DOCUMENTOS DE TRABAJO

The Effect of Cognitive Skills on Fertility Timing

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N° 1001 Noviembre 2023 (Updated Febrero 2026)

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Fertility Timing[*]

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Abstract

Early childbirth varies sharply with cognitive ability: in a nationally representative U.S. cohort, 69% of women in the lowest cognitive ability quartile have had a first birth before age 22, compared with 22% in the highest quartile. I estimate a dynamic life-cycle model of schooling, work, marriage, and contraceptive effort to ask whether standard opportunity-cost channels can account for this gradient. They cannot: a nested speci-fication test rejects the hypothesis that opportunity costs alone explain the early-birth gap. Matching the data requires that cognitive ability also raises the effectiveness of contraceptive effort in reducing pregnancy risk—a mechanism absent from the existing structural fertility literature. Two counterfactuals illustrate its quantitative importance. First, equalizing contraceptive effectiveness to high-ability levels reduces pregnancies be-fore age 22 by 50% and raises college attendance by 15%. Second, a cost-reduction policy that lowers aggregate early pregnancies by 10% generates welfare gains equivalent to 10% of lifetime consumption for the lowest ability quartile, but near-zero gains for the highest—reflecting that the binding constraint for disadvantaged women is contraceptive effectiveness, not cost.

Resumen

La maternidad temprana varía marcadamente según la capacidad cognitiva: en una cohorte representativa a nivel nacional de Estados Unidos, el 69% de las mujeres en el cuartil de menor capacidad cognitiva tuvo su primer hijo antes de los 22 años, en comparación con el 22% en el cuartil más alto. En este paper, estimo un modelo dinámico de ciclo de vida que incorpora decisiones de educación, trabajo, matrimonio y esfuerzo anticonceptivo para examinar si las diferencias en el costo de oportunidad pueden explicar esta relación. La respuesta es negativa: un test anidado rechaza la hipótesis de que los costos de oportunidad por sí solos explican la brecha en la maternidad temprana. Reproducir los datos requiere que la capacidad cognitiva también incremente la efectividad del esfuerzo anticonceptivo para reducir el riesgo de embarazo, un mecanismo ausente en la literatura estructural sobre fecundidad. Dos contrafactuales ilustran su importancia cuantitativa. En primer lugar, igualar la efectividad anticonceptiva a los niveles del cuartil de mayor capacidad reduce el número de embarazos antes de los 22 años en un 50% e incrementa la asistencia universitaria en un 15%. En segundo lugar, una política de reducción de costos que disminuye los embarazos tempranos agregados en un 10% genera ganancias de bienestar equivalentes al 10% del consumo de por vida para el cuartil de menor capacidad, pero ganancias cercanas a cero para el cuartil más alto, lo que refleja que la restricción vinculante para las mujeres en desventaja es la efectividad anticonceptiva, no el costo.

1 Introduction

Early childbearing varies sharply with cognitive ability. In a nationally representative cohort of U.S. women born in the late 1950s and early 1960s—the 1979 National Longitudinal Survey of Youth (NLSY79)—69% of women in the lowest cognitive ability quartile have had a first birth before age 22, compared with 22% in the highest quartile. This gap reflects a pronounced difference in the timing of first births rather than in whether women eventually become mothers: first birth hazard rates are sharply decreasing in cognitive ability during the teenage years but converge across ability groups by the late twenties, so that mean age at first birth differs by 5.4 years across quartiles, with higher-ability women postponing rather than forgoing motherhood.

The correlation between cognitive ability and fertility cannot be dismissed as a mechanical consequence of ability's correlation with schooling and income. Reduced-form evidence from other settings corroborates this pattern. Heckman et al. (2006) show that both cognitive and noncognitive skills independently predict teen pregnancy in the NLSY79, with effects that operate partly but not entirely through schooling decisions. Fe et al. (2022) find that theory-of-mind and cognitive ability measured at age eight both predict lower fertility at age 25 in the Avon Longitudinal Study of Parents and Children (ALSPAC), with educational participation serving as a partial but incomplete mediator. These patterns raise the question addressed in this paper: can a structural life-cycle model in which cognitive ability operates through the education channel—by increasing schooling attainment and wages, and by changing contraceptive behavior—account quantitatively for the observed ability gradient in fertility timing?

To answer this question, I develop and estimate a structural life-cycle model in which cognitive ability is an early, persistent trait[1], and in which women jointly choose schooling, labor supply, experience accumulation, marriage, and fertility control. In particular, women choose contraceptive effort. By contraceptive effort, I mean the deliberate actions and resources women devote to preventing pregnancy—incurring social, monetary, and psychological costs. This includes paying for and accessing contraceptive methods, learning

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

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

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

Recent structural work models imperfect fertility control (Choi, 2017; Ejrnæs and Jørgensen, 2020), but these papers do not allow innate ability to directly affect the productivity of contraceptive effort within education groups. Choi (2017) models fertility risk and abortion in a life-cycle framework in which conception risk depends on a continuous effort choice and varies with observables such as age, marital status, and education type; however, conditional on these observables, the effort–risk mapping is common across women and does not incorporate within-education heterogeneity linked to cognitive ability. Ejrnæs and Jørgensen (2020) model abortion as insurance against income shocks in the presence of imperfect contraceptive control, but likewise do not introduce ability heterogeneity in contraceptive effectiveness. Similarly, while Fe et al. (2022) document robust reduced-form associations between cognitive skills and fertility using ALSPAC data, they do not embed these patterns in a structural framework that identifies the mechanism or separates ability-driven differences in opportunity costs from ability-driven differences in pregnancy risk.

This question is at the center of several literatures in economics—human capital and labor supply, family formation, and the determinants of inequality—because the timing of fertility shapes women's schooling, career experience, marriage trajectories, and the intergenerational persistence of education and earnings. It is also directly policy-relevant because the main policy tools used to influence early childbearing are (i) education-and-opportunity policies—such as compulsory-schooling reforms, school-quality investments, and college-aid expansions that raise educational attainment and the returns to experience—and (ii) contraception access-and-cost policies—such as subsidized contraception, clinic expansions, and insurance coverage that lower the monetary and social costs of using effective methods. If ability-related differences in contraceptive effectiveness operate beyond these policy margins—as the nested specification test indicates—then the welfare gains from policies that reduce the utility cost of contraceptive effort will be heterogeneous across skill groups: such policies generate the largest welfare gains for the most disadvantaged women, who face the highest baseline pregnancy rates, while high-ability women—who already have low pregnancy rates and high contraception use—benefit little. The model also implies that technology-shifting interventions—as LARC-based programs provide—can generate welfare gains that exceed those from cost-reduction policies, particularly for the most disadvantaged women, by raising the effectiveness of contraception rather than merely reducing its cost. This finding aligns with evidence of substantial socioeconomic gradients in contraceptive failure rates for user-dependent methods (Bradley et al., 2019; Sundaram et al., 2017), and with evidence that long-acting reversible contraceptives—which decouple effectiveness from user effort—exhibit dramatically lower failure rates with no gradient by age (Winner et al., 2012).

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

of fertility-timing interventions.

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

Second, I use the estimated model to quantify the policy-relevant implications of this decomposition. The counterfactuals show that the direct "fertility-control" channel is quantitatively important: equalizing contraception frictions to those faced by high-ability teens reduces pregnancies before age 18 by 50% (36% before age 22) and increases college attendance by 15%, while aligning both contraception and schooling opportunities raises college attendance by 31% and reduces pregnancies before age 18 by 55%. The welfare analysis reveals that heterogeneity in effective fertility control has substantial heterogeneity in consumption-equivalent value: a policy that reduces the utility cost of contraceptive effort enough to lower aggregate teen pregnancy by 10% generates the largest welfare gains for the lowest-ability women—the most disadvantaged group—amounting to 10% of lifetime consumption, with gains declining monotonically for higher ability groups. This pattern arises because low-ability women face the highest baseline pregnancy rates and exhibit the largest behavioral response to cost reductions; high-ability women, who already use contraception at high rates and face low baseline pregnancy risk, benefit little from further cost reductions. These findings underscore that ability-dependent contraceptive effectiveness is an economically meaningful source of inequality—one that cost-reduction policies address most powerfully for the most disadvantaged women, though technology-shifting interventions that raise contraceptive effectiveness could generate even larger gains by circumventing the effectiveness barrier. The

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

2 Literature

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

This paper contributes to this structural tradition by introducing cognitive ability as an 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. This mechanism— where cognitive ability directly shifts the mapping from contraceptive effort to conception risk—distinguishes the paper from prior work that models education-dependent or income-dependent fertility control frictions.

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

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

Fourth, the paper connects to a broader literature documenting that cognitive (and noncognitive) skills predict a wide range of life outcomes.[2] In this tradition, Heckman et al.

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

([2006](#)) show that higher cognitive and noncognitive skills reduce risky behaviors, including teen pregnancy and early marriage, while Fe et al. ([2022](#)) links childhood cognition to adult behaviors and outcomes, including lower fertility in young adulthood. This paper's contribution is to embed these empirical patterns in a disciplined life-cycle model and to rationalize them through a mechanism consistent with the data: an ability-dependent fertility-control technology that operates in addition to education and wages. To my knowledge, no existing structural model of fertility timing incorporates cognitive ability as a direct shifter of contraceptive effectiveness while simultaneously allowing for endogenous schooling, labor supply, marriage, and sequential fertility decisions.

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](#)). Di Nola et al. ([2025](#)) develop a structural model of teenage risky sexual behavior with parental investments and welfare state institutions, but do not incorporate cognitive ability as a shifter of contraceptive effectiveness.

3 Empirical Evidence

This section documents the relationship between cognitive skills and fertility using the National Longitudinal Survey of Youth 1979 (NLSY79). First, I describe the survey, sample construction, and key measures—cognitive skills, fertility timing (teen pregnancy and age at first birth), schooling, marriage formation, and work-experience accumulation. I then present descriptive facts linking cognitive skills to early pregnancy and first-birth timing, and examine how this relationship interacts with education, marriage, and on-the-job experience. These patterns, consistent with prior work documenting ability–fertility gradients that persist beyond education (e.g., Fe et al., [2022](#); Heckman et al., [2006](#)), provide the empirical targets that discipline the structural model.

([2007](#)).

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 measures derived from the ASVAB administered early in the panel. The AFQT is widely used as a measure of cognitive skills in economics (e.g., Heckman et al., 2006; Neal and Johnson, 1996) and captures reasoning ability. I treat invalid/nonresponse codes as missing and exclude women with missing AFQT. After applying these restrictions, the working sample contains 5,634 women. Additional details on sample construction, variable definitions, and the cleaning conventions 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 this paper 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 Ability and the Timing of First Birth

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

Panel A of Table 1 reports conditional first-birth probabilities by age bin and cognitive-skill quartile. Each cell is computed among women who are childless at the beginning of the

Table 1. Fertility Timing and Outcomes by Ability Quartile

	Ability Quartile			
	Q1 (Low)	Q2	Q3	Q4 (High)
Panel A: Conditional First-Birth Probability by Age Bin (%)				
14–17	28	16	9	3
18–21	49	38	25	16
22–29	54	53	46	45
Panel B: Age at First Birth and Completed Fertility				
Age at first child	20.14	21.66	23.45	25.56
Married at first pregnancy	0.38	0.56	0.72	0.84
At least one child by age 40	0.87	0.82	0.74	0.72

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

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

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

Consistent with postponement, mean age at first birth rises by about 5.4 years from quartile 1 to quartile 4 (20.14 to 25.56). High-ability women are also much more likely to be married at first pregnancy (0.84 vs. 0.38), suggesting that ability is associated not only with delayed fertility but also with greater control over the circumstances surrounding first births. Lower-ability women are less likely to have a first birth by age 40 (0.72 vs. 0.87). This pattern—large ability gradients in early fertility that dissipate at older ages—is a key target for the structural model.

Table 2. Educational Attainment by Cognitive Ability Quartile

Education outcome	Cognitive Ability (AFQT) Quartile				
	Q1 (Low)	Q2	Q3	Q4 (High)	All
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. Education measured as highest degree completed; college attendance includes those who attended between ages 18–22. Cognitive ability measured using AFQT percentile scores. Entries report column percentages (share of women in each quartile with indicated education level).

3.2.2   Ability and Education

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

Table 2 shows a strong, monotone relationship between cognitive ability and educational attainment. Relative to women in the lowest AFQT quartile, those in the highest quartile are far less likely to leave school as high school dropouts (1% vs. 29%, a 28 pp gap) and far more likely to complete college (52% vs. 4%). College attendance also rises sharply with ability—from 11% in quartile 1 to 67% in quartile 4—while the middle of the distribution is concentrated in high-school completion. Because education affects both opportunity costs of childbearing and, potentially, the effectiveness of fertility control (Rosenzweig and Schultz, 1989), these ability–education gradients could, in principle, fully account for the ability–fertility relationship documented in Table 1. A central question for the structural model is whether they do.

