College as a Commitment Device: Parental Altruism and the Samaritan's Dilemma*

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Abstract

Why do parents invest so much in their children's college education? I propose that college serves as a commitment device for altruistic parents facing a Samaritan's dilemma. In a dynastic model where parents and adult children interact non-cooperatively, children who anticipate parental support under-save and over-consume. College mitigates this problem from the parent's perspective: by permanently raising the child's income and making shocks less persistent, it shrinks the set of states where parents optimally transfer, reducing the lifetime costs of moral hazard. However, the net effect on college attendance is theoretically ambiguous: anticipated transfers subsidize enrollment, raising attendance, but also cushion non-college children against income risk, reducing their incentive to invest in human capital. I document four facts from matched parent-child data (PSID and HRS) consistent with this mechanism: parents whose children attend college consume 8% more, accumulate wealth differently, face a substantially weaker precautionary saving motive, yet transfer only modestly less—suggesting that the option value of forgone transfers, rather than realized transfer flows, drives parental behavior. The structural model, estimated by the simulated method of moments, quantifies these opposing forces and shows that the sign of the moral hazard effect on college varies across the ability–wealth distribution.

JEL: D15, D64, I22, I23
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1 Introduction

Parents play a central role in financing college education in the United States. In 2017, federal and state governments spent $248 billion on student aid, yet the average household with two dependent children was still expected to contribute $6,500 per child annually.[1] Perhaps as a consequence, holding cognitive ability constant, children from the wealthiest families are far more likely to graduate from college than children from the poorest families (Belley and Lochner, 2007; Brown et al., 2012). Borrowing constraints are part of the explanation (Lochner and Monge-Naranjo, 2011), but they cannot fully account for the gradient: even among children with access to financial aid and student loans, parental wealth remains a strong predictor of college completion (Carneiro and Heckman, 2002; Belley and Lochner, 2007). This paper proposes an additional channel rooted in moral hazard. When parents are altruistic and cannot commit to withholding future support, college serves as a commitment device: it permanently raises the child's income, shrinking the set of states in which parents would optimally transfer resources, and thereby reducing the lifetime costs of the Samaritan's dilemma.

The mechanism rests on a classical insight (Buchanan, 1975; Lindbeck and Weibull, 1988). Altruistic parents who cannot credibly refuse transfers create an incentive for their children to under-save and over-consume, anticipating parental support when times are bad. This strategic response forces parents into more frequent and larger transfers than they would make under commitment—the Samaritan's dilemma. From the parent's perspective, college mitigates this problem: by permanently raising the child's earnings and making income shocks less persistent, college shifts the child away from the *transfer region*—the set of states where parental support is triggered. A dollar of tuition is therefore more efficient than a dollar transferred directly: tuition generates a permanent change in the child's income, while a direct transfer provides temporary relief and may itself exacerbate moral hazard by rewarding under-saving. The net effect on college attendance, however, is theoretically ambiguous. The Samaritan's dilemma creates two opposing forces on the child's education decision: anticipated transfers during the college years subsidize enrollment, but anticipated lifetime transfers also cushion children who forgo college, reducing their need to invest in

[1] See College Board, *Trends in Student Aid 2019*; Forbes, *2017 Guide to College Financial Aid.*

human capital. The structural model quantifies these forces and shows that the sign of the moral hazard effect varies across the ability–wealth distribution.

I formalize this mechanism in a dynastic model in which altruistic parents and their children interact non-cooperatively over a finite overlap period, building on Barczyk and Kredler (2014a,b) and Boar (2021). Parents choose consumption and a non-negative transfer flow; children choose consumption and, at the start of the dynasty, whether to attend college. In equilibrium, the state space is partitioned into a transfer region, where parents actively support their children, and a no-transfer region, where the child is self-sufficient. The boundary between these regions is determined endogenously as part of the equilibrium. College is an endogenous, irreversible investment that permanently raises the child's expected earnings and makes income shocks less persistent, shrinking the transfer region. The college decision thus depends not only on the human capital return but also on the parent's desire to reduce the likelihood of having to support the child in the future.

I estimate the model by the simulated method of moments, targeting college enrollment rates by ability and wealth, the college premium, transfer patterns, and intergenerational wealth dynamics from the NLSY97 and PSID.

I document four descriptive facts from the Panel Study of Income Dynamics (PSID) and the Health and Retirement Study (HRS) that are consistent with the model's predictions. Throughout, I compare parents whose children attended college with parents whose children did not, conditioning on parent income to isolate the role of child education from parental resources. *First*, parent consumption is 8% higher when children attend college—consistent with college shrinking the transfer region and releasing precautionary resources. *Second*, parent wealth paths diverge by child college status: an initial reduction from tuition costs is followed by slower wealth decumulation, consistent with reduced lifetime transfer obligations. *Third*, adapting the framework of Boar (2021), I show that college nearly eliminates dynastic precautionary saving: the negative effect of child income uncertainty on parent consumption falls by over 90% for college-educated children. *Fourth*, college-educated children receive modestly fewer transfers from their parents. However, inter-vivos transfers are notoriously difficult to measure in survey data and are typically underreported (McGarry, 1999), so the magnitude of this differential should be interpreted with caution.

The paper makes three contributions. First, I develop a dynastic model that distinguishes college's role as a commitment device—reducing the moral hazard costs of the Samaritan's dilemma—from its standard human capital return, and show that the Samaritan's dilemma generates two opposing forces on college attendance whose net effect is theoretically ambiguous. The model generates sharp, testable predictions about how college alters transfers, consumption, and wealth accumulation within the family. Second, I provide descriptive evidence that, conditional on parent income, college attendance is associated with systematic differences in transfers, consumption, and wealth between parents and adult children. Third, I quantify the role of parental altruism and the moral hazard it generates in shaping the wealth gradient in college attainment, showing that the sign of the moral hazard effect varies across the ability–wealth distribution, with implications for the design of financial aid and college subsidies.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the model. Section 4 documents the four descriptive facts. Section 5 describes the estimation strategy. Section 6 discusses the model fit and the role of parental altruism. Section 7 introduces the full commitment benchmark, formalizes the two opposing forces of moral hazard on college, and presents the quantitative decomposition. Section 8 concludes.

2 Related Literature

This paper connects four strands of the literature: intergenerational transfers and family insurance, the determinants of college attainment, dynastic models with strategic interaction, and the Samaritan's dilemma.

Intergenerational transfers and family insurance. The modern literature on intergenerational transfers builds on the foundational models of Becker and Tomes (1979, 1986), who study how altruistic parents invest in children's human capital and transmit economic status across generations. Two broad motives for transfers have been proposed: altruism, supported by evidence that transfers flow disproportionately to less well-off children (McGarry, 1999, 2016), and strategic exchange, as in Bernheim et al. (1985). The seminal tests of Altonji et al. (1992) and Hayashi et al. (1996) reject perfect insurance within the extended family, but more recent work by Attanasio et al. (2018) finds substantial insurance potential between parents and adult children. Kaplan (2012) shows that the option to move back home provides insurance against labor market risk. Boar (2021) identifies a novel channel—dynastic precautionary savings—showing that parents accumulate wealth to insure their children against permanent income uncertainty. I build directly on her framework, extending it to test whether college education attenuates the dynastic precautionary motive.

