finally, the *Contraception* block explains a small share of the cohort gap in this Shapley attribution (-0.72 pp, 3.5% for teen childbearing; +0.44 pp, 4.7% for college attendance).

Table 13. Cohort Decomposition

	Teen Pregnancy		College Attendance	
Mechanism	**pp**	**% of Gap**	**pp**	**% of Gap**
Wage Process	-1.27	6.2%	-1.20	-12.9%
Child Utility	20.98	-102.7%	-12.55	-135.3%
College Cost	-9.13	44.7%	8.50	91.6%
Contraception	-0.72	3.5%	0.44	4.7%
Labor Disutility	1.75	-8.6%	-1.43	-15.4%
Other Factors	-32.05	156.9%	15.53	167.3%
Total	**-20.43**	**100.0%**	**9.28**	**100.0%**

Notes: Shapley values report the average marginal contribution of each mechanism across all possible orderings of block replacements. Values sum exactly to the total change between cohorts. Contributions can be negative (or exceed 100%) when mechanisms offset each other in the nonlinear equilibrium mapping from parameters to outcomes.

9 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. Using the NLSY79, the data show a steep negative relationship between AFQT 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 simulated method of moments to jointly match fertility timing by ability, education outcomes, marriage profiles, labor supply, and contraception use. This joint discipline matters: it ties the ability gradient in fertility timing to observed behavior in schooling, work, and contraceptive take-up, rather than attributing it to a reduced-form correlation.

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 counterfactual analysis clarifies the direction of causality between early fertility and schooling. 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 52.7% and pregnancies before age 22 fall by 35.1%. College attendance rises by 19.8%, 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 substantially but produces comparatively modest declines in early fertility. The largest joint improvements arise when both margins move together: equalizing both contraception and schooling opportunities increases college attendance by 45.2% while reducing pregnancies before age 18 by 60.0% and before age 22 by 41.5%. Two policy lessons follow. Policies that primarily reduce teen pregnancies need not mechanically generate large gains in educational attainment if the main barrier for low-ability women is the cost of schooling; conversely, policies that improve schooling incentives without addressing fertility control generate limited reductions in early pregnancies.

Finally, I use the model to shed light on the large decline in teen pregnancies during the 1990s by re-estimating key elements for the NLSY97 cohort and decomposing cross-cohort changes. In the model, improved schooling opportunities explain an important share of both the decline in teen childbearing and the rise in college attendance, while other residual cohort shifts (captured outside wages, college costs, contraception technology, and labor disutility) are quantitatively central for jointly matching the trends. This decomposition underscores that understanding changes in early fertility requires accounting for simultaneous movements in education incentives and other cohort-specific forces that shape preferences, family formation, and behavior.

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, but that sustained improvements in educational attainment are most likely when policies also alter the costs and returns to schooling.

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Online Appendix (Not for Publication)

OA.1 Data Construction and Cleaning: NLSY79 and NLSY97

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

OA.1.1 Data sources and cohort coverage

NLSY79. 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.

NLSY97. The NLSY97 follows a nationally representative cohort born 1980–1984 who were ages 12–16 as of December 31, 1996, first interviewed in 1997–98. Interviews are annual from 1997–2011 and biennial thereafter.

OA.1.2 Panel structure and alignment to model time

For each cohort, 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 NLSY97, the birth year is taken directly from the created birth-date variables. 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, ... 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

NLS variables commonly use negative values to encode nonresponse and survey routing (e.g., refusal, don't know, valid skip, non-interview). In both cohorts 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

NLSY79. 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.

NLSY97. I use the created variable `ASVAB_MATH_VERBAL_SCORE_PCT`, a percentile score constructed by NLS staff from four CAT-ASVAB subtests; the documentation describes the construction using age-group normalization and sampling weights and yields a 0–99 percentile scale. I drop invalid (negative) codes and form within-cohort quartiles analogously to NLSY79.

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. In NLSY97, I use the "ever" created schooling measure and drop observations with invalid schooling codes.

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

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

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. In NLSY79, 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.

In NLSY97, I use the created child birth-date variables (year and month) for the first child and collapse repeated values across rounds to a single first-birth year/month. Negative/invalid codes are treated as missing and dropped when they imply inconsistent dates.