3.2.3   Pregnancy Timing and Education

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

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

Age at first pregnancy	Education Outcome		
	HS Dropout	HS Graduate	College Graduate
14–17	42	14	3
18–21	32	31	8
22–29	14	28	37

Notes: Entries report the share (%) of women in each education group whose first pregnancy occurred in the indicated age bin (column percentages).

first birth occurs in each displayed age bin.[3]

Two patterns stand out. First, early motherhood is concentrated among less educated women: by ages 14–17, the first-birth share is 42% for high-school dropouts, compared with 14% for high-school graduates and 3% for college graduates. By age 21 (14–17 plus 18–21), roughly 74% of dropouts have had a first birth versus 11% of college graduates. Second, more educated women shift first births into later ages: in the 22–29 bin, the share is 37% for college graduates versus 28% for high-school graduates and 14% for dropouts, consistent with postponement along the education gradient. These patterns could reflect either causal effects of education on fertility timing (through opportunity costs or contraceptive knowledge) or selection of women with different underlying fertility-control capabilities into different education levels—a distinction the structural model is designed to address.

3.2.4 Early Pregnancies and Marriage

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

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

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

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

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

	Education Outcome		
Age at first pregnancy	HS Dropout	HS Graduate	College Graduate
Panel A: Premarital First Pregnancy			
14–17	67	81	83
18–21	58	75	72
22–29	46	59	69
Panel B: No Premarital Pregnancy			
All ages	94	96	98

Notes: Panel A conditions on first pregnancy occurring before first marriage; probabilities shown by age at first pregnancy. Panel B conditions on no pregnancy prior to first marriage (includes women who never marry). Entries report share (%) ever married during the survey window.

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.	In-wed.	Out-wed.	In-wed.	Out-wed.	In-wed.
14–17	35,089	34,563	—	—	—	—
18–21	35,806	39,064	44,602	46,000	—	—
22–29	33,622	35,806	43,719	55,143	66,025	73,628

Notes: Husband's average annual wage (2016 dollars) by woman's education, age at first pregnancy, and whether first pregnancy occurred out of wedlock. Sample restricted to married women; spouse-years require $\geq$2,000 hours worked and $\geq$\$2.50/hour. Empty cells indicate insufficient observations.

characteristics, marriage-market conditions, and preferences.

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

Table 5 reports average husbands' annual wages (in 2016 dollars) by the woman's com-

pleted education, age at first pregnancy, and whether the first pregnancy occurs out of wed-
lock, conditional on marrying during the survey window. In most education groups and age
bins, women with an out-of-wedlock first pregnancy marry lower-earning husbands on average.
The implied spousal-earnings differential is largest for high-school graduates—about $1,400
for ages 18–21 (46,000 vs. 44,602) and about $11,400 for ages 22–29 (55,143 vs. 43,719). For
college graduates (ages 22–29), the gap is about $7,600 (73,628 vs. 66,025). For high-school
dropouts, differences are smaller (roughly $2,000–$3,300), and the teen (14–17) dropout cell
shows a negligible difference ($526). These spousal-earnings penalties associated with pre-
marital childbearing represent an additional cost of imperfect fertility control that the model
incorporates through the marriage-market.

3.2.5 Education, Experience, and Labor-Market Outcomes

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

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

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

Panel C documents experience accumulation: higher-ability women accumulate substan-
tially more work experience by a given age. At age 25, quartile 1 averages 1.85 years versus

3.99 years in quartile 4; by age 40, the gap widens to 7.94 vs. 14.44 years. This pattern is consistent with stronger labor-force attachment at higher ability, which raises the extent of experience losses from career interruptions.

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

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

3.3 Discussion

The empirical evidence documents several regularities that jointly motivate the structural model. Women in the lowest cognitive-ability quartile are roughly nine times more likely to have a first birth by age 17 than those in the highest quartile, and the gap remains substantial through age 21. Yet this ability gradient in conditional first-birth probabilities largely dissipates by ages 22–29, suggesting that low-ability women experience mistimed rather than unwanted fertility. Higher-ability women attain substantially more education, which could in principle fully account for the ability–fertility gradient through standard opportunity-cost channels. The opportunity cost of early childbearing is indeed higher for high-ability women, who face faster wage growth and larger experience penalties from career interruptions. These costs are amplified in the marriage market: out-of-wedlock births are associated with lower marriage rates and lower spousal earnings.

A natural question is whether the standard opportunity-cost mechanism—whereby higher ability raises education, which raises the cost of early childbearing—can fully explain these patterns. The structural model addresses this question by allowing ability to affect fertility

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Table 6. Descriptive Statistics by Ability: Labor Market Outcomes

Outcome	Q1 (Low)	Q2	Q3	Q4 (High)
		Ability Quartile		
Panel A: Wage at Given Age (2016 $, workers only)				
Age 20	19,688	21,554	22,811	23,042
Age 25	23,954	27,850	32,250	38,412
Age 30	27,778	33,689	38,978	49,126
Age 40	30,382	40,112	46,392	65,713
Panel B: Return to Experience (log wage growth, %)				
5 years potential exp.	24	35	45	57
10 years potential exp.	39	52	65	78
15 years potential exp.	47	61	75	90
Panel C: Cumulative Work Experience (years)				
At age 25	1.85	3.20	3.85	3.99
At age 30	3.60	6.04	7.20	7.51
At age 40	7.94	12.65	14.64	14.44
Panel D: Annualized Log Wage Growth Rate (%)				
Average	2.69	3.12	3.53	4.33
Panel E: Wage Changes Around Non-Work Spells				
Δ log wage after 1-year gap	0.02	−0.01	0.00	0.04
Δ log wage after 3-year gap	−0.02	−0.03	0.05	0.05
Δ log wage after 5-year gap	−0.01	−0.12	0.02	0.07
Time out after first child (years)	0.31	0.50	0.56	0.60

Notes: "Work" defined as $\geq$20 hours/week for $\geq$26 weeks at $\geq$ minimum wage. Panel A: average wages for workers at each age. Panel B: $\ln w_{t+x} - \ln w_t$ where t is first working year; potential experience cumulates only working years. Panel C: cumulative years meeting work definition. Panel E: log wage change between last working year and 1/3/5 years after gap; "time out" = weeks not working in 5 years post-birth $\div$ 52.

through two distinct channels: (i) indirectly, via schooling and wages (the opportunity-cost channel), and (ii) directly, by shifting the effectiveness of contraceptive effort (the fertility-control channel). The model's nested specification test, presented in Section 6, shows that shutting down the direct fertility-control channel prevents the model from matching the observed ability gradient, even when the opportunity-cost channel operates freely. This finding suggests that cognitive ability shapes fertility timing not only by raising the returns to delay, but also by improving women's ability to avoid unintended pregnancies successfully.

4 Model

I develop a dynamic life-cycle model of fertility timing with imperfect fertility control, building on structural work that embeds unintended pregnancy risk in forward-looking settings (e.g., Choi (2017); Ejrnæs and Jørgensen (2020)). Like Keane and Wolpin (2010), the model jointly endogenizes schooling, labor supply, marriage, and fertility within a unified dynamic

framework. The key innovation is the fertility-control technology: whereas Choi (2017) models a continuous contraceptive-effort choice that affects conception risk, with the effort–risk mapping varying by age, marital status, and education type, and Ejrnæs and Jørgensen (2020) emphasize how income risk interacts with imperfect control and abortion, I allow cognitive ability to shift the productivity of contraceptive effort—how effectively effort translates into reduced conception risk. This connects the structural mechanism to evidence that typical-use failures reflect imperfect compliance (the gap between perfect and typical use) and that more educated women use methods more effectively (Black et al., 2010; Rosenzweig and Schultz, 1989; Trussell, 2011).

The model is used to quantify how cognitive ability shapes the timing of first birth and to test whether standard education and opportunity-cost mechanisms can account for the observed ability gradient in early fertility. Time is discrete, with each period representing four years. Women enter the model at age 14 with cognitive ability θ and initial assets $a_1 = 0$. They remain fertile through ages 14–37 and can work until age 61. From ages 62 to 78, households are retired and receive Social Security income that depends on educational attainment. The unit of decision-making is the household: before marriage, it is a single-adult unit, and after marriage, it is a two-adult unit that pools income and makes joint decisions. Marriage is absorbing (no divorce).

Each woman can have at most one child. If a birth occurs, the child resides with the household for one period; 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 income uncertainty to focus on the joint determination of fertility timing, schooling, work experience, and marriage.

4.1 State variables, choices, and timing

The household state at the beginning of period t is

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

where a_t denotes assets; $\theta_i \in \{1, 2, 3, 4\}$ is the cognitive-ability quartile (1 lowest, 4 highest); $e_t \in \{HSD, HS, C\}$ is education attainment/status; x_t is accumulated labor-market

experience; $m_t \in \{0,1\}$ is marital status; $k_t \in \{1,2,3\}$ records childbearing status (1: no prior birth, 2: first birth occurs in period t, 3: first birth occurred in an earlier period); and $m_k \in \{0,1\}$ records marital status at the first birth (only relevant when $k_t \neq 1$).

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

Figure 1. Women Attending College Life Cycle
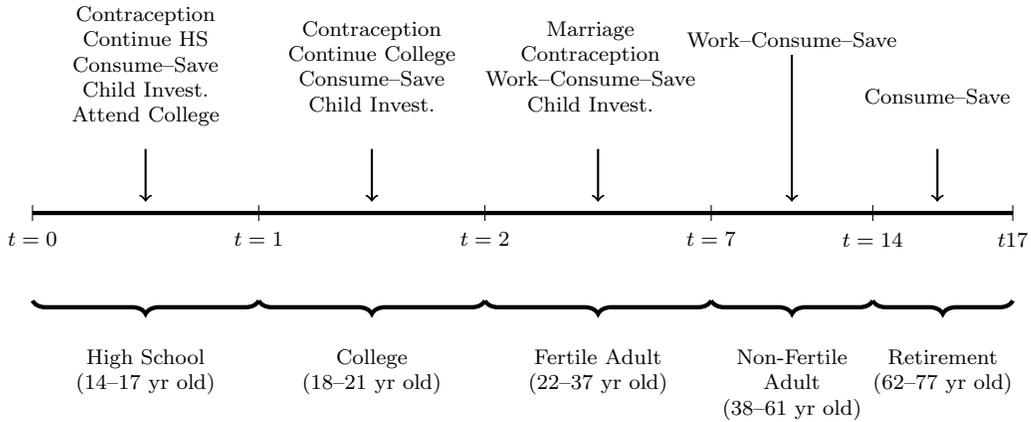
Notes: The figure describes women's life cycle. The life cycle is divided into four stages: (i) teen, (ii) college age, (iii) young adult, and (iv) rest of life. Above the timeline, we show women's decisions in each period.

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

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

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

4.2 Dynamic Household Problem and Value Functions

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

Marriage. If single ($m_t = 0$), the woman meets a potential husband with probability $\mu(e_t, t)$. Conditional on meeting, she compares continuation values under marriage and sin-

glehood. Let $\Omega_{it}(m)$ denote the state with m_t set to $m \in \{0, 1\}$. Then

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

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

$$
V_t^2(\Omega_{it}) = \max_{s_t \geq 0} \left\{ -\phi_s\, s_t + p_t(\theta_i, e_t, s_t)\, V_t^{3, j=2}(\Omega_{it}) + (1 - p_t(\theta_i, e_t, s_t))\, V_t^{3, j=1}(\Omega_{it}) \right\}.
$$

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

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

Working-stage problem with and without a newborn. In fertile ages $(t \leq T_F)$, 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

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

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

$$
v_t^{3, j=2}(\Omega_{it}, l) = \max_{a_{t+1} \geq 0,\, c_t \geq 0,\, i_t \geq 0} \left\{ u(c_t) + \psi_l^{j=2}\, 1_{\{l=1\}} + u_k(i_t) + \beta\, \mathbb{E}\left[V_{t+1}(\Omega_{i,t+1}) \mid \Omega_{it}, l, a_{t+1}, j = 2 \right] \right\}
$$

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

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

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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:

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

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

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

College. At the end of $t = 1$, teens who complete high school ($d = HSG$) draw a Type-I extreme value shock and choose whether to enroll in college at $t = 2$, $d_C \in \{C, NC\}$. Let $v_2^1(\cdot)$ denote the beginning-of-period value at $t = 2$ given the education choice. College enrollment entails a non-pecuniary ("psychic") entry cost, $\kappa_C(\theta, j)$, capturing the disutility of attending college—e.g., effort costs, adjustment costs, and other non-monetary barriers—which may vary with ability θ and with pregnancy status j. Then

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

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

4.3 Preferences, technologies and transfer system

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

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

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

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

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

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

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

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

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

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

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

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

$$\kappa_c(\theta, k_t) = \frac{\xi_c}{\theta^{\omega_c}} + 1_{\{k_t>0\}} \, \phi_{kbac},$$

where the first term captures the standard finding that psychic costs decline with cognitive ability, and the second term captures the additional burden of attending college while raising a child from a prior birth.[5] This formulation allows early motherhood to impose lasting costs on human capital accumulation: women who gave birth as teenagers face higher utility costs of subsequent college attendance, reflecting the practical difficulties of balancing childcare with academic demands. I allow continuation (graduate vs. dropout) to be differentially

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[5]Psychic (non-pecuniary) costs or tastes for schooling are a standard ingredient in structural models of educational choice (e.g., Keane and Wolpin, 1997, 2010). These frameworks typically allow the utility cost of attending school to be heterogeneous (often interpreted as effort/adjustment costs), and they emphasize that unmeasured monetary costs can be observationally equivalent to psychic costs (Keane and Wolpin, 2010). Consistent with this modeling approach, a large empirical literature shows that both cognitive and noncognitive skills are strong predictors of schooling attainment (Heckman et al., 2006), and structural estimates often find substantial heterogeneity in the instantaneous utility cost of attending school that is related to latent "school ability".

costly when a child is present via an additional cost. High-school continuation/dropout is modeled analogously through a cost wedge that can increase when a birth occurs in the high-school period.