Determinants of college attainment. The role of financial constraints in college attendance has been debated extensively. Early work by Cameron and Heckman (1998) and Keane and Wolpin (2001) found that, conditional on ability, family income played a small role, suggesting that constraints were not binding. More recently, Belley and Lochner (2007) document a growing importance of family resources in the 2000s, and Lochner and Monge-Naranjo (2011) provide evidence of binding credit constraints for some students. Heckman and Mosso (2014) provide a comprehensive review of the human capital formation literature, emphasizing how family environments shape skill development and educational outcomes. On the quantitative side, Restuccia and Urrutia (2004) study how parental investments in early and college education drive intergenerational earnings persistence, and Caucutt and Lochner (2020) analyze the interaction between borrowing constraints and the timing of human capital investments within the family. Abbott et al. (2019) develop a general equilibrium model with parental transfers and show that crowding out of private transfers by government aid is quantitatively important. My paper complements this literature by providing a mechanism—moral hazard reduction—through which parental wealth affects college enrollment beyond direct cost subsidies and paternalism.

Dynastic models with strategic interaction. The quantitative literature on family dynamics without commitment builds on the pioneering work of Laitner (1988) and Lindbeck and Weibull (1988). Nishiyama (2002) studies how bequests and inter-vivos transfers jointly shape the wealth distribution in an OLG model with altruistic links. Lee and Seshadri (2019) develop a dynastic model with parental investments in children's human capital to study the intergenerational transmission of economic status. Barczyk and Kredler (2014a,b) develop the framework I adopt, in which parents and children simultaneously choose consumption and transfers without commitment, and characterize the equilibrium transfer region. Barczyk and Kredler (2018) and Barczyk et al. (2019) apply this framework to long-term care and housing decisions. My contribution is to embed endogenous college decisions into this class of models, allowing me to study how the transfer region—and the moral hazard it generates—interacts with education choice.

The Samaritan's dilemma. The Samaritan's dilemma, formalized by Buchanan (1975) and analyzed in dynamic settings by Lindbeck and Weibull (1988) and Bruce and Waldman (1990), arises when an altruistic agent cannot commit to withholding support. Coate (1995) studies how government transfer policy interacts with private altruistic transfers under this dilemma. The anticipation of future transfers distorts the recipient's behavior. In my model, this distortion takes the form of strategic under-saving by the child, which raises the parent's lifetime transfer costs. College mitigates the dilemma by permanently shifting the child's income, reducing the frequency with which the child enters the transfer region.

3 Model

This section presents a continuous-time, non-cooperative dynastic model without commitment that captures the interactions between altruistic parents and their adult children. The model extends the framework of Barczyk and Kredler (2014a,b) by incorporating endogenous college decisions, allowing me to study how family transfers affect college financial support, graduation, and parent retirement consumption. I first describe the demographic structure and income processes, then present the coupled parent-child optimization problem, the transfer variational inequality, and the college decision.

3.1 Demographics and Timing

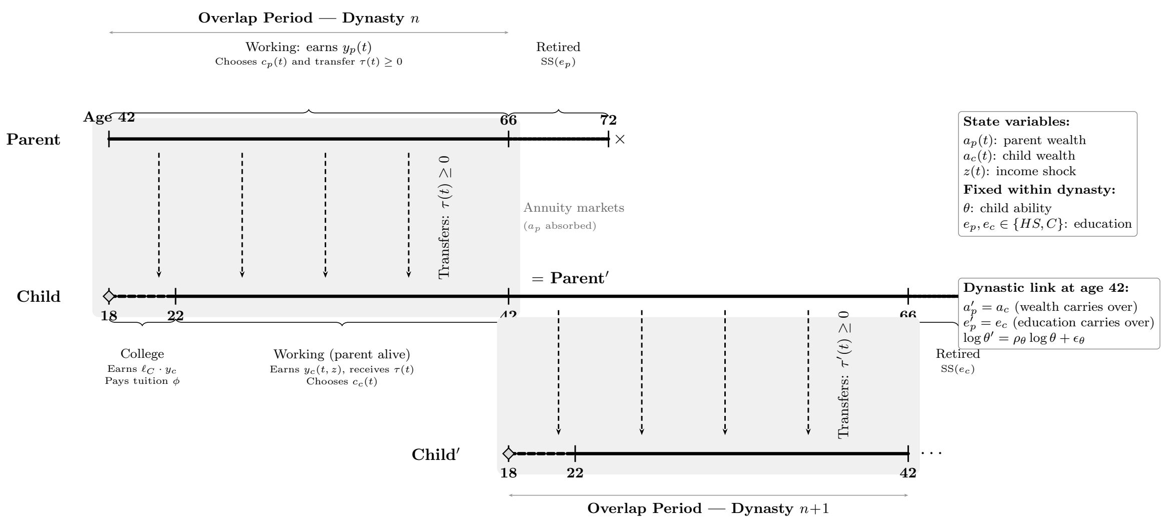
Time is continuous. Each dynasty consists of one parent and one child who overlap for a finite period, as illustrated in Figure 1. The child enters the model at age 18, at which point the parent is 42. During the overlap period (child ages 18–42, parent ages 42–66), the parent can continuously transfer resources to the child. At age 66, the parent retires and receives social security income $\mathrm{SS}(e_p)$ until death at age 72. Following Abbott et al. (2019), the parent purchases actuarially fair annuities during retirement: remaining parent wealth at death is absorbed by the annuity market rather than bequeathed to the child.[2] The child then continues alone until their own retirement at 66 and death at 72.

At the beginning of the dynasty, the child makes a one-time, irreversible college decision. Children who attend college spend four years (ages 18–22) earning a fraction ℓ_C of full-time income while paying annual tuition ϕ. After college, the child enters the labor force with a permanently higher income process. Children who do not attend college enter the labor market immediately at age 18.

Both parent and child can save in a risk-free bond paying interest rate r. Markets are incomplete: no state-contingent insurance is available against the child's income risk. The parent and child are connected only through the transfer flow during the overlap period. Inter-vivos transfers are the sole channel of intergenerational resource transmission, as in Lee and Seshadri (2019).

[2]This assumption, standard in the dynastic PE literature (Barczyk and Kredler, 2018; Boar, 2021), prevents explosive intergenerational wealth accumulation in partial equilibrium. The warm-glow motive ϕ_b still disciplines wealth decumulation by giving the parent utility from terminal wealth, even though the wealth itself does not transfer.

Figure 1. Dynasty Timeline



Notes: Life-cycle structure of a dynasty. The parent (top) and child (bottom) overlap for 24 years (child ages 18–42, parent ages 42–66). The shaded region indicates the overlap period during which transfers $\tau(t)$ flow from parent to child. Dashed arrows represent the transfer flow. The dashed segment on the child timeline denotes the college phase (ages 18–22). Remaining parent wealth at death is absorbed by actuarially fair annuities and does not transfer to the child. The lower portion illustrates the dynastic link: when the overlap period ends, the child becomes the parent of a new dynasty, carrying forward their accumulated wealth ($a_p' = a_c$), education ($e_p' = e_c$), and transmitting ability to the next generation via an AR(1) process.

3.2 State Variables and Income Processes

The state of a dynasty at any instant t during the overlap phase is $(a_p(t), a_c(t), z(t); \theta, e_p, e_c)$, where a_p and a_c are parent and child wealth, z is a stochastic productivity shock, θ is the child's cognitive ability, and $e_p, e_c \in \{HS, C\}$ denote the education levels of parent and child.