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.[12]

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

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

[12] 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.

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

NLSY97 harmonization. In NLSY97, contraceptive use at conception is reported in the self-administered fertility questionnaires by (a) the respondent and, in some rounds, (b) the partner. I form a single pregnancy-level measure by prioritizing the respondent report when non-missing; if it is missing, I use the partner report. If both are observed but disagree, I code $\text{NoContraception}_{ip} = 0$ (i.e., "some method used") to avoid classifying a conception as unprotected when either source reports contraceptive use.

Mapping to the model. The model features a period-level contraception choice that applies to women who are *at risk* of conception. The NLSY measure used in Table A5 reports contraception use among sexually active women who are not currently pregnant. 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. This definition matches the denominator underlying Table A5.

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. In NLSY79, 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 (NLSY79). 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 $\text{CumExp}_{it} = \sum_{\tau \leq t} \text{ExpYear}_{i\tau}$.

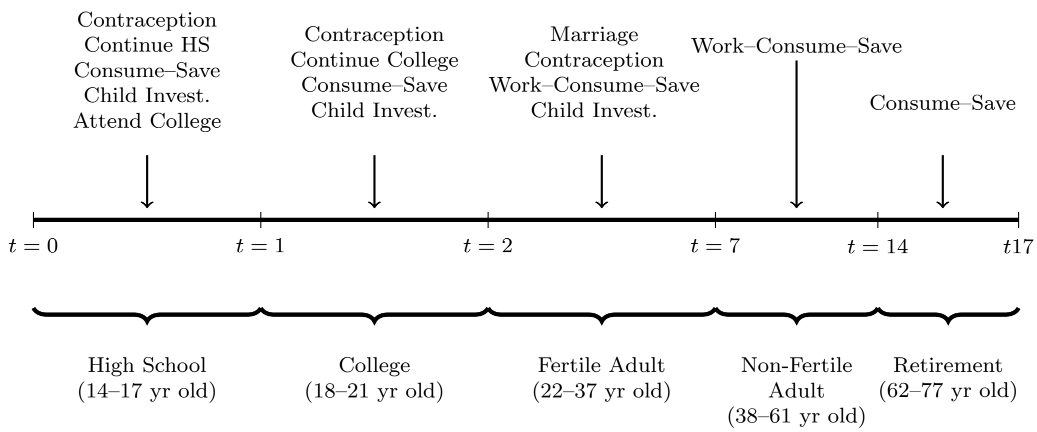
OA.2 The Model

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.

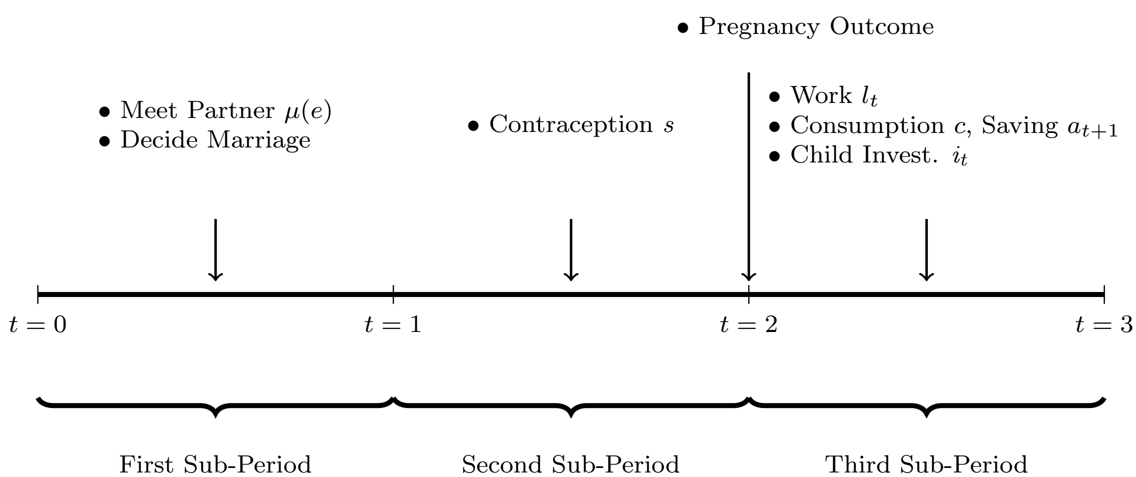
Life-cycle mapping and within-period timing. Figure OA.1 maps periods to ages, while Figure OA.2 summarizes within-period sequencing in fertile working ages.