Fertility and contraception. Fertility is stochastic and can be controlled imperfectly through contraceptive effort $s \geq 0$. For a woman who has not yet had a birth, the probability of conceiving in model period t depends on age (through an age-group index g), education e, and effort s, while cognitive ability θ affects how effectively effort reduces conception risk.[6]

The specification is motivated by two empirical regularities. First, "typical use" failure rates for contraceptive methods substantially exceed "perfect use" rates, with the gap driven primarily by inconsistent or incorrect use (Trussell, 2011). Second, typical-use failure rates vary systematically with socioeconomic characteristics: more educated women appear to use methods more effectively, consistent with heterogeneity in compliance and correct use (Black et al., 2010; Rosenzweig and Schultz, 1989). These patterns suggest that ability affects not only the quantity of contraceptive effort but also the quality—that is, how effectively a given level of intended control translates into reduced conception risk.

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

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

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

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

Interpretation and relationship to the literature. The parameter $\eta_{\theta g}$ captures a reduced-form wedge in "effective" fertility control. Conceptually, it reflects several mech-

---

[6]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). The key distinction in my specification is that ability shifts the effectiveness of effort, not merely its cost or the baseline risk level.

anisms through which cognitive ability may improve the mapping from intended to realized contraception. Higher-ability individuals may be more likely to use contraceptive methods correctly (e.g., taking pills at regular intervals, using condoms properly) and consistently (e.g., not skipping doses, not having unprotected intercourse). They may also be better at anticipating situations where contraception is needed and preparing accordingly, reducing the incidence of unprotected intercourse. Additionally, higher-ability individuals may be quicker to recognize method failure or side effects and switch to more effective methods, or more persistent in using methods with high learning curves. Finally, they may be more effective at negotiating contraceptive use with partners, particularly for methods requiring partner cooperation. I do not model these mechanisms separately; instead, $\eta_{\theta g}$ summarizes their combined effect on the effort–risk mapping, consistent with the medical literature documenting large gaps between perfect-use and typical-use failure rates that vary with user characteristics (Black et al., 2010).

The present model allows the technology of fertility control—the mapping from effort to conception risk—to vary with cognitive ability. This distinction is important for identification: if ability affects only the cost of effort, then high-ability women should exert more effort but achieve similar conception probabilities per unit of effort. If ability affects effectiveness, then high-ability women achieve lower conception probabilities even holding effort fixed. Section 5.2 exploits this distinction to identify $\eta_{\theta g}$ separately from the opportunity-cost channel.

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

To build intuition, consider two women with the same education and age (and thus the same λ_{ge}) but different cognitive ability. Both face identical baseline conception risk if they exert no effort. However, when both exert the same level of effort s, the high-ability woman

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achieves a lower conception probability because her effort is more effective ($\eta_{\theta,H} > \eta_{\theta,L}$).

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

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

Figure 3. Conception Technology: Role of Ability-Dependent Effectiveness
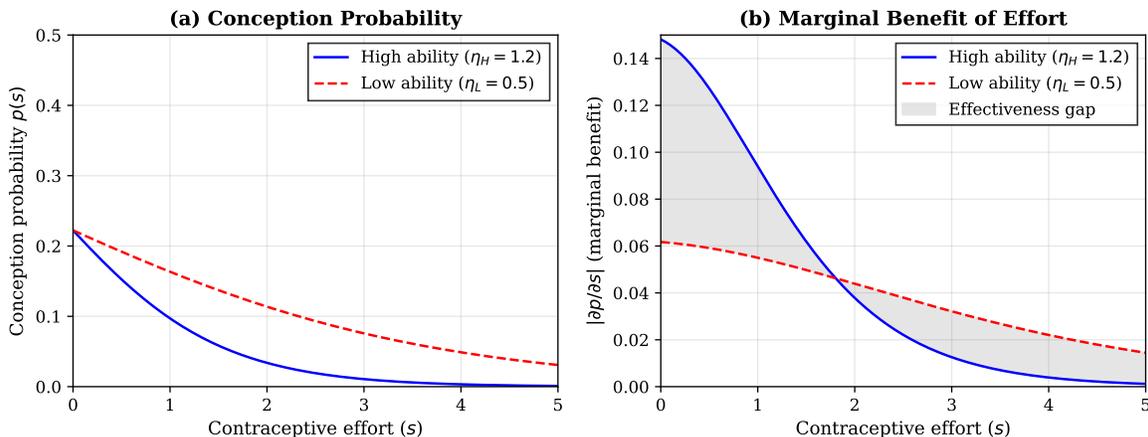
Notes: Both panels assume identical baseline conception odds λ_{ge} across ability types. Panel (a): conception probability as a function of contraceptive effort. The high-ability type (solid blue, $\eta_H = 1.2$) achieves lower conception probability than the low-ability type (dashed red, $\eta_L = 0.5$) at any positive effort level. Panel (b): marginal benefit of effort, $|\partial p/\partial s|$. At low effort, the high-ability type has higher marginal benefit; at high effort, the curves cross and the low-ability type has higher marginal benefit. The shaded region shows effort levels where high-ability types have a marginal-benefit advantage.

To impose that higher ability weakly increases the productivity of contraceptive effort, I restrict $\eta_{\theta g}$ to be weakly increasing in ability quartiles (implemented via nonnegative incre-

ments). This discipline is motivated by two empirical facts. First, for user-dependent methods, "typical use" failure rates substantially exceed "perfect use" rates, reflecting incorrect or inconsistent use and hence an effort/compliance margin (Trussell, 2011). Second, typical-use failure rates exhibit large socioeconomic gradients within method categories—for example, pill, condom, and withdrawal failure are markedly higher among poorer women—consistent with heterogeneity in how effectively intended fertility-control investments translate into reduced conception risk (Sundaram et al., 2017). More broadly, a long-standing human-capital view emphasizes that schooling can raise the efficiency of fertility control by improving knowledge, planning, and correct use (Rosenzweig and Schultz, 1989). Finally, $(\lambda_{\min}, \lambda_{\max})$ bound conception probabilities away from 0 and 1, capturing imperfect control even at high effort and ruling out deterministic fecundity differences across groups.

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

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

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

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

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

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

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

Ability therefore affects contraception behavior through two distinct channels:

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

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

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

Nesting the standard opportunity-cost model. The model nests the opportunity-cost explanation as a special case. If $\eta_{\theta g} = \eta_g$ for all θ (i.e., effectiveness does not vary with ability), then the only channel through which ability affects fertility timing is the incentive channel: higher-ability women delay childbearing because they face higher opportunity costs, not because they are better at avoiding conception. In this restricted model, ability gradients in fertility should disappear after conditioning on education, wages, and experience profiles. The nested specification test in Section 6 formally evaluates this restriction by estimating both the unrestricted model and the restricted model with $\eta_{\theta g} = \eta_g$, and comparing their ability to match the within-education ability gradient in early fertility.

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

schooling allowances when enrolled, or Social Security in retirement). Disposable annual income is

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

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

5   Estimation

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

5.1   Externally Set Parameters and Earnings Process

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

Externally estimated earnings process.   A key input to the model is the earnings process. I estimate reduced-form earnings profiles in the NLSY79 and use the fitted values to parameterize the model's deterministic component of earnings as a function of observed states. Specifically, I predict annual real wage-and-salary earnings and treat the fitted profiles as the earnings opportunities faced by women and husbands in each model period. Estimating the earnings process outside the structural model ensures that wage–experience profiles by ability are disciplined by labor-market data alone, preventing the optimizer from distorting

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Table 7. Externally Set Parameters

Parameter	Value	Source / Interpretation
Discount factor β_a	0.959 (annual)	Standard value (Adda et al., 2017)
Risk aversion ρ	1.98	CRRA curvature (Adda et al., 2017)
Risk-free rate r_a	0.04 (annual)	Real return (Adda et al., 2017)
College tuition TC	$10,200	Annual tuition, 2016 $ (Vandenbroucke, 2023)
Tax progressivity τ	0.18	(Daruich and Fernández, 2024)
Tax scale λ	0.85	
Transfer floor T_S (single)	$8,634	Annual floor, 2016 $ (Daruich and Fernández, 2024)
Transfer floor T_C (couple)	$12,943	
Conception bounds $(\underline{\lambda}, \bar{\lambda})$	(0.05, 0.80)	Imperfect control bounds (Trussell, 2004)
Contraception cost ϕ_s	0.001	Normalization

Notes: Monetary values in 2016 dollars per year. Annual flows converted to four-year model periods as described in text.

these profiles to improve fertility fit (Eisenhauer et al., 2015). Appendix OA.3 provides full details on the estimation sample and specification.

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

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

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

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

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

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

5.2 Estimation and Identification

Estimation. I estimate the model by Simulated Method of Moments (SMM). SMM is well-suited for dynamic life-cycle models with discrete choices, unobserved taste shocks, and nonlinear state transitions (Gourieroux et al., 1993; McFadden, 1989; Pakes and Pollard, 1989). As emphasized by Eisenhauer et al. (2015), the finite-sample properties of SMM depend critically on the choice of moments; I therefore include both static moments (levels and shares at given ages) and dynamic moments (transitions and hazards) to sharpen identification of the model's life-cycle dynamics. I choose parameters Θ to minimize the distance between an empirical moment vector $m^{data} \in \mathbb{R}^{118}$ and its model analogue $m^{sim}(\Theta)$:

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

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

Moment blocks. The 118 targets are organized into blocks aligned with the model mechanisms. The first block contains 12 moments capturing schooling and early fertility: high school dropout rates with and without pregnancy at ages 14–17, college attendance conditional on pregnancy at ages 14–17, college attendance by ability quartile, and college graduation conditional on pregnancy at ages 18–21. Child investment contributes 2 moments measuring relative investment ratios by mother's education. Fertility timing is targeted through 35 moments, including the ratio of first- to fourth-quartile pregnancy rates across ages 14–38 and pregnancy rates by age bin and ability quartile. Marriage patterns contribute 17 moments (share married by age bin and education), labor supply contributes 36 moments (employment rates by age bin and education), and contraception use contributes 18 moments (use rates by age bin and education).

All parameters are disciplined by the joint fit across blocks through the model's cross-equation restrictions; the block structure is a guide to the main sources of identifying variation rather than a claim of one-to-one identification. This approach follows the standard practice in structural life-cycle estimation of organizing moments by the margins they primarily dis-

cipline while recognizing that identification ultimately relies on the full set of cross-equation restrictions implied by the model (Adda et al., 2017; Keane and Wolpin, 1997, 2010).[7]

Identification: separating opportunity costs from fertility control. Cognitive ability affects fertility timing through (i) opportunity costs (schooling, wages, experience accumulation), (ii) marriage-market incentives and spousal resources, and (iii) fertility control. Identification leverages the life-cycle structure: the same latent ability type that matches schooling, labor supply, and marriage outcomes must also rationalize fertility timing, limiting the scope for reallocating fit across margins without degrading non-fertility moments. This logic parallels the identification strategy in Keane and Wolpin (2010), where unobserved heterogeneity ("types") must simultaneously explain education, work, marriage, fertility, and welfare participation—any reallocation of explanatory burden across margins degrades fit on the other margins.

Key restrictions and mapping to moments. Identification of the fertility-control channel relies on three restrictions that prevent within-education teen birth gradients from being absorbed elsewhere. First, the earnings process is estimated outside the structural SMM step using wage data, so wage–experience profiles by ability are not chosen to improve fertility fit. Second, schooling-cost parameters and education-stage taste-shock scales are disciplined primarily by schooling outcomes—including schooling moments conditional on early fertility—ensuring the model matches the joint distribution of education and ability before attributing residual fertility gradients to fertility control. Third, baseline birth risk $\lambda_h(g, e)$ is common within age–education cells, so within-cell ability gradients in first-birth hazards load on the ability shifter in fertility control rather than on baseline risk differences.[8]

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

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

[8]The effort cost parameter ϕ_s is normalized. Intuitively, ϕ_s and λ_h jointly determine the level of contraceptive effort and resulting conception risk, but the data identify only their ratio: a higher cost with proportionally higher baseline risk yields observationally equivalent birth probabilities. The normalization pins down the scale of effort without loss of generality.