Child income. The child's labor income at time t is:

$$y_c(t) = w \cdot \theta^{\lambda_{e_c}} \cdot \exp\big(\gamma(t, e_c) + z(t)\big)$$

where $h(\theta, e_c) = \theta^{\lambda_{e_c}}$ maps ability into human capital with an education-specific ability gradient λ_{e_c}, following Abbott et al. (2019). The gradient $\lambda_C > \lambda_{HS}$ implies that cognitive ability and college education are complements: higher-ability individuals benefit more from college. The deterministic age-income profile $\gamma(t, e_c) = \gamma_{1,e}\, t - \gamma_{2,e}\, t^2$ is estimated from the PSID, and $z(t)$ follows an Ornstein-Uhlenbeck process:

$$dz = -\kappa_{e_c}\, z\, dt + \sigma_{e_c}\, dW$$

with education-specific mean-reversion rate κ_{e_c} and volatility σ_{e_c}. The OU specification implies that income shocks are persistent but mean-reverting. College graduates have faster mean-reversion ($\kappa_C > \kappa_{HS}$), so negative shocks fade more quickly—a feature that is both empirically documented (Meghir and Pistaferri, 2004) and central to the mechanism. During college ($t \in [0, 4]$ for $e_c = C$), child income is reduced to a fraction ℓ_C of full-time earnings, reflecting part-time work while enrolled.

Parent income. Parent income is deterministic and depends on education and age: $y_p(t) = w \cdot \theta_p^{\lambda_{e_p}} \cdot \exp(\gamma(t, e_p))$ before retirement, and $y_p(t) = \mathrm{SS}(e_p)$ after retirement at age 66. Making parent income deterministic focuses the analysis on the child's income risk as the driver of transfers.

Ability transmission. Cognitive ability is transmitted across generations through a log-normal AR(1) process: $\log \theta' = \rho_\theta \log \theta + \epsilon_\theta$, with $\epsilon_\theta \sim N(0, \sigma_\theta^2)$. This generates realistic intergenerational persistence in ability while allowing for regression to the mean.

3.3 The Coupled Parent-Child Problem

During the overlap period, parent and child simultaneously choose consumption and savings, while the parent additionally chooses a non-negative transfer flow $\tau(t) \geq 0$. The interaction is non-cooperative: each agent optimizes taking the other's policy as given, but the parent internalizes the child's welfare through the altruism parameter $\eta > 0$.

The continuous-time formulation follows Barczyk and Kredler (2014a), who show that simultaneity of moves in continuous time yields a well-defined equilibrium—an advantage over discrete-time formulations where the timing protocol (who moves first within a period) can affect the equilibrium outcome.

3.3.1 Parent's Problem

The parent chooses consumption c_p and transfer flow $\tau \geq 0$ to maximize lifetime utility, weighting the child's instantaneous utility by η. The parent's value function $V^p(a_p, a_c, z; t)$ satisfies:

$$\rho V^p = \max_{c_p,\, \tau \geq 0} \Big\{ u(c_p) + \eta\, u(c_c^*) + V^p_{a_p}[r a_p + y_p - c_p - \tau] \\ + V^p_{a_c}[r a_c + y_c - c_c^* + \tau] + V^p_z(-\kappa z) + \tfrac{1}{2}\sigma^2 V^p_{zz} + V^p_t \Big\} \tag{1}$$

where ρ is the continuous-time discount rate, $u(c) = c^{1-\gamma}/(1-\gamma)$ is CRRA utility with $\gamma = 1.5$, and c_c^* is the child's equilibrium consumption policy, taken as given by the parent. The terms involving V^p_z and V^p_{zz} capture the effect of income uncertainty on the parent's value function.

3.3.2 Child's Problem

The child chooses consumption c_c to maximize own lifetime utility:

$$\rho V^c = \max_{c_c} \Big\{ u(c_c) + V^c_{a_c}[r a_c + y_c - c_c + \tau^*] \\ + V^c_{a_p}\left[r a_p + y_p - c_p^* - \tau^*\right] + V^c_z(-\kappa z) + \tfrac{1}{2}\sigma^2 V^c_{zz} + V^c_t \Big\} \tag{2}$$

where τ^* and c_p^* are the parent's equilibrium policies, taken as given. The child tracks parent wealth a_p because it affects expected future transfers: wealthier parents are more likely to provide support.

3.3.3 Transfer Decision

The parent's optimal transfer is characterized by a complementarity condition:

$$\tau^* \geq 0, \quad V^p_{a_p} \geq V^p_{a_c}, \quad \tau^*\Big(V^p_{a_p} - V^p_{a_c}\Big) = 0 \tag{3}$$

This partitions the state space into two regions. In the *no-transfer region* ($\mathcal{N}$), the parent's marginal value of own wealth exceeds the marginal value of child wealth ($V^p_{a_p} > V^p_{a_c}$), and

$\tau^* = 0$. In the *transfer region* ($\mathcal{T}$), these marginal values are equalized ($V^p_{a_p} = V^p_{a_c}$) and $\tau^* > 0$. The boundary between $\mathcal{N}$ and $\mathcal{T}$ is a free boundary, endogenously determined as part of the equilibrium. The parent transfers when the child is relatively poor (low a_c), faces negative productivity shocks (low z), or when the parent is relatively wealthy (high a_p).

This variational inequality is the continuous-time analog of the transfer decision in discrete-time dynastic models, but with two key advantages. First, transfers are a continuous flow rather than lump-sum payments, eliminating the timing discreteness that affects transfer amounts in discrete models. Second, the free boundary provides a clean characterization of the states where moral hazard is operative.

3.3.4 Consumption Policies and Wealth Dynamics

The first-order conditions for consumption are:

$$u'(c_p^*) = V^p_{a_p}, \tag{4}$$

$$u'(c_c^*) = V^c_{a_c}. \tag{5}$$

Under CRRA utility, these invert to $c_p^* = (V^p_{a_p})^{-1/\gamma}$ and $c_c^* = (V^c_{a_c})^{-1/\gamma}$. Wealth evolves as:

$$\dot{a}_p = ra_p + y_p(t) - c_p - \tau, \tag{6}$$

$$\dot{a}_c = ra_c + y_c(t,z) - c_c + \tau, \tag{7}$$

with non-negativity constraints $a_p \geq 0$ and $a_c \geq 0$ (the latter modified during college to allow student borrowing; see Section 3.7).

3.4 Child-Alone Problem and the Dynastic Link

When the overlap period ends (parent age 66, child age 42), the child solves a consumption-savings problem with their own accumulated wealth for the remainder of their working life:

$$\rho V^{c,\text{alone}} = \max_{c_c} \left\{ u(c_c) + V^{c,\text{alone}}_{a_c}[ra_c + y_c(t,z) - c_c] + V^{c,\text{alone}}_z(-\kappa z) + \tfrac{1}{2}\sigma^2 V^{c,\text{alone}}_{zz} + V^{c,\text{alone}}_t \right\} \tag{8}$$

At this point, the child becomes a parent in a new dynasty: their own child is born with ability θ' drawn from the intergenerational transmission process (Section 3), and the new parent-child pair solves the coupled problem described above. The child's accumulated wealth a_c at the end of the overlap period becomes the initial parent wealth a_p for the new dynasty. The solution of (8) at $t = 0$ provides the terminal condition for the coupled system.