Appendix Figure OA.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.

Appendix Figure OA.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.

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 $l_t \in \{0, 1\}$,[13] 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:

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

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

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

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

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

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

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 σ_d, define the choice-specific value net of shocks $v_t(\Omega, d)$. The ex-ante value is

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

where γ is the Euler 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

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

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.[14]

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 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

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

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

[14] 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).

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 $\mu(e_t)$. 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

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

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

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

For $d = CD$ (drop out and work as HS graduate), the household chooses labor supply $l_2 \in \{0, 1\}$ and solves

$$\begin{aligned} v_2^{3,j}(\Omega_{i2}; CD) = & \max_{l_2 \in \{0,1\},\, a_3 \geq 0,\, c_2 \geq 0,\, i_2 \geq 0} \left\{ u(c_2) + \psi_l^j\, 1_{\{l_2=1\}} + 1_{\{j=k\}}\, u_k(i_2) + \beta V_3^1(\Omega_{i3}) \right\} \\ & \text{s.t.} \qquad \phi_c(m_2)\, c_2 + a_3 = (1+r)a_2 + y_2(\Omega_{i2}, l_2) - 1_{\{j=k\}}\, i_2, \\ & \qquad\qquad x_3 = x_2 + 1_{\{l_2=1\}}. \end{aligned}$$

In the dropout branch, disposable non-asset income is

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

while in the college-student branch disposable resources are given directly by the student allowance net of direct schooling costs, $w_C - TC$.[15]

[15] 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.

Sub-stage 2: continue college vs. drop out. After observing j, college women choose $d \in \{G, CD\}$ with Type-I extreme value shocks:

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

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 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

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

Resources satisfy $y_1(\Omega_{i1}; d) = w_{HS}$ if $d = HSG$, while if $d = HSD$ the teen works as a dropout and income is based on $w(\Omega_{i1})$ (with the tax/transfer mapping applied accordingly).

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.

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.2.9 Solution method (full details)

The model is solved using a hybrid approach. In post-fertile working ages, where the problem takes the standard discrete–continuous form with a smooth savings policy, I use the discrete-choice endogenous grid method (DC-EGM) of Iskhakov et al. (2017). In fertile ages and schooling periods, where additional discrete margins and occasionally binding constraints make the endogenous-grid construction less convenient, I solve the problem by value-function iteration with grid search over savings. The computational appendix in the paper provides the full algorithmic description and implementation details.

OA.3 Wage Process Estimation

This appendix describes how I estimate the (cohort-specific) wage profiles used to parameterize the earnings opportunities in the structural model. The goal is to recover flexible conditional mean earnings profiles by age, education, 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). 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.

OA.3.2 Baseline specification: NLSY79 women

For NLSY79 women, I estimate:

$$
\begin{aligned}
w_{it} &= \alpha_t + \beta_1 \mathrm{Age}_{it} + \beta_2 \mathrm{Age}_{it}^2 \\
&+ \sum_{e \in \{\mathrm{HSD,HSG,COL}\}} \sum_{q=1}^{4} (\gamma_{eq} + \delta_{eq}\, \mathrm{CumExp}_{it})\, 1\{\mathrm{Educ}_i = e,\ \mathrm{Ability}_i = q\} + \varepsilon_{it},
\end{aligned}
$$

where α_t are calendar-year fixed effects capturing aggregate wage growth and inflation residual to CPI deflation (and other cohort-wide shifts). The interaction structure CumExp $\times$ Educ $\times$ Ability allows returns to experience to vary flexibly across education and cognitive-ability quartiles.