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

Intuition for identification of $\eta_{\theta,g}$. To build intuition, consider two women with the same education, age, and wage profile but different cognitive ability. If ability affected fertility only through opportunity costs, these women would face identical incentives to avoid conception and—holding contraceptive technology fixed—would achieve identical birth hazards. Any residual ability gradient in birth hazards within this cell must therefore reflect either (i) differences in contraceptive effort or (ii) differences in the effectiveness of that effort. The model matches average contraception use by age and education, so residual within-cell ability gradients in birth hazards identify $\eta_{\theta,g}$: high-ability women achieve lower conception risk not merely because they exert more effort, but because their effort is more effective.

Overidentification and specification checks. The model is overidentified: 118 empirical moments discipline 60 estimated structural parameters (with the earnings process estimated externally), implying 58 overidentifying restrictions. Overidentification is used as discipline rather than as a formal test of a single restriction: I assess whether the model matches fertility hazards without degrading contraception, schooling, marriage, and labor-supply moments. Following Keane and Wolpin (2007), I assess model fit using within-sample comparisons between simulated and empirical moments, and fit improvement across nested model variants.

Nested specification test. A key contribution of this paper is to formally test whether the standard opportunity-cost model—in which ability affects fertility only through schooling, wages, and marriage incentives—can account for the observed ability gradient in early fertility. To implement this test, I estimate a restricted model that imposes $\eta_{\theta,g} = \eta_g$ for all θ: effectiveness does not vary with ability, so the only channel through which ability affects

fertility is the incentive channel. Comparing the unrestricted and restricted models provides a direct test of whether ability-dependent fertility control is quantitatively necessary to explain the data.

The restricted model is nested within the unrestricted model, so any deterioration in fit is informative about the empirical relevance of the fertility-control channel. Section 6.2 shows that restricting contraceptive effectiveness to be equal across ability groups nearly doubles the total SSE relative to the full model, with the sharpest deterioration on the pregnancy-and-ability moments, confirming that this channel cannot be absorbed by opportunity-cost mechanisms alone.

6 Results

Three main findings emerge from the estimated model. First, the model accounts for the sharp ability gradient in early fertility while simultaneously fitting education, marriage, labor supply, and contraception profiles (Section 6.1). Second, this pattern cannot be explained by schooling choices and wage-based opportunity costs alone. Nested specification tests show that restricting contraceptive effectiveness to be equal across ability groups ($\eta = 1$) causes the model to underpredict the ability–fertility gradient by a factor of five; only when effectiveness is allowed to vary by ability does the model match both the steep gradient in birth hazards and the relatively flat gradient in contraception use, providing direct evidence that ability-dependent fertility control is quantitatively necessary (Section 6.2). Third, a policy reducing contraception costs by 7.8%—sufficient to lower teen pregnancy by approximately 10%—generates the largest welfare gains for low-ability women (10% consumption-equivalent variation), with gains declining monotonically as ability increases (Section 6.3).

6.1 Model fit

This section evaluates how well the estimated model matches the targeted moments. The estimation uses 118 moments organized into five blocks: fertility timing by ability, education outcomes, marriage, labor supply, and contraception use. I discuss fit for each block in turn, highlighting where the model succeeds and where it falls short.

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

6.1.1 Fertility timing by cognitive ability

Figure 4 (panel (a)) compares the cumulative fraction of women who have had a first birth by age and ability quartile. Throughout, Q1 denotes the lowest cognitive ability quartile and Q4 the highest. The model reproduces the sharp ability gradient in the onset of motherhood. Before age 22, where the gradient is steepest and most informative about fertility-control incentives, the model closely tracks the data for Q3 and Q4; for Q1 and Q2 it slightly underpredicts the cumulative fraction (model: 62.5% and 47.8%, respectively; data: 69.1% and 54.0%). This gradient persists through the twenties: by age 30, over 80% of Q1 women have had a first birth, while Q4 women continue accumulating first births into their thirties, a pattern the model captures well. At older ages (30+), the model slightly overpredicts the ability gradient—predicting somewhat too little convergence across ability groups. For example, the data Q1–Q4 gap narrows to 13.7 percentage points by age 42, while the model gap is 21.6 percentage points.

6.1.2 Schooling and child-related outcomes

Table 8 evaluates whether the model captures the joint distribution of schooling attainment and early fertility. The model successfully reproduces several key patterns. First, it matches the strong association between teen pregnancy and high school dropout: among women without a pregnancy by age 14, the dropout rate is 7.0% in the data and 6.8% in the model, while among those with a pregnancy by age 14, the dropout rate rises to 29% in the data and 29.7% in the model. The model closely reproduces this gap, and correctly captures the qualitative pattern that early pregnancy is strongly associated with school leaving.

Second, the model captures the steep ability gradient in college attendance. In the data, attendance rises monotonically from 11% in Q1 to 67% in Q4; the model reproduces this gradient with rates of 11.3%, 30.3%, 42.2%, and 48.9% for Q1 through Q4, respectively. The fit is excellent for Q1 and Q3, but the model underpredicts attendance for Q4 (49% vs. 67%). This shortfall is consistent with the model's abstraction from parental resources,

financial aid, and credit constraints—factors that covary strongly with measured ability and disproportionately boost college-going for high-ability youth from advantaged backgrounds.

Third, the model reproduces the negative association between pregnancy and college outcomes. College attendance conditional on no pregnancy by age 14 is 41% in the data and 40.8% in the model; conditional on pregnancy, it falls to 8% in the data and 7.2% in the model. Similarly, college graduation conditional on attendance and no pregnancy by age 18 is 62% in the data and 61.5% in the model; conditional on pregnancy, it falls to 26% in the data and 25.6% in the model. The model closely reproduces graduation rates for both groups and accurately predicts the severe penalty of early pregnancy on college completion.

Finally, child-investment moments are disciplined using external evidence on expenditure gradients from Caucutt and Lochner (2020). The model reasonably matches the college-versus-dropout ratio (3.81 vs. 4.6) and the high-school-versus-dropout ratio (1.97 vs. 1.2).

Table 8. Education Moments: Model vs. Data

Moment	Data	Model	Moment	Data	Model
High School Dropout (Age 14)			*College Attendance*		
HS Dropout (No Pregnancy)	0.070	0.068	College Attend (No Preg. at 14)	0.410	0.408
HS Dropout (Pregnancy)	0.290	0.297	College Attend (Preg. at 14)	0.080	0.072
College Attendance (Ability)			*College Graduation (Given Attendance)*		
College Attend (Ability Q1)	0.110	0.113	College Grad (No Preg. at 18)	0.620	0.615
College Attend (Ability Q2)	0.250	0.303	College Grad (Preg. at 18)	0.260	0.256
College Attend (Ability Q3)	0.410	0.422	*Child Investment (Relative to HSD)*		
College Attend (Ability Q4)	0.670	0.489	Child Inv: HS/HSD Ratio	1.20	1.97
			Child Inv: College/HSD Ratio	4.60	3.81

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

6.1.3 Labor-market profiles: participation and experience

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

Labor-force participation (panel b). The model reproduces the education gradient in participation: college graduates participate at rates of 65–75% during prime working ages, high school graduates at 50–56%, and high school dropouts at 20–26%. The model also

captures the life-cycle pattern—rising participation in the twenties, a plateau through the fifties, and decline after age 58. The fit is tightest for college graduates and high school dropouts; for high school graduates, the model slightly underpredicts participation at young ages (before age 25) and slightly overpredicts at ages 38–50.

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

6.1.4 Marriage: levels and education gradient

Panel (d) displays marriage rates by age and education. The model successfully reproduces the broad life-cycle pattern of marriage: rates rise with age across all education groups and largely converge by the early thirties, consistent with the data. By ages 30–38, the model tracks the data closely for college graduates and high school dropouts (e.g., age 38: college model 84.8% vs. data 80.7%; HSD model 69.1% vs. data 74.4%).

Two more limited discrepancies arise at younger ages and for high school graduates. First, the model somewhat overpredicts marriage rates for high school graduates at older ages—by age 38, the model predicts 96.3% compared to 81.4% in the data. Second, the model slightly overpredicts marriage for college graduates at ages 22–26 (model: 35.7%–64.1% vs. data: 30.8%–56.7%), consistent with the delayed entry of college women into the marriage market; this gap closes by age 30 and is negligible thereafter.

These discrepancies have a natural interpretation. The model features perfect assortative matching on education and a marital surplus that depends solely on partner earnings and consumption smoothing. It does not capture non-pecuniary dimensions of match quality— such as shared values, lifestyle compatibility, or complementarities in home production—nor the insurance value of dual-earner households.

6.1.5 Contraception use

Panel (e) displays contraception use by age and education. The model matches the education gradient in contraception use: college-educated women report higher use than high school graduates, who in turn report higher use than dropouts. The model also captures the declining age profile—contraception use falls from roughly 73%–88% at ages 17–22 to 20%–48% by the late thirties—reflecting the transition from fertility postponement to completed fertility.

For college graduates, the model predicts universal contraception use at ages 18–30, while the data shows rates of 74%–88%; the model substantially overpredicts college contraception use at young ages. A first consideration mitigates this concern: pregnancy rates among college women are very low in both the data and the model, so the few pregnancies that do occur are fully consistent with the residual conception probability embedded in the fertility-control technology. Even at maximum contraceptive effort, the model retains a 5% baseline failure rate reflecting method failure, so the small number of college pregnancies is compatible with near-universal use without requiring any mismatch in pregnancy levels.

A second consideration concerns the mapping between the model and the data. In the model, any strictly positive effort $s > 0$ is recorded as using contraception, but women in the data may report use only when effort exceeds some higher perceived threshold—for instance, when using a prescription method consistently rather than relying on low-effort alternatives. Under this interpretation, a college woman whom the model assigns low but positive s would be coded as a user in the model but a non-user in the survey. Crucially, the model predicts substantial heterogeneity in effort among college women even when all are recorded as users, so the apparent overprediction of the use rate partly reflects a difference in thresholds rather than a fundamental mismatch. The fit on college pregnancy rates—the outcome directly governed by the effort choice—remains close to the data, which is the margin that matters for the fertility-control channel identified in the paper.

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

The model allows cognitive ability to affect fertility timing through two channels: (i) opportunity costs, operating through schooling choices and wage profiles, and (ii) fertility-control

Figure 4. Model Fit: Fertility Timing, Labor Market, Marriage, and Contraception
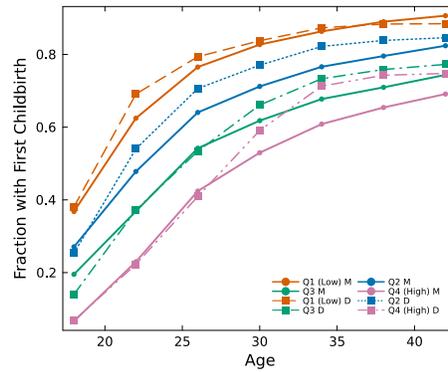
(a) Cumulative first births by age and ability quartile
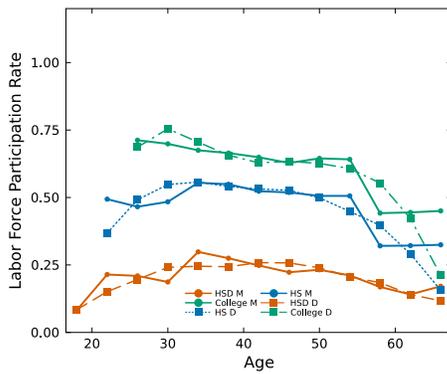
(b) Labor-force participation by education
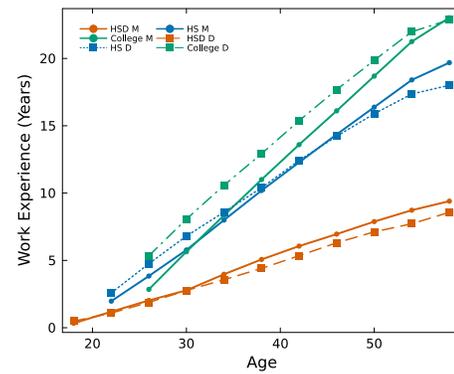
(c) Accumulated work experience by education
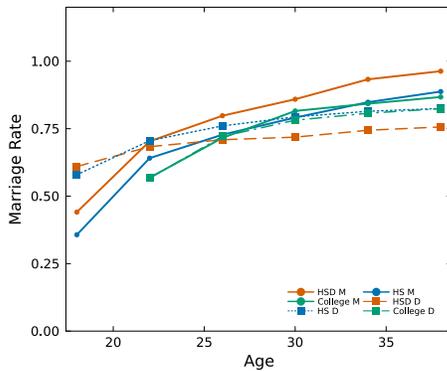
(d) Marriage rates by education
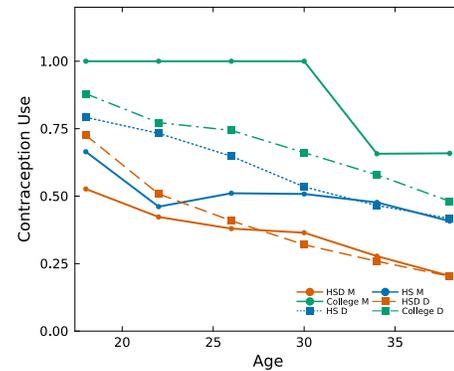
(e) Contraception use by education

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

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effectiveness, operating through the parameter $\eta_{\theta g}$ that governs how effort maps into conception risk. A natural question is whether the second channel is empirically necessary, or whether the standard opportunity-cost channel alone can explain the ability gradient in fertility timing. To address this question, I estimate three nested specifications that progressively relax restrictions on the fertility-control technology:

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

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

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

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

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

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

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

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

First, adding education heterogeneity in baseline risk (column 2) yields only modest improvement in total fit (11%) and improves fit on the contraception-use moments (SSE falls from 0.65 to 0.56). However, it worsens fit on the pregnancy-and-ability block (SSE rises from 1.32 to 1.64, a 24% deterioration). This occurs because, with η fixed at 1, the model can generate some ability gradient through sorting into education groups with different baseline risk, but this is insufficient to match the steep within-education gradient in teen birth hazards.