3.5 Terminal Conditions

At parent death ($t = T$), the boundary conditions are:

$$V^p(a_p, a_c, z; T) = \frac{u\big(ra_p + \mathrm{SS}(e_p) + \delta a_p\big)}{\rho} + \phi_b \frac{a_p^{1-\gamma}}{1-\gamma} + \eta \cdot V^{c,\text{alone}}(a_c, z; 0), \tag{9}$$

$$V^c(a_p, a_c, z; T) = V^{c,\text{alone}}(a_c, z; 0), \tag{10}$$

where δ is an annuitization rate and $\phi_b \geq 0$ is a warm-glow weight that captures the parent's direct utility from terminal wealth, following De Nardi (2004). Crucially, the child's continuation value $V^{c,\text{alone}}$ is evaluated at a_c—the child's own accumulated wealth—not at $a_c + a_p$, because remaining parent wealth is absorbed by the annuity market at death. The warm-glow component $\phi_b\, u(a_p)$ nevertheless gives the parent an incentive to hold wealth through retirement, disciplining the model's wealth decumulation rate. The altruistic component $\eta \cdot V^{c,\text{alone}}(a_c, z)$ motivates inter-vivos transfers during the overlap period, since higher child wealth a_c at parent death improves the child's continuation.

3.6 College Decision

At the beginning of the dynasty ($t = 0$), the child decides whether to attend college. I model this as a logit choice. Let V_C and V_{HS} denote the child's equilibrium continuation values under college and high school, evaluated at the initial state $(a_p, a_c = 0, z = 0)$:

$$V_C \equiv V^c(a_p, 0, 0;\, 0 \mid e_c = C), \qquad V_{HS} \equiv V^c(a_p, 0, 0;\, 0 \mid e_c = HS).$$

The probability of attending college is:

$$\Pr(e_c = C) = \frac{\exp\big[(V_C - \psi(\theta))/\sigma_{cd}\big]}{\exp\big[(V_C - \psi(\theta))/\sigma_{cd}\big] + \exp\big[V_{HS}/\sigma_{cd}\big]} \tag{11}$$

where $\psi(\theta) = \omega_{c_1}/\theta^{\omega_{c_2}}$ is the psychic cost of college, decreasing in ability (following Cunha et al. 2005 and Heckman et al. 2006), and σ_{cd} is the scale parameter of the Type-I extreme value taste shock.

The college decision is endogenous in two senses. First, parental altruism affects the child's continuation value: parents who anticipate supporting their child during and after college raise the value of attending. Second, the continuation values under $e_c = C$ and $e_c = HS$ incorporate the entire future trajectory of transfers, which depends on the child's income path and hence on education. This creates a channel through which parent wealth affects college enrollment beyond the direct cost channel. Importantly, anticipated transfers affect both V_C and V_{HS}: transfers subsidize college enrollment (raising V_C) but also cushion non-college children against income risk (raising V_{HS}). The net effect of the Samaritan's dilemma on the college decision is therefore theoretically ambiguous; Section 7.2 formalizes this result.

3.7 College Financial System

I model the college financial system following Abbott et al. (2019). The gross annual cost of attending college is ϕ = \$12,200, based on average tuition reported in the NLSY97. During college, students work a fraction $\ell_C = 0.56$ of full-time hours.

Students are classified into three financial aid types $q \in \{1, 2, 3\}$ based on parental wealth:

$$q(a_p) = \begin{cases} 1 & \text{if } a_p < \bar{a}_1 \quad \text{(subsidized loans + full grants)} \\ 2 & \text{if } \bar{a}_1 \leq a_p < \bar{a}_2 \quad \text{(unsubsidized loans + partial grants)} \\ 3 & \text{if } a_p \geq \bar{a}_2 \quad \text{(private loans, minimal grants)} \end{cases}$$

where the thresholds $\bar{a}_1$ and $\bar{a}_2$ are calibrated to NCES data on financial aid eligibility. The government provides annual need-based grants $g(q)$, with $g(1)$ = \$2,820, $g(2)$ = \$670, and $g(3)$ = \$140, reflecting the structure of Federal Pell Grants and state need-based aid.

During college, students can borrow up to a cumulative limit $\bar{b}(q)$ at interest rates that vary by aid type: subsidized rates for $q = 1$ students, unsubsidized federal rates for $q = 2$, and private loan rates for $q = 3$. This is implemented by allowing $a_c \geq -\bar{b}(q)$ during $t \in [0, 4]$, with the standard constraint $a_c \geq 0$ after graduation. The child's wealth dynamics during college become:

$$\dot{a}_c = r_s(q) \cdot a_c + \ell_C \cdot y_c(t, z) - c_c - \phi_{\text{net}}(q) + \tau, \qquad a_c \geq -\bar{b}(q)$$

where $\phi_{\text{net}}(q) = \phi - g(q)$ is net tuition and $r_s(q)$ is the student interest rate.

This system generates heterogeneity in the effective cost of college across the wealth distribution. Students from low-wealth families face lower net tuition through grants but have limited borrowing capacity. Parental transfers supplement institutional aid, and as Abbott et al. (2019) document, government grants can crowd out private contributions.

3.8 Equilibrium

A Markov-Perfect Equilibrium (MPE) consists of value functions V^p, V^c, consumption policies c_p^*, c_c^*, a transfer policy τ^*, and a college enrollment rule e_c^*, for each (θ, e_p, e_c) pair, such that: (i) given c_c^* and τ^*, the parent's HJB (1) and the variational inequality (3) are satisfied; (ii) given c_p^* and τ^*, the child's HJB (2) is satisfied; (iii) after parent death, $V^{c,\text{alone}}$ satisfies (8); (iv) the college rule follows from (11); and (v) boundary conditions (9)–(10) and borrowing constraints hold at all times.

The equilibrium is solved backward: first the child-alone problem, then the coupled system during the overlap period, and finally the college choice at $t = 0$. Within the coupled system, the transfer region and consumption policies are determined jointly through policy iteration on the variational inequality. Appendix H derives the equilibrium properties, including the Samaritan's dilemma distortion in continuous time, and Appendix I describes the numerical solution algorithm.

3.9 Model Predictions: How College Affects the Transfer Region

The model generates predictions about how college alters the financial relationship between parents and adult children. The central mechanism operates through the transfer region $\mathcal{T}$—

the set of states where the parent optimally transfers resources to the child. College education shifts the boundary of this region, and the consequences propagate to consumption, wealth, and precautionary behavior.

Why college shrinks the transfer region. Recall that the parent transfers when the marginal value of own wealth equals the marginal value of child wealth ($V^p_{a_p} = V^p_{a_c}$). Because the parent weighs the child's utility by η in the objective (1), $V^p_{a_c}$ is increasing in η: more altruistic parents have a larger transfer region. This condition is more likely to bind when the child is relatively poor or faces negative income shocks. College raises the child's expected income through two channels: a higher ability gradient ($\lambda_C > \lambda_{HS}$) and a steeper life-cycle earnings profile. The resulting increase in child wealth pushes states away from the transfer boundary, so college-educated children spend less time in $\mathcal{T}$. In addition, college income shocks mean-revert faster ($\kappa_C > \kappa_{HS}$), so negative shocks are less persistent and less likely to push the child back into the transfer region. Together, these forces shrink $\mathcal{T}$ for college-educated children relative to high-school-educated children.

Figure 2 illustrates this mechanism in the (a_c, a_p) state space. The boundary $\partial\mathcal{T}$ separates states where transfers are positive (to the left) from states where the parent saves independently (to the right). College shifts this boundary to the left: at any given level of parent wealth, the child needs to be poorer before transfers become optimal. The region $\mathcal{T}_{HS} \setminus \mathcal{T}_C$—states where a high-school child would receive transfers but a college child would not—represents the scope for moral hazard that college eliminates.