OA.3.3 Baseline specification: NLSY79 husbands/partners

For husbands/partners in NLSY79 I estimate:

$$
\begin{aligned}
w_{it}^m &= \alpha_t^m + \sum_{e \in \{\mathrm{HSD,HSG,COL}\}} \left(\beta_{1e}^m \mathrm{Age}_{it} + \beta_{2e}^m \mathrm{Age}_{it}^2\right) 1\{\mathrm{Educ}_i = e\} \\
&+ \sum_{e \in \{\mathrm{HSD,HSG,COL}\}} \kappa_e^m\, 1\{\mathrm{Educ}_i = e\} \times 1\{\mathrm{MarryBeforeBirth}_i = 1\} + u_{it},
\end{aligned}
$$

with year fixed effects α_t^m and an indicator $1\{\mathrm{MarryBeforeBirth} = 1\}$ capturing systematic differences in spouse earnings associated with marrying prior to first birth (a reduced-form proxy for assortative matching on earnings capacity around family formation). This parsimonious specification intentionally omits separate education intercepts for husbands' earnings; education enters through education-specific age profiles and the MarryBeforeBirth $\times$ Educ interaction.

OA.3.4 NLSY97 estimation and cross-cohort harmonization

NLSY97 respondents are observed over a shorter portion of the lifecycle in many waves relative to NLSY79. To stabilize age-profile estimation and facilitate comparisons across cohorts, I proceed in two steps:

1. **Impose NLSY79 age profile.** Using estimates from (OA.3.2) (women) and (OA.3.3) (husbands), I compute the predicted age component $\widehat{f}_{79}(\text{Age})$ (and education-specific components for husbands).

2. **Estimate remaining parameters on age-demeaned wages.** Define $w_{it}^{\perp} = w_{it} - \widehat{f}_{79}(\text{Age}_{it})$ and regress $w_{it}^{\perp}$ on the remaining terms (experience and interaction structure) with year fixed effects. This yields cohort-specific returns that are comparable by construction while preserving the common lifecycle shape implied by NLSY79.

I apply the same procedure for husbands/partners in NLSY97: subtract the education-specific NLSY79 age profile and estimate the remaining terms (education and marriage-timing differentials) with year fixed effects.

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 $t \geq T_R$, individual 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 (NLSY79 vs. NLSY97). To discipline retirement income in the model, I calibrate education-specific replacement rates using the Social Security Administration Office of the Chief Actuary's Replacement Rates, which reports replacement rates (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 the SSA replacement-rate 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.[16]

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

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

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

[16] 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.

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.1–OA.5 report the data moments and model moments for each targeted statistic. The model achieves a reasonable fit across all moment categories, capturing both the levels and the heterogeneity across education and ability groups.

Appendix Table OA.1. Model Fit: Schooling, Early Fertility, and Child Investment

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.2. 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.3. 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.4. 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.5. 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 Parameters: NLSY79 vs. NLSY97

This appendix compares the structural parameters estimated on the NLSY79 and NLSY97 cohorts using the same model, moments, and SMM objective. The goal is to summarize how the estimated fertility, marriage, education, and preference primitives differ across cohorts, and to provide a compact input for the cohort-change counterfactuals. Throughout, parameters are reported in the model's units; interpretation follows the definitions in the main text.

Table OA.6 reports the full set of SMM-estimated parameters for each cohort. Parameters are grouped by economic block. The first block (λ_h) governs the baseline conception risk by education and age; the second block (η) shifts the effectiveness of contraceptive effort by ability quartile and age. The marriage parameters ($\omega_0, \omega_1, \omega_2$) summarize cohort differences in household formation and equivalence scales. The child block ($\phi_k^e, \xi_{\text{cf}}$) governs the mapping from parental characteristics into child outcomes and fixed costs. The remaining blocks capture cohort differences in the distribution of ability conditional on education (μ), policy/price shifters that move schooling incentives (HS and college allowances), preferences for children (ω_{ch}), labor-supply disutility shifters (ψ_ℓ and $\psi_{\ell k}$), and the standard deviations of idiosyncratic shocks.