Second, allowing η to vary by ability (column 3) generates a substantial improvement in total fit (51% reduction in SSE relative to baseline). The improvement is especially broad-based: the pregnancy-and-ability block improves by 78%, the labor-market block improves by 64%, and the education outcomes block improves by 48%. The contraception-use block worsens relative to baseline (SSE rises from 0.65 to 0.95, a 46% deterioration), reflecting that the model now attributes a larger share of the ability gradient to effectiveness differences rather than effort differences.

Third, the bottom panel of Table 9 reports the model-implied correlation between first-birth probability and ability by age group. The data show a strong negative correlation (approximately -0.26 for ages 14–17 and -0.27 for ages 18–21), indicating that high-ability women are substantially less likely to have a first birth at young ages. Specifications (1) and (2) overpredict the magnitude of this gradient: the implied correlations are -0.34 and -0.35 for ages 14–17, respectively, and -0.31 and -0.32 for ages 18–21. Despite generating correlations of the right sign, the restricted models achieve this through mechanisms that distort

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[9]For details on the estimated parameters, consult Appendix OA.5.

the pregnancy-and-ability SSE block, as shown in Panel A. The full model (specification 3) closely replicates the data correlations (-0.26 for ages 14–17 and -0.29 for ages 18–21) while simultaneously delivering the largest overall reduction in SSE.

The key finding is that fixing $\eta = 1$—that is, restricting contraceptive effectiveness to be the same across ability groups—prevents the model from jointly matching the observed ability gradient in fertility timing and the overall structure of birth hazards across moment blocks. Specifications (1) and (2) can produce correlations between ability and birth probability of the right sign, but do so at the cost of large misfit on the pregnancy-and-ability moment block (SSE of 1.32–1.64 vs. 0.30 in the full model) and total SSE nearly twice as large as specification (3). Only when η is allowed to vary by ability does the model achieve the substantial improvement in overall fit—a 51% reduction in total SSE—that identifies ability-dependent fertility-control effectiveness as a quantitatively important and distinct channel from the standard opportunity-cost mechanism.

6.3 Welfare Implications: Reducing Early Pregnancy

The estimated model implies substantial heterogeneity in fertility-control frictions across women. A central implication of the ability-dependent effectiveness parameter $\eta_{\theta g}$ is that policies reducing early pregnancy should generate differential welfare gains across groups. To quantify these effects in economically interpretable units, I evaluate a policy counterfactual that reduces early pregnancy (defined as a first birth before age 22) by 10%—a target anchored in observable outcomes rather than arbitrary parameter perturbations. The model then reveals the contraception-cost reduction required to achieve this target and the resulting welfare gains by group.

Welfare is reported in consumption-equivalent variation (CEV): the permanent proportional increase in consumption that would make agents indifferent between the baseline and counterfactual environments. For group g, I compute

$$\tau_g \;=\; 100 \left[\left(1 + \frac{\overline{U}_g^{cf} - \overline{U}_g^{base}}{\overline{W}_g^{c,base}} \right)^{\frac{1}{1-\rho}} - 1 \right],$$

where $\overline{U}_g^{base}$ and $\overline{U}_g^{cf}$ denote average lifetime utility in baseline and counterfactual simu-

Table 9. Nested Specification Test: Model Fit Decomposition

	Specification		
	(1) Baseline ($\eta = 1$)	(2) + Education Het. in λ ($\eta = 1$)	(3) Full Model (+ Ability in η)
Panel A: Sum of Squared Errors by Moment Block			
Total SSE	6.82	6.06	3.34
Pregnancy $\times$ Ability	1.32	1.64	0.30
Education outcomes	0.70	0.79	0.37
Marriage	0.78	0.81	0.66
Labor supply	2.93	2.39	1.06
Contraception use	0.65	0.56	0.95
Panel B: Fit Improvement Relative to Baseline (%)			
Total	—	11	51
Pregnancy $\times$ Ability	—	−24	78
Education outcomes	—	−12	48
Marriage	—	−4	15
Labor supply	—	18	64
Contraception use	—	14	−46
Panel C: Corr. of First-Birth Probability with Ability			
Ages 14–17 (*Data: −0.26*)	−0.34	−0.35	−0.26
Ages 18–21 (*Data: −0.27*)	−0.31	−0.32	−0.29
Ages 22–29 (*Data: −0.07*)	−0.18	−0.19	−0.23
Ages 14–29 (*Data: −0.24*)	−0.18	−0.19	−0.23

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

lations, respectively, and $\overline{W}_g^{c,base}$ is average discounted consumption-utility in baseline. A value of $\tau_g = 2$ indicates that the policy is worth a 2% permanent increase in consumption for that group.

Table 10 reports the behavioral responses and welfare gains by ability quartile. The policy targets an approximate 10% reduction in early pregnancy (from 40.7% to 36.8%), achieved through a 7.8% decrease in the contraception cost parameter ϕ_s. The results reveal considerable heterogeneity: welfare gains are largest for Q1 women (+10% CEV) and decline monotonically across the ability distribution, reaching essentially zero for Q4 (+0% CEV), with intermediate gains for Q2 (+4%) and Q3 (+3%).

Figure 5 summarizes the CEV results by ability and education. The welfare pattern is monotonically decreasing in ability: gains are largest for Q1 (+10% CEV) and fall to zero for Q4 (+0% CEV). By education, high school dropouts gain the most (+10%), followed by high

Table 10. Behavioral Responses and Welfare Gains from Reducing Early Pregnancy

Ability	Contraception		Effort		Early Preg.		Δ	CEV
	Base	Policy	Base	Policy	Base	Policy		
Panel A: Contraception and Fertility (Ages 14–22)								
Q1 (Low)	69.2	72.0	1.39	1.81	58.9	51.2	−7.7	+10
Q2	76.9	78.6	1.87	2.09	45.5	41.1	−4.4	+4
Q3	80.9	82.1	1.94	2.09	36.1	33.1	−3.0	+3
Q4 (High)	87.1	87.3	1.33	1.36	22.5	22.1	−0.4	+0
All	78.6	80.0	1.63	1.84	40.7	36.8	−3.9	+4

Ability	College		HS Dropout	
	Base	Policy	Base	Policy
Panel B: Education at Age 22 (%)				
Q1 (Low)	11.4	12.5	24.6	23.2
Q2	20.8	21.6	11.9	10.7
Q3	23.7	24.5	8.5	7.8
Q4 (High)	26.8	26.8	4.1	3.9

Notes: Policy reduces contraception cost ϕ_s by 7.8%, lowering early pregnancy from 40.7% to 36.8%. Panel A: "Contraception" = extensive margin (% using any); "Effort" = intensive margin (0–1 scale); "Early Preg." = ever pregnant before age 22 (%); Δ = change in pp. CEV = consumption-equivalent variation (%), measuring welfare gain as permanent increase in consumption.

school graduates (+4%) and college graduates (+1%). This pattern reflects the interaction between baseline early pregnancy risk, behavioral responsiveness to cost reductions, and the opportunity cost of an early first birth, and carries important policy implications.

Why do Q1 women gain the most? The large welfare gain for Q1 women reflects three reinforcing channels. First, Q1 women face the highest baseline early pregnancy rate (58.9%), creating substantial scope for welfare improvement from any meaningful fertility reduction. Second, Q1 women exhibit the largest behavioral response to the cost reduction: the extensive margin of contraception rises 2.8 percentage points (69.2% to 72.0%) and effort intensity increases by 30% (1.39 to 1.81), generating a 7.7 percentage point reduction in early pregnancy—the largest of any group. Third, reduced early pregnancy generates meaningful educational gains for Q1 women: college attendance rises from 11.4% to 12.5% and high school dropout rates fall from 24.6% to 23.2%. The compounded lifetime value of averted early births— through improved education, higher wages, and better consumption paths—is large precisely because Q1 women face substantial penalties from early childbearing, both in terms of foregone schooling and reduced lifetime earnings.

Why do Q4 women gain so little? The near-zero welfare gain for Q4 women is equally instructive. Three features of the model combine to produce this result.

First, the behavioral response channel is attenuated. Table 10 shows that Q4 women exhibit minimal changes in contraceptive behavior: the extensive margin rises only 0.2 percentage points (87.1% to 87.3%) and effort intensity increases negligibly (1.33 to 1.36). The resulting reduction in early pregnancy is only 0.4 percentage points—compared to 7.7 pp for Q1.

Second, Q4 women already face a low baseline early pregnancy rate (22.5%) and high contraceptive use (87.1%). Their fertility timing is already well-aligned with human capital investment, so the marginal welfare value of further reductions in early pregnancy is small.

Third, the absence of educational gains reinforces the welfare stagnation. College attendance for Q4 women remains unchanged at 26.8% under the policy, reflecting that their educational trajectories are not constrained by fertility timing at the margin. The ability-dependent effectiveness parameter $\eta_{\theta g}$ implies that Q4 women already translate contraceptive effort into fertility control very efficiently; a reduction in the cost of effort generates little additional behavioral change for this group.

Policy implications. Policies that reduce the utility cost of contraception disproportionately benefit the most disadvantaged women. In the model, ϕ_s captures the disutility cost of exerting contraceptive effort—the psychic, time, and hassle costs of consistent method use—rather than monetary expenditure. A 7.8% reduction in this utility cost generates the largest welfare gains for Q1 women—who face the highest baseline early pregnancy rates—and essentially no gain for Q4 women, who are already near their optimal fertility path. The same policy has diminishing returns up the ability distribution: by the time women reach Q4, baseline early pregnancy risk is low enough and existing contraceptive use is high enough that cost reductions generate no meaningful behavioral or welfare response.

This finding aligns with evidence that typical-use failure rates for user-dependent methods vary sharply by socioeconomic status, even within method (Sundaram et al., 2017), and with Demographic and Health Surveys evidence that the poorest women face higher failure-related unintended pregnancy risk (Bradley et al., 2019). The large perfect–typical use gap for pills versus the much smaller gap for IUDs Trussell et al. (2018) highlights the user-effort margin

captured by the model. Consistent with this mechanism, the age gradient in unintended pregnancy risk is pronounced for pills/patch/ring but not for IUDs/implants (Winner et al., 2012).

In the language of the model, these patterns reflect the mechanism captured by $\eta_{\theta g}$: user-dependent methods require consistent effort that translates differentially into reduced conception risk across women, while LARCs decouple effectiveness from user effort. For Q4 women, further reductions in effort costs generate negligible gains because they already use contraception effectively. For Q1 women, the gains from cost reductions are large precisely because they have the most room to improve their fertility outcomes. Effective interventions for the most disadvantaged women can therefore work through two complementary channels: reducing the utility cost of effort (lowering ϕ_s, as in this counterfactual) or shifting the technology of contraception toward methods where the gap between perfect and typical use is negligible. Evidence from the latter channel supports the model's predictions: Colorado's Family Planning Initiative, which expanded LARC access, reduced teen birth rates by approximately 6% overall and by larger margins in higher-poverty counties (Lindo and Packham, 2017); in the Contraceptive CHOICE Project, early pregnancy rates among participants who received no-cost LARCs with comprehensive counseling were approximately 79% lower than national rates among sexually experienced young women (Secura et al., 2014). Both channels operate most powerfully at the bottom of the ability distribution, consistent with the model's prediction that Q1 women are the primary beneficiaries of contraception-cost policies.