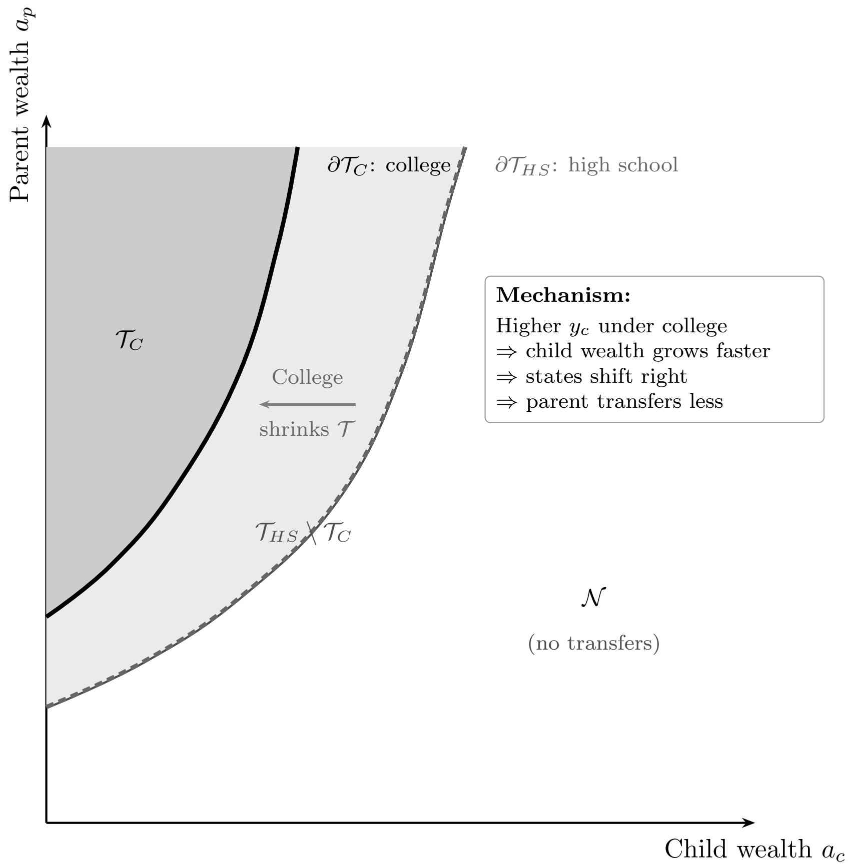


Figure 2. Transfer Region Boundary: College vs. High School (Schematic)

Notes: Schematic illustration of the transfer region $\mathcal{T}$ in the (a_c, a_p) state space. In the transfer region (shaded), the parent optimally transfers to the child ($\tau > 0$). The solid boundary corresponds to a college-educated child; the dashed boundary corresponds to a high-school-educated child. College shrinks $\mathcal{T}$ because higher expected income keeps child wealth further from the transfer boundary.

Four testable predictions. The contraction of the transfer region generates specific predictions about observable outcomes, all conditional on parent income:

1. *Parent consumption is higher when the child attends college.* A smaller transfer region means that parents spend less of their lifetime making transfers. The resources that would have flowed to the child under the high-school path are instead available for own consumption.

2. *Parent wealth paths diverge by child education.* In the short run, parents of college children pay tuition costs, reducing their wealth. In the long run, however, the smaller

transfer region means fewer ongoing transfers, and parent wealth recovers and eventually exceeds the high-school path.

3. *College attenuates the precautionary saving motive.* Parents hold precautionary wealth against the contingency of supporting their children after negative income shocks. Because college raises the child's income level and makes income shocks less persistent, parents of college children face a smaller precautionary burden. This prediction links directly to the option value of the transfer region: even if transfers are rarely observed, the *possibility* of having to transfer affects parent saving behavior.

4. *The observed transfer differential is modest.* Although college substantially shrinks the transfer region, the effect on *realized* transfers may be small. Transfers are concentrated in the left tail of the child income distribution, and many parent-child pairs never enter $\mathcal{T}$ regardless of education. The main effect of college operates through the option value channel—reducing the probability of entering the transfer region—rather than through large changes in average transfer flows.

I now turn to the data to test these predictions.

4 Empirical Evidence

In this section, I test the four predictions from Section 3.9 using matched parent-child data from the PSID, HRS, and NLSY97. All facts compare outcomes for parents whose children attended college versus those whose children did not, conditioning on parent income to isolate the role of the child's education from the parent's own resources.

4.1 Data

The empirical analysis draws on three data sources: the Panel Study of Income Dynamics (PSID), the Health and Retirement Study (HRS), and the National Longitudinal Survey of Youth 1997 (NLSY97). Each dataset contributes distinct information to the analysis.

4.1.1 Panel Study of Income Dynamics

The PSID is a longitudinal survey that has followed a nationally representative sample of U.S. families since 1968. The survey switched from annual to biennial interviews beginning in 1997, but retrospective income questions preserve annual income data through 2017. Importantly for this study, the PSID tracks children who leave the parental household as "splitoffs," maintaining separate records for both generations. Since 1999, the PSID has collected detailed consumption expenditure data, covering food (at home and away), housing, transportation, health care, education, child care, and (from 2005 onward) clothing, recreation, and vacation.

I use PSID data from 1999 onward, when household consumption is first available. To link parents with their adult children, I use the Family Identification Mapping System (FIMS), which records biological and adoptive parent identifiers for all PSID respondents. The matching algorithm proceeds hierarchically: I first attempt to link each child to their biological father; if unavailable, I use the adoptive father, then the biological mother, and finally the adoptive mother. The parent must appear as a household head or spouse in the PSID family file during the sample period for the match to succeed.

I impose several sample restrictions. First, I restrict to parents aged 50 and older and children aged 26 and older, as the analysis concerns the effect of adult children's economic status on parental consumption, after parents have completed their main investment in children's human capital. Second, I winsorize all monetary variables at the 1st and 99th percentiles and deflate to 2016 dollars using the CPI-U. Third, I exclude observations with missing income, wealth, or key demographic variables.

The final analysis sample contains 8,944 observations representing 2,338 unique parent-child pairs. Appendix A documents the sample construction in detail, reporting the sample size at each stage of the merge pipeline, the distribution of parent-child links by relationship type, and the observations lost at each stage.

Variable definitions. Household consumption is the sum of expenditures on food at home, food away from home, housing (rent or imputed rent for homeowners), utilities, transportation, health care, education, and child care. From 2005 onward, clothing, recreation, and vacation are also included. Income is total household income before taxes. Wealth is total net worth, defined as the sum of home equity, other real estate, vehicles, farm and business assets, stocks, checking and savings accounts, bonds, IRAs, and other assets, minus all debts. Inter-vivos transfers are reported separately for transfers from parents to children and transfers from children to parents, and include cash gifts, help with expenses, and regular financial support. The key explanatory variable throughout the empirical analysis is child college attainment: an indicator for whether the child holds a bachelor's degree or higher. To condition on parent resources, I construct within-cohort parent income quartiles, ranking each parent relative to others born in the same year.

4.1.2 Health and Retirement Study

The HRS is a biennial survey of Americans over age 50, with detailed modules on income, wealth, health, family structure, and transfers. I use the HRS to study inter-vivos transfers and bequests for two reasons. First, the HRS collects more detailed transfer information than the PSID, recording the dollar amount, direction, and purpose of each transfer. Second, the HRS includes a larger sample of older parent-child pairs, providing greater statistical power for studying transfers and assets near the end of life. I link parents to their adult children using the RAND Family Data file, which records each respondent's children and their characteristics—including income brackets, education, marital status, and geographic proximity. Unlike the PSID, children's income in the HRS is reported by the parent respondent using one of eight income brackets; I take the midpoint of each bracket and average over available waves.