Appendix Table OA.6. Comparison of Estimated Parameters: NLSY79 vs. NLSY97

Parameter	**NLSY79**	**NLSY97**
Baseline conception risk by education and age (λ_1)		
λ_1 HSD increment, ages 14–22	5.0060	3.0187
λ_1 HSD increment, ages 22–30	3.6768	4.5661
λ_1 HSD increment, ages 30–38	1.8960	3.1715
λ_1 HS increment, ages 14–22	2.5305	2.8868
λ_1 HS increment, ages 22–30	0.9868	0.7732
λ_1 HS increment, ages 30–38	0.0747	5.9446
λ_1 College base, ages 14–22	5.6717	7.6044
λ_1 College base, ages 22–30	6.0935	7.4359
λ_1 College base, ages 30–38	4.3309	6.0734
Contraceptive-effort effectiveness by ability and age (η)		
η Q2 increment, ages 14–22	0.5596	1.3641
η Q3 increment, ages 14–22	1.0588	1.0861
η Q4 increment, ages 14–22	1.4836	1.0232
η Q2 increment, ages 22–30	1.3559	1.1607
η Q3 increment, ages 22–30	1.1874	1.3191
η Q4 increment, ages 22–30	0.0643	0.2723
η Q2 increment, ages 30–38	1.2492	0.7680
η Q3 increment, ages 30–38	1.0089	1.0574
η Q4 increment, ages 30–38	1.4708	0.6666
Marriage and equivalence scales (ω)		
ω_0 marriage intercept	-0.0115	-0.2106
ω_1 equivalence scale, married	0.2167	0.3910
ω_2 equivalence scale, children	0.0914	0.0156
Child block (production and fixed costs)		
ϕ_k^{HSD} child ability, HSD mother	-0.3004	-0.2738
ϕ_k^{HS} child ability, HS mother	-0.4905	-0.3873
ϕ_k^{BA} child ability, college mother	-0.4662	-0.2424

Continued on next page

Table OA.6 (continued): Comparison of Estimated Parameters: NLSY79 vs. NLSY97

Parameter	**NLSY79**	**NLSY97**
ξ_{cf} child fixed cost	-0.4591	-0.0688
Mean ability by education (μ)		
μ ability, HSD	0.6372	0.6339
μ ability, HS	0.5498	0.5962
μ ability, College	0.5109	0.5007
Schooling incentives and preferences		
HS allowance (HS education subsidy)	40.1299	26.1049
College allowance (college education subsidy)	73.1557	94.9635
ω_{ch} utility weight on children	1.1822	1.8595
Labor-supply disutility shifters (ψ)		
ψ_ℓ HSD, ages 14–26	-0.0224	-0.0180
ψ_ℓ HSD, ages 30–50	-0.0149	-0.0142
ψ_ℓ HSD, ages 54–62	-0.0173	-0.0167
ψ_ℓ HS, ages 14–26	-0.0055	-0.0097
ψ_ℓ HS, ages 30–50	-0.0042	-0.0050
ψ_ℓ HS, ages 54–62	-0.0116	-0.0108
ψ_ℓ College, ages 14–26	-0.0002	-0.0002
ψ_ℓ College, ages 30–50	-0.0001	-0.0014
ψ_ℓ College, ages 54–62	-0.0071	-0.0081
$\psi_{\ell k}$ education 1	-0.5430	-0.8806
$\psi_{\ell k}$ education 2	-1.2873	-0.2042
$\psi_{\ell k}$ education 3	-0.0545	-0.9948
ϕ_{nk} education 1	0.2500	0.4324
ϕ_{nk} education 2	0.2711	0.4355
ϕ_{nk} education 3	0.2699	0.1653
Shock standard deviations (σ)		
σ_ℓ labor supply shock	0.0091	0.0088
σ_{cd} child ability shock, divorced	0.3550	0.2908

Continued on next page

Table OA.6 (continued): Comparison of Estimated Parameters: NLSY79 vs. NLSY97

Parameter	**NLSY79**	**NLSY97**
σ_{cg} child ability shock, general	0.2144	0.4911
σ_{cgh} child ability shock, husband	0.0857	0.1019

Notes: This table reports the parameters estimated by Simulated Method of Moments (SMM) for the full model separately on the NLSY79 and NLSY97 cohorts. "HSD," "HS," and "College" denote education groups as defined in the data section. Age ranges refer to model periods mapped to ages in the data. Parameters are grouped by economic block: baseline conception risk (λ_h), contraceptive-effort effectiveness (η), marriage and equivalence scales (ω), child block (ϕ_k^e and ξ_{cf}), mean ability by education (μ), schooling incentives (allowances), labor-supply shifters (ψ), and shock standard deviations (σ).