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

Teen motherhood is strongly associated with low educational attainment, but this correlation is difficult to interpret causally. Adolescents who become teen mothers differ systematically from their peers along many dimensions—family background, prior achievement, discount rates, and expectations—so naive comparisons may overstate the causal impact of childbearing on education. Consistent with this concern, Hotz et al. (2005) use miscarriages as an instrument and find limited long-run effects of teen births on completed schooling. Similarly,

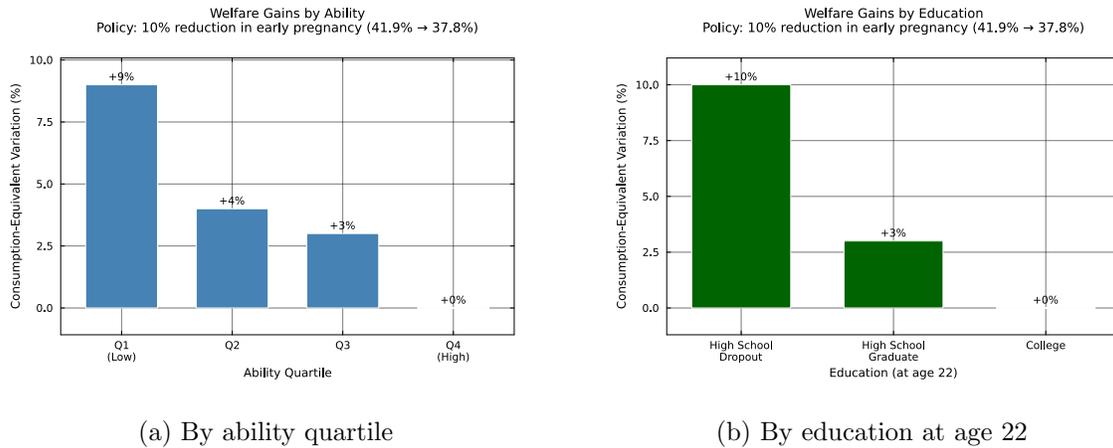(a) By ability quartile   (b) By education at age 22

Figure 5. Consumption-Equivalent Welfare Gains from a 10% Reduction in Early Pregnancy

Notes: Each bar reports group-average CEV (percent). Panel (a): Q1 (lowest ability) through Q4 (highest). Panel (b): HSD = high school dropout, HS = high school graduate, College = some college or more. Education measured at age 22. Early pregnancy is defined as a first birth before age 22.

Levine and Painter (2003) use propensity-score matching and conclude that a substantial share of the raw association reflects selection rather than causation, though meaningful negative effects on college attendance remain.

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

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

Table 11. Counterfactual Experiments: Decomposing the Fertility–Schooling Gradient

| | Counterfactual | | |
	(1) Equalize Fertility Control	(2) Equalize Educ./Wages	(3) Equalize Both
Outcome			
Panel A: Percentage Change Relative to Baseline			
College attendance	+14.6	+13.0	+31.4
Pregnancies by age 18	−50.2	+12.7	−55.2
Pregnancies by age 22	−36.4	+7.1	−42.0

Notes: Each column equalizes parameters to highest-ability quartile values. (1) Fertility-control parameters (λ_{ge}, $\eta_{\theta g}$, ϕ_s). (2) College costs and wage profile. (3) Both fertility-control and education/wage parameters. "Pregnancies by age X" = cumulative share with first birth by age X.

7.1 Counterfactual Design

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

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

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

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

7.2 Results

Table 11 reports percentage changes in key outcomes relative to the baseline economy. Three findings emerge.

Fertility-control frictions are a first-order driver of early fertility. Column 1 shows that equalizing the fertility-control environment to the high-ability level reduces pregnancies by age 18 by 50.2% and pregnancies by age 22 by 36.4%. These are large effects: half of teen pregnancies in the baseline economy would not occur if low-ability women had access to the same effective fertility control as their high-ability peers. This finding corroborates the welfare results in Section 6.3 and confirms that ability-dependent effectiveness is quantitatively important for early fertility outcomes.

Improved fertility control generates meaningful spillovers to education. The same counterfactual (Column 1) increases college attendance by 14.6% relative to baseline. This spillover arises endogenously: when early pregnancies are avoided, women who would otherwise have dropped out or foregone college now find it optimal to continue their education. The mechanism operates through the career-cost channel—avoiding early childbirth preserves the option to accumulate human capital and experience—and through the direct effect of not having child-rearing responsibilities during the college years.

Schooling opportunities raise education but do not reduce early fertility. Column 2 isolates the education-and-earnings channel. Equalizing college costs and wage profiles to the high-ability level increases college attendance by 13.0%—roughly comparable to the effect of equalizing fertility control alone. Notably, however, this intervention does not reduce early fertility: pregnancies by age 18 rise by 12.7% and pregnancies by age 22 rise by 7.1%. The intuition is that higher returns to schooling attract women toward college investment, but for women in the lower ability quartiles whose binding constraint is contraceptive effectiveness rather than foregone wages, equalizing schooling opportunities without improving fertility control cannot prevent early conception. When college-going becomes more attractive but the fertility-control technology remains unchanged, the net effect on early births is slightly positive.

Complementarities. Column 3 combines both channels. When fertility control and schooling opportunities are simultaneously equalized, college attendance rises by 31.4%, pregnancies by age 18 fall by 55.2%, and pregnancies by age 22 fall by 42.0%. The reduction in early

fertility is driven almost entirely by the fertility-control channel, since equalizing schooling alone slightly increases early pregnancies (Column 2). For college attendance, however, the channels are complementary: the combined gain (31.4%) substantially exceeds each channel in isolation (14.6% and 13.0%, respectively). The intuition is as follows: reducing early pregnancies increases the pool of women who can benefit from improved schooling opportunities, while improved schooling opportunities raise the value of avoiding early births. Together these forces amplify the educational response beyond what either policy achieves alone.

7.3 Policy Implications

These counterfactuals have three implications for policy design.

First, interventions that improve access to effective fertility control—such as subsidized long-acting reversible contraceptives (LARCs), improved sex education, or expanded access to family planning services—can generate large reductions in teen pregnancy. The 50.2% reduction in pregnancies by age 18 under the fertility-control counterfactual is comparable in order of magnitude to the effects documented in evaluations of LARC programs: the Contraceptive CHOICE Project found that teen pregnancy rates among participants were roughly 78% lower than national rates for sexually experienced teens (Secura et al., 2014).

A caveat is warranted when comparing these magnitudes. The LARC evaluations are not randomized experiments: women who enroll in programs offering free contraception may be more motivated to avoid pregnancy than the general population, so the estimated program effects likely reflect both the true causal effect of LARCs and positive selection into take-up. My counterfactual, by contrast, holds preferences fixed and varies only the fertility-control technology, isolating the technology channel. That my estimate (50.2%) is smaller than the CHOICE Project's (78%) is consistent with this interpretation: the CHOICE estimate includes positive selection, while mine does not. Despite these methodological differences, the comparison is informative because LARCs operate through the same mechanism my model emphasizes: they largely eliminate the scope for user error by providing contraception that does not require daily compliance or correct use. In the language of my model, LARCs raise η—the effectiveness with which effort translates into reduced conception risk—toward its upper bound. The CHOICE Project's dramatic reductions in unintended pregnancy thus

provide external validation that the effectiveness channel is quantitatively important, even if the precise magnitudes are not directly comparable.

Second, reducing teen pregnancy does generate meaningful increases in educational attainment, but the spillover is partial. The 14.6% increase in college attendance under the fertility-control counterfactual implies that roughly one-quarter to one-third of the fertility–schooling gradient reflects a causal effect of childbearing on education. The remainder reflects selection: women who become teen mothers would have had lower educational attainment even absent the pregnancy, because they face higher schooling costs and lower returns.

Third, the most effective strategy for jointly improving fertility and education outcomes is to address both margins simultaneously. Policies that only target fertility control will reduce teen births substantially but leave underlying educational barriers in place. Policies that only improve schooling opportunities will raise attainment but, without complementary improvements in fertility control, may produce little reduction—or even a slight increase—in early fertility. Bundled interventions—for example, comprehensive programs that combine contraception access with educational support, mentoring, or college preparation—have the potential to achieve the largest joint gains.

8   Conclusion

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

To interpret these patterns, I develop and estimate a dynamic model in which young women make decisions over schooling, marriage, fertility, labor supply, and contraceptive effort. A central feature is a fertility-control technology in which age and education shift

baseline conception risk, while cognitive ability shifts the productivity of contraceptive effort. The model is estimated by the simulated method of moments to jointly match fertility timing by ability, education outcomes, marriage profiles, labor supply, and contraception use.

The estimated model delivers three main conclusions. First, it accounts for the sharp ability gradient in early 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 generate heterogeneous welfare effects across ability groups: policies that reduce the utility cost of contraceptive effort generate the largest welfare gains for Q1 women—the most disadvantaged group—with gains declining monotonically to near zero for Q4 women.

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

The counterfactuals clarify which margin is quantitatively central for the teen fertility–schooling gradient. When all women face the contraception environment of the highest-ability group, the model predicts large reductions in early fertility: pregnancies before age 18 fall by 50.2% and pregnancies before age 22 fall by 36.4%. College attendance rises by 14.6%, indicating that lowering early pregnancy risk can generate meaningful schooling responses. In contrast, equalizing college costs and wage profiles to the highest-ability group raises college attendance by 13.0% but increases early fertility: pregnancies before age 18 rise by 12.7% and before age 22 by 7.1%. The largest joint improvements arise when both margins move together: equalizing both contraception and schooling opportunities increases college

attendance by 31.4% while reducing pregnancies before age 18 by 55.2% and before age 22 by 42.0%. These results imply two policy lessons. First, policies that reduce fertility-control frictions can generate large declines in teen pregnancies, but educational gains may be limited if schooling costs and returns remain unchanged. Second, policies that improve schooling incentives without addressing fertility control deliver large increases in college-going but may produce little or no reduction in early pregnancies.

The welfare analysis reveals considerable heterogeneity in the effects of policies that reduce the utility cost of contraceptive effort. A policy that lowers contraception costs enough to reduce aggregate teen pregnancy by 10% generates the largest welfare gains for low-ability women—who face the highest baseline pregnancy rates—amounting to 10% of lifetime consumption in consumption-equivalent variation. Gains decline monotonically across the ability distribution. This pattern arises because low-ability women exhibit the largest behavioral response to the cost reduction: their extensive margin of contraception rises by 2.8 percentage points and effort intensity increases by 30%, generating a 7.7 percentage point reduction in early pregnancy. By contrast, high-ability women show minimal changes in contraceptive behavior (extensive margin rises only 0.2 pp) and achieve only a 0.4 percentage point reduction in early pregnancy. The ability-dependent effectiveness parameter $\eta_{\theta g}$ implies that each unit of effort remains less productive for low-ability women than for their high-ability counterparts; nevertheless, the large scope for pregnancy reduction at the bottom of the ability distribution means that cost reductions deliver substantial welfare gains precisely for the most disadvantaged women.

This finding carries an important policy implication: cost-based contraception policies primarily benefit the most disadvantaged women, while high-ability women who already use contraception effectively gain little. The model's prediction is consistent with epidemiological evidence of persistent socioeconomic gradients in typical-use contraceptive failure for user-dependent methods (Bradley et al., 2019; Sundaram et al., 2017). In contrast, long-acting reversible contraceptives (LARCs) largely decouple effectiveness from user effort: they exhibit very low failure rates and high continuation, with continuation reported to be unaffected by race or socioeconomic status (Parks and Peipert, 2016), and their effectiveness does not vary by age in a large prospective cohort (Winner et al., 2012). In the language of

the model, LARCs operate primarily by improving the fertility-control technology (raising $\eta_{\theta g}$) rather than lowering the utility cost of contraceptive effort ϕ_s. Evidence from interventions that expanded access to these technologies is consistent with this interpretation: in the Contraceptive CHOICE Project, teens offered no-cost contraception with comprehensive counseling (and with high LARC uptake) had pregnancy rates far below national rates for sexually experienced teens (Secura et al., 2014); and Colorado's Family Planning Initiative reduced teen birth rates by 6.4% in counties with funded clinics, with effects concentrated in higher-poverty counties (Lindo and Packham, 2017). The model thus implies that technology-shifting interventions—those that raise contraceptive effectiveness by decoupling it from user effort—could generate welfare gains that substantially exceed those from cost reductions alone, particularly for the most disadvantaged women, by circumventing the effectiveness barrier captured by $\eta_{\theta g}$.

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 costs deliver the largest welfare gains for the most disadvantaged women, while high-ability women who already use contraception at near-optimal rates benefit little from further cost reductions. Technology-shifting interventions that raise contraceptive effectiveness—such as LARC-based programs—hold the promise of generating even larger gains for the most disadvantaged women by circumventing the effectiveness barrier captured by $\eta_{\theta g}$. Improvements in educational attainment are most likely when policies also strengthen schooling incentives and returns.