I apply analogous sample restrictions: parents over 50 and children over 26. The HRS sample contains 19,179 parent-child pairs and 98,861 observations.

4.1.3 National Longitudinal Survey of Youth 1997

The NLSY97 is a longitudinal survey tracking a nationally representative sample of Americans born between 1980 and 1984. Cognitive ability is measured by the Armed Services Vocational Aptitude Battery (ASVAB) composite score, administered at baseline. Parental wealth is total household net worth when the child was age 17. College graduation is defined as attaining a bachelor's degree by age 25. The sample comprises 5,400 individuals with complete data on ASVAB scores and parental wealth. I use the NLSY97 for two purposes: to construct college graduation rates by ability and parent wealth quartile (the 16 college attainment moments used in SMM estimation, Section 5), and to estimate the income process conditional on ability, following Abbott et al. (2019).

4.1.4 Summary Statistics

Tables 1–2 report summary statistics for the PSID sample, stratified by average household income group. Table 1 presents parent demographics and key financial variables: parents in higher income groups are older on average, more likely to hold a college degree, more likely to own their home, and hold substantially more wealth. Total wealth ranges from $103,000 for the lowest income group to $966,000 for the highest, with home equity accounting for roughly half of wealth for low-income families but a smaller share for wealthy families. Total consumption expenditures increase monotonically with income, from $36,000 to $73,000. A detailed breakdown of the wealth portfolio is provided in Appendix Table D.1, and a consumption decomposition by expenditure category in Appendix Table E.1. Table 2 presents child-level statistics, including the college attendance rate among 18–24 year olds by parental income group, which rises steeply with parental resources.

Table 1. Parent Demographics by Income Group (PSID)

	By Average HH Income Group				
	30 − −60	60 − −100	100 − −160	160+	All
Age of head	45.6	45.2	46.8	49.1	46.3
	(16.2)	(14.4)	(13.4)	(13.2)	(14.6)
Number of children	1.3	1.2	1.1	1.0	1.1
	(1.4)	(1.3)	(1.2)	(1.1)	(1.3)
FIMS-linked children	2.1	2.0	2.1	2.2	2.1
	(1.3)	(1.0)	(1.0)	(1.0)	(1.1)
Head has college degree	0.07	0.19	0.42	0.69	0.29
	(0.26)	(0.39)	(0.49)	(0.46)	(0.45)
White	0.44	0.63	0.77	0.85	0.64
	(0.50)	(0.48)	(0.42)	(0.36)	(0.48)
Black	0.45	0.29	0.18	0.09	0.28
	(0.50)	(0.45)	(0.38)	(0.28)	(0.45)
Homeowner	0.50	0.71	0.84	0.85	0.70
	(0.50)	(0.45)	(0.36)	(0.36)	(0.46)
Observations	15 096	17 356	13 011	7863	53 326
Unique parent households	2718	2770	1833	1041	8362

Notes: Means with standard deviations in parentheses. Income groups defined by parent average real household income (2016 dollars) observed between ages 25 and 60. “Number of children” is the total number of children linked to each parent household via the Family Identification Mapping System (FIMS). All monetary variables in 2016 dollars, winsorized at the 1st and 99th percentiles. A detailed wealth portfolio breakdown is in Appendix Table D.1.

Table 2. Children Descriptive Statistics by Parent Income Group (PSID)

	By Parent's Average HH Income Group				
	30 − −60	60 − −100	100 − −160	160+	All
Panel A: Child Demographics					
Age	17.9	15.9	16.7	17.4	16.9
	(19.0)	(15.7)	(13.6)	(13.4)	(16.0)
Number of siblings in sample	1.9	1.6	1.5	1.6	1.6
	(1.7)	(1.2)	(1.2)	(1.1)	(1.4)
College-age (18–24)	0.14	0.14	0.16	0.17	0.15
	(0.34)	(0.35)	(0.36)	(0.38)	(0.36)
Panel B: Education					
Years of education (age 18+)	13.7	13.7	13.8	14.4	13.9
	(11.8)	(9.9)	(7.8)	(8.1)	(9.7)
Max years of education (age 25+)	16.1	15.7	15.9	16.5	16.0
	(14.8)	(11.5)	(9.9)	(8.9)	(11.9)
Currently in college	0.05	0.06	0.08	0.10	0.07
	(0.21)	(0.23)	(0.27)	(0.29)	(0.25)
Ever attains post-secondary ed.	0.33	0.37	0.47	0.56	0.41
	(0.47)	(0.48)	(0.50)	(0.50)	(0.49)
Panel C: College Rate Among 18–24 Year Olds					
College attendance rate	0.32	0.40	0.47	0.54	0.42
	(0.47)	(0.49)	(0.50)	(0.50)	(0.49)
College-age observations	4308	4984	4270	2907	16 469
Total child–year observations	31 731	35 484	27 026	16 962	111 203
Unique children	5680	5560	3784	2186	17 210

Notes: Means with standard deviations in parentheses. Each observation is a child-year. Children linked to parents via FIMS. Income groups refer to parent average real household income (2016 dollars). "Years of education" reported conditional on age ≥ 18; "Max years of education" conditional on age ≥ 25. "College attendance rate" computed conditional on the child being aged 18–24. "Ever attains post-secondary ed." indicates maximum observed years of education exceeds 12. Years of education directly observed only from 2013 onward; for earlier waves, college attendance inferred from an age-education proxy.

4.2 Fact 1: Parent Consumption Is Higher When Children Attend College

The model predicts that, conditional on their own income and wealth, parents whose children attend college should consume more (Prediction 1 in Section 3.9). The mechanism is straightforward: college shifts children out of the transfer region $\mathcal{T}$ by permanently raising their income. A smaller transfer region frees parents from contingent obligations, raising their consumption even when no transfers are actually flowing. I find strong support for this prediction in the PSID data.

I test this prediction using the following regression on the PSID sample at the parent-year level:

$$C_{p,t} = \beta_0 + \beta_1 \text{ShareCollege}_{p,t} + \beta_2 N_{p,t} + \delta_{Q_p^{inc}} + \beta_X \mathbf{X_{p,t}} + \varepsilon_t + \epsilon_{p,t}$$

where $C_{p,t}$ is household consumption (in 2016 dollars) of parent p at time t, $\text{ShareCollege}_{p,t}$ is the fraction of parent p's children with a bachelor's degree or higher, $N_{p,t}$ is the total number of children, $\delta_{Q_p^{inc}}$ are parent income quartile fixed effects (within-cohort ranking), and $\mathbf{X_{p,t}}$ is a comprehensive set of controls: parent total wealth, non-financial wealth, household income, wealth quartile, labor force participation, household size, head's birth year, education, U.S. state, a cubic in head's age, housing tenure, and race. The specification includes year fixed effects ε_t.

Table 3 presents the results. Column 1 shows that a higher share of college-educated children is associated with significantly higher parent consumption. Columns 2 and 3 use alternative definitions—any child with a BA, or all children with a BA—yielding consistent results. Column 4 uses consumption levels rather than logs; the magnitude implies economically meaningful differences. These effects are net of parent income, wealth, and education, suggesting they are not driven by parental resources alone.