OA.6 Computational Details: Solution and Calibration

This appendix documents the numerical solution, simulation, and calibration procedures used to solve and estimate the model. The implementation is in Julia and is modularized into four main scripts: (i) `main_code.jl` (master script for solving and simulating at the estimated parameters), (ii) `vfi_dcegm.jl` (solution algorithm and policy-function construction), (iii) `simulationF.jl` (forward simulation), and (iv) `calibration_hpc.jl` (HPC calibration and optimization).

The overall workflow is:

$$\texttt{calibration\_hpc.jl:} \quad x \mapsto \{\text{solve} \to \text{simulate} \to \text{moments} \to \text{loss}\} \quad \Rightarrow \quad \hat{x},$$

followed by

$$\texttt{main\_code.jl:} \quad \hat{x} \mapsto \{\text{solve} \to \text{simulate} \to \text{tables/figures}\}.$$

OA.6.1 State space, grids, and timing

Time is discrete in four-year periods, indexed by $t = 1, \ldots, T$. 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 $\mathcal{A} = \{a^1, \ldots, a^{N_a}\}$ with cubic spacing:

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

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.6.2 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:

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

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:

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

Solution method. Given a_{t+1}, the budget constraint implies $c_t \cdot \text{den} + i_t = \text{available}$, 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: $r(i_t) = c_t(i_t)^{-\rho} - \text{den}(m_t, k_t)\, \omega_1 \omega_2\, i_t^{\omega_2 - 1}$.
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 $c_t \cdot \text{den} + i_t = \text{available}$, 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:

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

OA.6.3 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 ($T - T_R - T_{NF} < t \leq T - T_R$), 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:

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

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

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

    (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 $V_t(a) = \max_j V_{t,l}(\text{segment}_j(a))$ over all segments.

3. *Credit constraint region.* For $a < \min(\{a_{t,l}(a')\})$, set $c_t = (a(1+r) + y_t - \underline{a})/\text{den}$ 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.6.4 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.6.3).

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.6.5 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 ~ 0.05–0.30 vs. college attendance ~ 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.6.6 Parameter identification

The model's 50 calibrated parameters are identified by distinct patterns in the data:

Fertility parameters (λ_h, η)**.** The baseline pregnancy probability matrix λ_h (education $\times$ age) and the ability shifter $\eta(\theta, t)$ are identified from pregnancy rates by education–age–ability cells (28 moments for ability $\times$ age, covering ages 14–38) and contraception use rates (18 moments).

Labor supply $(\psi_l, \psi_{lk}, \sigma_l)$. Labor force participation by education-age (36 moments) identifies the deterministic labor disutility ψ_l. The additional disutility with children ψ_{lk} is identified by differences in work rates between mothers and non-mothers at the same age-education. The taste shock scale σ_l controls the smoothness of participation profiles.

Education decisions $(\phi_k^{hsd}, \phi_k^d, \phi_k^{bac}, \xi_{cf}, \sigma_{cd}, \sigma_{cg}, \sigma_{cgh})$. High school dropout (2 moments: conditional on pregnancy at 14), college attendance (4 moments: by ability quartile), and college graduation (2 moments: conditional on pregnancy during college) separately identify the utility costs of education with children (ϕ_k), the cognitive cost of college (ξ_{cf}), and the taste shock scales (σ_c).

Child investment $(\omega_0, \omega_1, \omega_2)$. The three child investment utility parameters are identified by: (i) the *level* of investment (moment: mean investment by education), and (ii) the *gradient* across education groups (2 moments: relative investment HS/HSD and College/HSD from Caucutt and Lochner (2020)).

Marriage (μ, ω_{ch}). Marriage rates by education-age (17 moments) identify the meeting probabilities μ by education. The spousal consumption weight ω_{ch} is identified by the joint distribution of marriage and fertility timing.

Other parameters. The terminal utility for remaining childless ϕ_{nk} by education is identified by the fraction of women who never have children, which varies by education. Allowances (hs_allow, $coll\_allow$) are identified by enrollment rates conditional on assets.

OA.6.7 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):* $\sim$15–20 seconds (30 asset grid points)
- *Simulation (10,000 agents):* $\sim$8–12 seconds
- *Total (solve + simulate + moments):* $\sim$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 $\sim$8GB per worker (solution), $\sim$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.