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Online Appendix (Not for Publication)

Appendix OA.1   Data Construction and Variable Definitions

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

OA.1.1   Data source and cohort coverage

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

OA.1.2   Panel structure and alignment to model time

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

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

Birth year is inferred from the respondent's age at baseline and used to impute age in years when this variable is missing.

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

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

yielding periods 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 period using the rules described below.

OA.1.3   Global cleaning conventions and special codes

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

constructing analysis variables:

1. **Invalid / nonresponse codes:** Values < 0 are treated as missing unless they have a structural interpretation (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.

3. **Deflation:** Nominal dollar amounts are converted to real 2016 dollars using CPI-based deflators merged by calendar year.

OA.1.4   Cognitive ability

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

OA.1.5   Education

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

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

To reduce spurious year-to-year reporting variation, I use the individual-specific maximum of HGC observed over the panel.

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

OA.1.6 Fertility and pregnancy histories

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

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

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

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

(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.[10]

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

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

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

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

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

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 woman 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.

---

[10]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 "valid skip" are treated as missing.

OA.1.7 Marriage and partner outcomes

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

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

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 treated as missing. Partner weeks worked and hours worked are used for partner employment definitions in the wage-process estimation.

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

Annual hours. Annual hours are constructed from the Work History and Weekly Status files, yielding (i) total annual hours and (ii) annual weeks worked. These variables are documented in the NLSY79 topical guides.

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

Interpolation and internal consistency checks. Because annual earnings can exhibit missingness and occasional spurious zeros in years with positive hours, I implement two consistency checks before estimation and aggregation: (1) set annual earnings to 0 when annual hours are 0; (2) treat earnings as missing in years with very low hours (but nonzero) when earnings are recorded as zero, and linearly interpolate earnings over time within individual (only across years with valid neighboring information). This procedure 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 of at least \$10,500 (2016 dollars). I then define annual experience as $\text{ExpYear}_{it} = 1\{\text{employed}\}$ and cumulative experience as $\text{CumExp}_{it} = \sum_{\tau \leq t} \text{ExpYear}_{i\tau}$.

Appendix 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. for $t \leq T_F = 6$. Women can work through age 61 and retire 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). Child investment is therefore a one-time choice made in the birth period.

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

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

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

where:

- a_t denotes assets;

- $\theta_i \in \{1, 2, 3, 4\}$ denotes the cognitive-ability quartile;

- $e_t \in \{\text{HSD}, \text{HSG}, \text{COL}\}$ denotes education attainment;

- x_t denotes accumulated labor-market experience (in four-year units);

- $m_t \in \{0, 1\}$ denotes marital status;

- $k_t \in \{1, 2, 3\}$ denotes child status, where $k_t = 1$ indicates the woman has never had a birth by period t; $k_t = 2$ indicates a first birth occurs in period t (a child is present in t) $k_t = 3$ indicates the woman 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 $l_t \in \{0, 1\}$,[11] 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 computed from gross income using a parsimonious approximation to the U.S. tax-and-transfer system:

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

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

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

Budget constraint. The within-period budget constraint is

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

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

Experience accumulation. Experience evolves according to

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

---

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

OA.2.3 Discrete choices and taste shocks

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

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

where γ is the Euler–Mascheroni constant.

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

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

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

$$V_t(\Omega_{it}) = \max_{a_{t+1} \geq 0, \, c_t \geq 0} \left\{ u(c_t) + \beta V_{t+1}(\Omega_{i,t+1}) \right\},$$

$$\phi_c(m_t) \, c_t + a_{t+1} = (1 + r)a_t + y_t,$$

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. In 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

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

Conditional on l, the choice-specific problem is

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

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

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

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), and spousal labor income, $w^h(\Omega_{it})$, is received only when married.[12]

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

In young adulthood, schooling is complete (e_t is 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.

---

[12]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).

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 it chooses child investment only when $j = k$. The choice-specific value function net of taste shocks is

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

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

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

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

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

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

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

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

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

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

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 period 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. At $t = 2$ they therefore 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 immediately 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

$$v_2^{3,j}(\Omega_{i2}; G) = \max_{a_3 \geq 0,\, c_2 \geq 0,\, i_2 \geq 0} \left\{ u(c_2) + 1_{\{j=k\}}\, u_k(i_2) - 1_{\{j=k\}}\, \kappa_{k,C} + \beta V_3^1(\Omega_{i3}) \right\}$$

$$\text{s.t.} \quad \phi_c(m_2, 1_{\{j=k\}})\, c_2 + a_3 = (1+r)a_2 + (w_C - TC) - 1_{\{j=k\}}\, i_2.$$

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

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

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

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

In the dropout branch, disposable non-asset income is

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

while in the college-student branch, disposable resources are given directly by the student allowance net of direct schooling costs, $w_C - TC$.[13]

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

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

---

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

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

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

OA.2.8 Teenage (ages 14–17; $t = 1$)

At $t = 1$, all women are in high school. The within-period timing is: (i) contraception, (ii) after observing the fertility outcome, 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 $d \in \{\text{HSG}, \text{HSD}\}$ (stay and complete high school vs. drop out) from sub-stage 2, teens solve

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

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

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

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

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

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

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

Appendix OA.3 Wage Process Estimation

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

OA.3.1 Wage measures and estimation samples

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

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

reflect the quality of partners that women of different education levels tend to attract in the marriage market.

OA.3.2   Baseline specification: women

I estimate:

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

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

OA.3.3   Baseline specification: husbands/partners

For husbands/partners I estimate:

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

$$
+ \lambda^m\, 1\{\text{MarryBeforeBirth}_i = 1\} + \sum_{e\in\{\text{HSG,COL}\}} \kappa_e^m\, 1\{\text{Educ}_i^f = e\} 1\{\text{MarryBeforeBirth}_i = 1\} + u_{it}.
$$

$$
\tag{OA.2}
$$

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

Table OA.1. Women's Earnings Process Estimates

Variable	Coef. (SE)	Variable	Coef. (SE)
Experience		*Education $\times$ ability*	
Cumulative experience	953***	HS grad $\times$ Q2	-50
	(33)		(632)
		HS grad $\times$ Q3	1801*
Education (base: HSD)			(1008)
HS graduate	1164***	HS grad $\times$ Q4	428
	(393)		(1743)
College graduate	2291**	College grad $\times$ Q2	6572***
	(904)		(1186)
		College grad $\times$ Q3	6423***
Education $\times$ experience			(1388)
HS grad $\times$ exp	228***	College grad $\times$ Q4	6990***
	(35)		(1951)
College grad $\times$ exp	916***		
	(77)	*Educ $\times$ ability $\times$ exp*	
		HS grad $\times$ Q2 $\times$ exp	134**
Ability (base: Q1)			(60)
Ability Q2	1414**	HS grad $\times$ Q3 $\times$ exp	-87
	(564)		(82)
Ability Q3	1202	HS grad $\times$ Q4 $\times$ exp	540***
	(963)		(93)
Ability Q4	3078*	College grad $\times$ Q2 $\times$ exp	-254**
	(1710)		(100)
		College grad $\times$ Q3 $\times$ exp	-12
Ability $\times$ experience			(115)
Q2 $\times$ exp	-29	College grad $\times$ Q4 $\times$ exp	748***
	(55)		(120)
Q3 $\times$ exp	257***		
	(78)	*Age profile*	
Q4 $\times$ exp	-170*	Age	1444***
	(89)		(118)
		Age^2	-22***
			(2)
		Constant	-7617***
			(1987)
Observations			94,156
Adjusted R^2			0.292

Notes: Robust standard errors in parentheses; year fixed effects included. Dependent variable is annual wage-and-salary income in 2016 dollars. Baselines: high school dropout (HSD) and ability quartile 1 (Q1). Coefficients and standard errors rounded to nearest dollar. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

OA.3.4 Estimated parameters

Interpreting the ability gradient. Table OA.1 shows the estimated parameters of the women's income process. The estimates reveal substantial wage premia associated with cognitive ability. The baseline ability effect (e.g., Q4 vs. Q1 for high school dropouts: \$3,078) reflects both direct productivity differences and indirect effects through sorting into higher-paying jobs. The college-ability interactions are particularly large (Q2–Q4 college graduates earn \$6,400–\$7,000 more than Q1 dropouts with the same experience), consistent with complementarity between cognitive ability and advanced education in the labor market.

Table OA.2. Husband/Partner Earnings Process Estimates

Variable	Coef. (SE)	Variable	Coef. (SE)
Wife's education (base: HSD)		*Age profile*	
HS graduate	-28089***	Age	794
	(7298)		(498)
College graduate	-106082***	HS grad × age	1149***
	(11760)		(427)
		College grad × age	5490***
Marriage timing (base: after birth)			(668)
Marry before birth	79	Age²	0
	(1301)		(8)
		HS grad × age²	-7
Education × marriage timing			(6)
HS grad × marry before	13913***	College grad × age²	-48***
	(1414)		(9)
College grad × marry before	15275***		
	(2563)	Constant	12431
			(7908)
Observations			37,728
Adjusted R^2			0.159

Notes: Robust standard errors in parentheses; year fixed effects included. Dependent variable is husband's annual wage-and-salary income in 2016 dollars. Wife's education serves as proxy for husband characteristics through assortative mating. Baselines: high school dropout (HSD) and first marriage after first birth. Coefficients and standard errors rounded to nearest dollar. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Interpreting the education coefficients. Table OA.2 shows the estimated parameters of the husband's income process. The negative main effects for wife's education (-\$28,089 for HS grad, -\$106,082 for college) reflect the specification's interaction structure. These coefficients capture husband earnings when the wife marries after first birth (the baseline) and when the husband is at age zero. The large positive age-education interactions (\$1,149/year for HS

grad wives, $5,490/year for college wives) indicate that more-educated women's husbands experience steeper earnings growth. At typical ages (e.g., age 35), college-educated women's husbands earn substantially more than dropout women's husbands, consistent with positive assortative mating. The marriage-timing interactions show that women who marry before first birth (a marker of deliberate family formation) have higher-earning husbands, with this premium larger for more-educated women.

OA.3.5 Retirement income process

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

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

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

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

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

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

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

held constant over all retirement ages.

Social Security replacement rates. To discipline retirement income in the model, I calibrate education-specific replacement rates using Social Security Administration Office of the Chief Actuary replacement-rate statistics (first-year retired-worker benefits as a percent

of wage-indexed career-average earnings). The model does not implement the statutory benefit formula (AIME/PIA) directly; instead, I use these statistics to discipline education-specific multipliers ϕ_e in a reduced-form retirement-income rule. In particular, ϕ_e should be interpreted as a replacement rate relative to late-career earnings in the model, proxied by $\bar{w}_e$, rather than literally relative to wage-indexed career-average earnings.[14]

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

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

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

Appendix 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 118 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

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[14]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.

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

Moment	Data	Model	Moment	Data	Model
Panel A: HS Dropout by Pregnancy Status at Age 14					
No pregnancy	0.070	0.068	Pregnancy	0.290	0.300
Panel B: College Attendance by Pregnancy Status at Age 14					
No pregnancy	0.410	0.408	Pregnancy	0.080	0.073
Panel C: College Attendance by Ability Quartile at Age 18					
Q1 (Low)	0.110	0.112	Q2	0.250	0.303
Q3	0.410	0.423	Q4 (High)	0.670	0.488
Panel D: College Graduation by Pregnancy Status at Age 18					
No pregnancy	0.620	0.615	Pregnancy	0.260	0.251
Panel E: Relative Child Investment by Education					
HS Grad / HS Dropout	1.200	1.972	College Grad / HS Dropout	4.600	3.824

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

Table OA.4. Model Fit: Fraction with Children by Ability Quartile and Age

	Q1 (Low)		Q2		Q3		Q4 (High)	
Age	Data	Model	Data	Model	Data	Model	Data	Model
18	0.381	0.370	0.254	0.271	0.140	0.195	0.068	0.066
22	0.691	0.625	0.540	0.478	0.372	0.368	0.223	0.230
26	0.794	0.766	0.706	0.640	0.534	0.541	0.409	0.424
30	0.838	0.828	0.770	0.712	0.661	0.617	0.591	0.530
34	0.873	0.864	0.822	0.766	0.733	0.676	0.713	0.608
38	0.884	0.890	0.838	0.795	0.759	0.708	0.743	0.654
42	0.885	0.907	0.846	0.824	0.773	0.743	0.748	0.691

Notes: Data moments from NLSY79. Ability quartiles based on AFQT scores. Ages represent end of 4-year periods.

life-cycle patterns that characterize women's decisions regarding education, fertility, marriage, labor supply, and family planning.

Tables OA.3–OA.7 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.