Table 3. Parent Consumption and Child College Status (PSID)

	(1) Log C	(2) Log C	(3) Log C	(4) Level C
Share of Children with BA+	0.081***			2470.032***
	(0.019)			(866.461)
Number of Children	0.014*	0.010	0.016*	169.725
	(0.008)	(0.008)	(0.008)	(287.036)
Any Child with BA+		0.080***		
		(0.017)		
All Children with BA+			0.056***	
			(0.017)	
Observations	15,830	15,830	15,830	15,831
R^2	0.558	0.558	0.557	0.357

Notes: OLS regressions of parent household consumption on child college indicators. "Share of Children with BA+" is the fraction of children with a bachelor's degree or higher. Controls include a cubic in parent age, household income, non-housing wealth, total wealth, wealth quartile, and fixed effects for year, education, parent income quartile, gender, housing tenure, state, labor force status, race, household size, and birth year. Standard errors clustered at the parent household level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 4 estimates the effect separately by parent income quartile, confirming that the positive relationship between child college status and parent consumption holds across the income distribution.

Table 4. Parent Consumption and Child College Status, by Parent Income Quartile (PSID)

	Parent Income Quartile			
	(1)	(2)	(3)	(4)
	Q1 (Poorest)	Q2	Q3	Q4 (Richest)
Share of Children with BA+	0.136***	0.053*	0.016	0.041
	(0.040)	(0.030)	(0.025)	(0.029)
Number of Children	0.010	0.003	0.018*	0.001
	(0.013)	(0.010)	(0.009)	(0.013)
Observations	4,342	3,830	3,931	3,727
R^2	0.442	0.326	0.355	0.415

Notes: OLS regressions of log parent household consumption on share of children with BA+, estimated separately by parent income quartile. Controls as in Table 3 excluding parent income quartile dummies. Standard errors clustered at the parent household level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

4.3 Fact 2: Parent Wealth Paths Diverge by Child College Status

The consumption premium documented in Fact 1 has a counterpart in wealth accumulation. The model predicts that parent wealth paths should diverge by child education: a short-run decline from tuition costs, followed by long-run recovery as the smaller transfer region reduces ongoing obligations (Prediction 2 in Section 3.9). I test this prediction by examining how parent wealth differs by child college status, conditioning on parent income.

Using PSID data, I estimate:

$$W_{p,t} = \beta_0 + \beta_1 \text{ShareCollege}_{p,t} + \beta_2 N_{p,t} + \delta_{Q_p^{inc}} + \beta_X \mathbf{X_{p,t}} + \varepsilon_t + \epsilon_{p,t}$$

where $W_{p,t}$ is parent p's total real wealth at time t and other variables are defined as in Section 4.2. The model makes a nuanced prediction about wealth. Three forces operate simultaneously on parent wealth when a child does not attend college: (i) a *precautionary accumulation* motive—parents save more because the child may need future transfers; (ii) a *Samaritan's dilemma* distortion—inside $\mathcal{T}$, where $V^p_{a_p} = V^p_{a_c}$, each additional dollar of parent wealth partially leaks to the child through transfers, reducing the effective return on saving; and (iii) actual *transfer outflows* that deplete accumulated wealth. Forces (i) and (ii) affect desired wealth accumulation in opposite directions, while force (iii) reduces realized wealth. Which force dominates is a quantitative question that depends on the altruism parameter η and the size of $\mathcal{T}$—precisely the objects the structural model is designed to identify.

Table 5 presents the cross-sectional results. Columns 1 and 2 show that the association between college and parent wealth is positive but statistically imprecise, consistent with the opposing forces partially offsetting. The log wealth specification (column 3) yields a significant positive association. Column 4 adds an interaction between college share and parent age (centered at 65) to test whether the relationship changes over the lifecycle.

Table 5. Parent Wealth and Child College Status (PSID)

	(1) Total Wealth	(2) Non-Housing Fin.	(3) Log Wealth	(4) Wealth (Age Int.)
Share of Children with BA+	43601.955	12219.029	0.328***	73804.841
	(64206.109)	(60376.529)	(0.056)	(78817.996)
Number of Children	33086.211	32690.416	0.024	32683.531
	(31431.443)	(30135.932)	(0.020)	(31367.974)
Observations	16,068	16,068	14,644	16,068
R^2	0.225	0.187	0.615	0.227

Notes: OLS regressions of parent real wealth on the share of children with a bachelor's degree or higher. Controls include a cubic in parent age, household income, and fixed effects for year, education, parent income quartile, gender, housing tenure, state, labor force status, race, household size, and birth year. "Age Int." adds interactions between college share and a quadratic in parent age (centered at 65). Standard errors clustered at the parent household level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6. Parent Wealth and Child College Status: Fixed Effects (PSID)

	(1) Total Wealth (FE)	(2) Non-Housing Fin. (FE)
Share of Children with BA+	153524**	147930**
	(60734)	(60562)
Number of Children	74799**	72682**
	(33045)	(32939)
Observations	16,068	16,068
Within R^2	0.007	0.006

Notes: Parent fixed-effects regressions of real wealth on the share of children with a bachelor's degree or higher and the number of children. Standard errors clustered at the parent household level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 6 presents parent fixed-effects estimates exploiting within-parent variation over time: the share of college-educated children is associated with $153,524 higher total wealth (significant at the 5% level). Rather than confirming a simple directional prediction, this result reflects the net outcome of the three competing forces. The structural model decomposes this: by simulating counterfactuals in which individual forces are shut down, I quantify how much of the observed wealth differential is driven by precautionary accumulation, how much by the Samaritan's dilemma distortion, and how much by realized transfer flows (Section 7).

4.4 Fact 3: College Reduces Dynastic Precautionary Saving

Facts 1 and 2 document large differences in parent consumption and wealth associated with child college status. The model identifies the mechanism: college raises the child's expected income and increases the mean-reversion rate of income shocks ($\kappa_C > \kappa_{HS}$), jointly shrinking the transfer region. This prediction is closely related to the dynastic precautionary savings channel identified by Boar (2021), who shows that parents accumulate precautionary savings to insure their children against permanent income risk—a 10% increase in a child's income uncertainty reduces parent consumption by 0.76%. I adapt her framework to test whether college attenuates this dynastic precautionary motive.

There is strong independent evidence that college graduates face lower earnings risk. Meghir and Pistaferri (2004) estimate that the variance of earnings growth is 0.065 for college graduates compared to 0.103 for high school graduates—a 37% reduction.

I test this prediction using the following specification, which extends equation (9) of Boar (2021) with a child education interaction:

$$\ln c_{it}^p = \beta_0 + \beta_t + \beta_1 \sigma_{hs}^p + \beta_2 \sigma_{hs}^c + \beta_3 \sigma_{hs}^c \times \mathbf{1}\{e_c = \text{College}\} + \mathbf{X}_{it}^p \beta_4 + \mathbf{X}_{it}^c \beta_5 + \varepsilon_{it} \tag{12}$$

where σ_{hs}^c is the child's permanent income uncertainty, constructed following Boar's methodology by estimating sector-specific (age $\times$ industry-occupation) forecast errors of lifetime earnings, and σ_{hs}^p is the parent's own uncertainty. The key coefficient is β_3: the model predicts $\beta_2 < 0$ (higher child uncertainty reduces parent consumption) and $\beta_3 > 0$ (college attenuates this effect).