Table OA.5. Model Fit: Fraction Married by Education and Age

	HS Dropout		HS Graduate		College Grad	
Age	Data	Model	Data	Model	Data	Model
22	0.610	0.440	0.683	0.701	—	—
26	0.709	0.797	0.719	0.860	0.744	0.933
30	0.756	0.963	0.579	0.356	0.706	0.639
34	0.760	0.725	0.794	0.787	0.814	0.845
38	0.825	0.885	0.567	0.570	0.721	0.718
42	0.782	0.818	0.807	0.844	0.824	0.869

Notes: Data moments from NLSY79. College graduates enter marriage market at age 22. Ages represent end of 4-year periods.

Table OA.6. Model Fit: Labor Force Participation by Education and Age

	HS Dropout		HS Graduate		College Grad	
Age	Data	Model	Data	Model	Data	Model
18	0.084	0.082	—	—	—	—
22	0.151	0.215	0.196	0.211	—	—
26	0.241	0.188	0.245	0.297	0.243	0.275
30	0.259	0.248	0.258	0.227	0.239	0.233
34	0.206	0.214	0.184	0.168	0.140	0.140
38	0.117	0.170	0.368	0.495	0.492	0.468
42	0.548	0.488	0.557	0.554	0.541	0.548
46	0.532	0.523	0.527	0.517	0.499	0.503
50	0.448	0.506	0.397	0.318	0.291	0.318
54	0.157	0.322	0.686	0.713	0.754	0.698
58	0.705	0.675	0.657	0.664	0.628	0.649
62	0.634	0.629	0.626	0.645	0.607	0.642
66	0.554	0.445	0.422	0.445	0.211	0.451

Notes: Data moments from NLSY79. Labor market entry: HS dropouts age 14, HS graduates age 18, college graduates age 22. Ages represent end of 4-year periods.

Table OA.7. Model Fit: Contraception Use by Education and Age

	HS Dropout		HS Graduate		College Grad	
Age	Data	Model	Data	Model	Data	Model
22	0.726	0.529	0.792	0.665	0.880	1.000
26	0.508	0.425	0.733	0.462	0.773	1.000
30	0.409	0.377	0.648	0.515	0.744	1.000
34	0.320	0.365	0.535	0.513	0.661	1.000
38	0.259	0.278	0.465	0.463	0.579	0.658
42	0.203	0.205	0.417	0.412	0.481	0.660

Notes: Data moments from NLSY79. Contraception measured among sexually active, non-pregnant women. Ages represent end of 4-year periods.

Appendix OA.5 Estimated Structural Parameters

This appendix reports the structural parameters estimated by Simulated Method of Moments (SMM) across the three nested model specifications used in the fit decomposition of Section 6.2. The *Baseline* model imposes no heterogeneity in fertility risk across education or cognitive ability (42 parameters). The *+ Educ. Het.* specification allows baseline conception odds $\lambda_h(g, e)$ to vary by education group (48 parameters). The *+ Ab. Cont.* specification—the full model—additionally allows contraceptive effort effectiveness $\eta_{\theta,g}$ to vary by cognitive ability quartile and age group (60 parameters). "–" denotes parameters restricted to zero or not separately identified in that specification; $\Delta\eta$ increments are additive deviations from the Q1 baseline.

Appendix OA.6 Computational Appendix

This appendix documents the numerical solution, simulation, and estimation procedures. The model is a finite-horizon discrete-time dynamic programming problem with both continuous (assets) and discrete (education, marital status, fertility) state variables. I solve the model by backward induction, using different numerical methods at different life stages depending on the structure of the within-period problem. The estimation uses the simulated method of moments (SMM), with a global optimization algorithm to search over the parameter space.

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

Table OA.8. Estimated Structural Parameters: Nested Model Specifications

Parameter	Description	Baseline	+ Educ. Het.	+ Ab. Cont.
Panel A: Baseline Conception Odds $\lambda_h(g,e)$				
$\lambda_{1,\text{HSD}}$	Ages 14–22, HSD	4.823	4.725	2.000
$\lambda_{1,\text{HS}}$	Ages 14–22, HS	–	1.403	1.417
$\lambda_{1,\text{Col}}$	Ages 14–22, College	–	1.192	0.172
$\lambda_{2,\text{HSD}}$	Ages 22–30, HSD	2.739	3.000	0.698
$\lambda_{2,\text{HS}}$	Ages 22–30, HS	–	1.037	1.104
$\lambda_{2,\text{Col}}$	Ages 22–30, College	–	0.393	1.243
$\lambda_{3,\text{HSD}}$	Ages 30–38, HSD	1.371	1.346	0.003
$\lambda_{3,\text{HS}}$	Ages 30–38, HS	–	0.544	0.550
$\lambda_{3,\text{Col}}$	Ages 30–38, College	–	0.674	0.297
Panel B: Contraceptive Effectiveness $\eta_{\theta,g}$				
$\eta_{Q1,g1}$	Q1, Ages 14–22	1.000	1.000	0.841
$\eta_{Q1,g2}$	Q1, Ages 22–30	1.000	1.000	7.916
$\eta_{Q1,g3}$	Q1, Ages 30–38	1.000	1.000	0.501
$\Delta\eta_{Q2,g1}$	Q2 incr., Ages 14–22	–	–	0.111
$\Delta\eta_{Q3,g1}$	Q3 incr., Ages 14–22	–	–	0.287
$\Delta\eta_{Q4,g1}$	Q4 incr., Ages 14–22	–	–	1.688
$\Delta\eta_{Q2,g2}$	Q2 incr., Ages 22–30	–	–	0.864
$\Delta\eta_{Q3,g2}$	Q3 incr., Ages 22–30	–	–	3.680
$\Delta\eta_{Q4,g2}$	Q4 incr., Ages 22–30	–	–	6.422
$\Delta\eta_{Q2,g3}$	Q2 incr., Ages 30–38	–	–	0.053
$\Delta\eta_{Q3,g3}$	Q3 incr., Ages 30–38	–	–	2.216
$\Delta\eta_{Q4,g3}$	Q4 incr., Ages 30–38	–	–	4.789
Panel C: Marriage Meeting Probabilities $\mu(e,g)$				
$\mu_{\text{HSD},g1}$	HSD, Ages 18–22	−0.232	−0.001	0.430
$\mu_{\text{HS},g1}$	HS, Ages 18–22	−0.188	−0.188	0.452
$\mu_{\text{Col},g1}$	College, Ages 22	−0.027	−0.034	0.590
$\mu_{\text{HSD},g2}$	HSD, Ages 26–30	0.416	0.191	0.305
$\mu_{\text{HS},g2}$	HS, Ages 26–30	−0.490	−0.461	0.234
$\mu_{\text{Col},g2}$	College, Ages 26–30	−0.415	−0.439	0.377
$\mu_{\text{HSD},g3}$	HSD, Ages 34–38	0.066	0.114	0.464
$\mu_{\text{HS},g3}$	HS, Ages 34–38	−0.470	−0.475	0.268
$\mu_{\text{Col},g3}$	College, Ages 34–38	0.451	0.442	0.132
Panel D: Child Utility and Cost Parameters				
ω_0	Utility baseline	−0.232	−0.001	−0.048
ω_1	Utility scale	0.416	0.191	0.166
ω_2	Utility curvature	0.066	0.114	0.019
ϕ_k^{HSD}	Cost shifter, HSD	−0.188	−0.188	−0.135
ϕ_k^{HS}	Cost shifter, HS	−0.490	−0.461	−0.387
ϕ_k^{BA}	Cost shifter, College	−0.470	−0.475	−0.484
ϕ_{grad}	Graduation cost	−0.027	−0.034	−0.475
ξ_{cf}	Cognitive college cost	−0.415	−0.439	−0.528
ω_{ch}	Cognitive convexity	0.312	0.298	1.298
Panel E: Education Subsidies				
	HS allowance	24.9	24.6	54.6
	College allowance	76.3	76.3	119.8
Panel F: Labor Supply Parameters				
ψ_ℓ (avg.)	Ages 14–26	0.408	0.417	−0.013
ψ_ℓ (avg.)	Ages 30–50	−0.010	−0.011	−0.007
ψ_ℓ (avg.)	Ages 54–62	−0.006	−0.007	−0.014
$\psi_{\ell k,1}$	Labor disutil., HSD	−0.008	−0.008	−0.274
$\psi_{\ell k,2}$	Labor disutil., HS	−0.878	−1.638	−0.656
$\psi_{\ell k,3}$	Labor disutil., College	−0.869	−1.231	−0.000
$\phi_{nk,1}$	Terminal util., HSD	−0.790	−1.659	0.112
$\phi_{nk,2}$	Terminal util., HS	0.281	0.268	0.094
$\phi_{nk,3}$	Terminal util., College	0.221	0.251	0.347
Panel G: Shock Standard Deviations				
σ_ℓ	Labor supply	0.229	0.233	0.010
σ_c (avg.)	Child-related	0.173	0.176	0.239
# parameters Estimated		42	48	60

Notes: HSD = high school dropout; HS = high school graduate; Col = college graduate. *Baseline*: no heterogeneity in fertility risk. *+ Educ. Het.*: adds education-specific $\lambda_h(g,e)$. *+ Ab. Cont.*: full model with ability-varying $\eta_{\theta,g}$. $\Delta\eta$ = additive increment from Q1 baseline. "–" = restricted or not identified.

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

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

Thus, the child-related equivalence-scale term ϕ_{ck} enters the budget constraint only in the birth period ($k_t = 2$), consistent with the "one-period child in the household" assumption.

After the birth period, the state moves from $k_t = 2$ to $k_{t+1} = 3$ (child has left the household), so that $\mathbf{1}\{k_{t+1} = 2\} = 0$ in all subsequent periods.

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

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

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

The stage-3 budget constraint is

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

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

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

The first-order condition equates marginal utility per dollar:

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

Solution method. Given a_{t+1}, the budget constraint implies $c_t \cdot \text{den} + i_t = \text{available}$, where 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 $\omega_2 < 1$.

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

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

with an interior FOC $p_t'(s_t) \left(V_t^{\text{birth}} - V_t^{\text{nobirth}}\right) = \phi_s$. 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:

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

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 $(T - T_R - T_{NF} < t \le T - T_R)$, solved by DC-EGM; (iii) fertile ages $(t \le T - T_R - T_{NF})$, solved by VFI with grid search (plus analytical or one-dimensional inner problems for i_t and s_t).

The rationale for this partition is computational efficiency. In retirement, there is no labor-leisure choice and the problem reduces to a standard consumption-saving model, for

which EGM is highly efficient. In non-fertile working ages, the discrete labor choice intro-
duces non-convexities that can generate discontinuous policy functions; DC-EGM handles this
by computing choice-specific consumption functions via EGM and then applying an upper-
envelope algorithm to recover the global optimum. In fertile ages, the additional discrete
margins (marriage, contraception, schooling) and the multi-stage within-period structure
make DC-EGM less practical, so the code reverts to grid search with analytical solutions for
the continuous sub-problems.

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).

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

I estimate the model using the simulated method of moments (SMM). SMM chooses parameters to minimize the distance between moments computed from simulated model output and their empirical counterparts.

Target moments and loss function. Let $m^{\text{data}} \in \mathbb{R}^{118}$ denote the vector of empirical moments and $m(\vartheta) \in \mathbb{R}^{118}$ the simulated moments under parameter vector ϑ. The SMM loss function is

$$\mathcal{L}(\vartheta) = \sum_{j=1}^{118} w_j \left(\frac{m_j(\vartheta) - m_j^{\text{data}}}{m_j(\vartheta) + 0.01} \right)^2,$$

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).

Choice of moments. The 118 target moments include: (i) fertility outcomes by age, education, and ability (pregnancy rates, birth timing, births out of wedlock); (ii) labor supply by age, education, and maternal status; (iii) marriage rates and timing; (iv) educational attainment by ability; and (v) wage profiles by education and experience.

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`). Differential evolution is a derivative-free global optimizer well suited to non-convex, high-dimensional problems where the objective function is noisy or discontinuous. It maintains a population of candidate solutions and iteratively improves them through mutation, crossover, and selection operations. 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 Computational performance and implementation

Hardware and software. Estimation was performed on a high-performance computing cluster with Intel Xeon Gold 6248R processors (48 cores per node, 3.0 GHz base frequency). The code is implemented in Julia 1.9.3, leveraging multithreading for EGM/DC-EGM steps

and distributed parallelism for calibration. Key packages: `Interpolations.jl` (v0.14), `BlackBoxOptim.jl` (v0.6), `Distributed.jl` (standard library).

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

- *VFI (backward induction):* ~15–20 seconds (30 asset grid points)

- *Simulation (10,000 agents):* ~8–12 seconds

- *Total (solve + simulate + moments):* ~25–35 seconds per parameter vector

Calibration runtime. The SMM estimation uses differential evolution (`de_rand_1_bin`) with 47 parallel workers, each running independent searches from perturbed starting values. Total calibration time: approximately 8,064 CPU-hours (168 hours wall-clock time with 48 cores). The algorithm evaluates approximately 420,000 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

- *Memory:* Peak usage ~8GB per worker (solution), ~2GB (simulation)

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

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

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