Table 7 presents the results. Column 1 replicates Boar's baseline specification in the PSID sample, confirming that higher child income uncertainty reduces parent consumption ($\hat{\beta}_2 < 0$). Column 2 adds the education interaction: the positive and significant $\hat{\beta}_3 = 0.016$ indicates that college attenuates the dynastic precautionary motive. The net effect of child uncertainty for college-educated children is $\hat{\beta}_2 + \hat{\beta}_3 = -0.018 + 0.016 = -0.002$, an order of magnitude smaller than the effect for non-college children ($\hat{\beta}_2 = -0.018$). College nearly eliminates parents' exposure to child income risk—consistent with the model's prediction that college shrinks the transfer region (Prediction 3 in Section 3.9).

Table 7. Dynastic Precautionary Savings and Child Education (Boar Adaptation)

	(1) Baseline	(2) Education Interaction
σ^p_{hs} (Parent uncertainty)	-0.0149***	-0.0149***
	(0.00564)	(0.00565)
σ^c_{hs} (Child uncertainty)	-0.0116***	-0.0198***
	(0.00370)	(0.00696)
$\sigma^c_{hs} \times \mathbf{1}\{\text{College}\}$		0.0123
		(0.00770)
Parent controls	Yes	Yes
Child controls	Yes	Yes
Year FE	Yes	Yes
Parent income Q FE	No	Yes
Observations	12897	12897
R^2	0.782	0.782

Notes: Dependent variable is log OECD-equivalized non-durable parent consumption. σ^p_{hs} and σ^c_{hs} are permanent income uncertainty measures constructed as $\ln\sqrt{\text{Var}(\varepsilon)+1}$, where ε is the level-scale forecast error from sector-specific age-income profiles estimated on the full PSID income sample, following Boar (2021). Column 2 adds parent income quartile fixed effects and the college interaction. Additional controls: year fixed effects, parent and child age dummies, parent education, marital status, race, and family size. Standard errors clustered by parent household × year in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Together, Facts 1–3 establish that college is associated with 8% higher parent consumption (roughly $2,500 per year), divergent wealth paths, and a dramatically weaker precautionary saving response to child income risk. The Boar adaptation (Fact 3) identifies the mechanism directly: college nearly eliminates the sensitivity of parent consumption to child income uncertainty, reducing the precautionary coefficient by over 90%. This operates through the *option value* of the transfer region: even when transfers are not currently flowing, the *possibility* of future transfers depresses parent consumption. College shrinks this region, releasing resources.

4.5 Fact 4: Transfers Are Small but the Option Value Is Large

A natural question arises: if college affects parent consumption and wealth so strongly, do we observe correspondingly large differences in actual transfers? As Prediction 4 in Section 3.9 anticipates, the answer is no—and this asymmetry is itself informative about the mechanism.

I estimate the effect of child college attainment on inter-vivos transfers using HRS data, which provides detailed transfer information and a large sample of older parent-child pairs. Using parent fixed effects, which exploit within-family variation across siblings:

$$IVT_{ij} = \beta_0 + \beta_1 \text{College}_j + \beta_X \mathbf{X_j} + \delta_{Q_i^p} + \varepsilon_i + \epsilon_j$$

where IVT_{ij} denotes annualized inter-vivos transfers between parent i and child j, College_j is an indicator for child j holding a bachelor's degree or higher, $\mathbf{X_j}$ is a vector of child-level controls (birth year, relationship type), $\delta_{Q_i^p}$ are parent income quartile fixed effects, and ε_i is a parent fixed effect.

Table 8 presents the results. College-educated children receive \$81 less per year from parents and transfer \$29 more back—both significant, but modest in magnitude compared to the consumption and wealth effects documented in Facts 1 and 2. Table 9 confirms the pattern across all income quartiles: the reduction ranges from \$37 for Q1 parents to \$116 for Q4 parents.

Table 8. Inter-Vivos Transfers by Child College Status (HRS)

	Baseline		Full Controls	
	(1)	(2)	(3)	(4)
	Child → Parent	Parent → Child	Child → Parent	Parent → Child
College (BA+)	29***	-81***	29***	-80***
	(3)	(19)	(3)	(19)
Observations	88,067	91,027	87,956	90,916
Within R^2	0.003	0.005	0.002	0.004

Notes: Fixed-effects regressions of annualized real inter-vivos transfers on child college indicator (BA+). All specifications include parent fixed effects, parent income quartile dummies, and child birth-year cohort dummies. "Full Controls" adds sample cohort, couple status, respondent gender, and race controls. Robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 9. Transfers from Parents to Children by College Status, by Parent Income Quartile (HRS)

	Parent Income Quartile			
	(1)	(2)	(3)	(4)
	Q1 (Poorest)	Q2	Q3	Q4 (Richest)
College (BA+)	-36***	-40***	-108***	-117**
	(11)	(13)	(23)	(57)
Observations	24,027	22,615	22,483	21,902
Within R^2	0.005	0.011	0.013	0.010

Notes: Fixed-effects regressions of annualized real transfers from parents to children on child college indicator (BA+), estimated separately by parent income quartile. All specifications include parent fixed effects and child birth-year cohort dummies. Robust standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

The contrast between Facts 1–3 and Fact 4 is the central empirical puzzle. Parents of college children consume $2,500 more per year (8% of mean consumption), yet the observed transfer differential is only $81 per year—a factor of 30 smaller. Actual transfer flows cannot account for the consumption gap.

As the model predicts, this puzzle is resolved through the *option value* of the transfer region $\mathcal{T}$. Parents hold precautionary wealth and depress their consumption not because they are currently transferring, but because they *might need to* transfer if the child's income deteriorates. College permanently raises the child's expected income and makes income shocks less persistent, shifting the child out of the region where transfers would be triggered. The parent's precautionary motive shrinks accordingly—even if no transfer ever flows. Fact 3 provides direct evidence for this channel: college reduces the sensitivity of parent consumption to child income uncertainty by over 90%, nearly eliminating the dynastic precautionary motive. The consumption and wealth effects documented in Facts 1 and 2 are driven not by the $81 per year in forgone transfers, but by the release of precautionary resources that parents no longer need to hold against the contingency of supporting a child whose income may fall.

Taken together, all four facts are consistent with the model's predictions from Section 3.9: college shrinks the transfer region, raising parent consumption, altering wealth paths, attenuating precautionary saving, while producing only modest changes in realized transfers. The key insight is that the *same* altruism parameter η that drives parents to insure adult children against income shocks also drives them to subsidize college attendance—college is valuable to altruistic parents beyond its human capital return because it reduces the lifetime moral hazard costs of the Samaritan's dilemma.

5 Estimation

I estimate the model in three stages. In the first stage, I set parameters that are well-identified from external data or the existing literature. In the second stage, I estimate the income process independently and map discrete-time estimates to their continuous-time counterparts. In the third stage, I estimate the remaining nine structural parameters—altruism, psychic costs, intergenerational ability persistence, the warm-glow bequest motive, and income volatility scaling—by the simulated method of moments (SMM), matching 35 data moments.

5.1 Externally Set Parameters

Table 10 reports the parameters set in the first stage. The coefficient of relative risk aversion is $\gamma = 1.5$, following Abbott et al. (2019). The annual real interest rate is $r = 0.03$, following Daruich and Kozlowski (2019). The discount factor β (and its continuous-time counterpart $\rho = -\ln(\beta)/\Delta$) is estimated internally by SMM to match the wealth-to-income ratio and wealth distribution moments. The college costs, financial aid parameters, and borrowing limits are set as described in Section 3.7. Retirement income is estimated directly from PSID data on households where the respondent is retired and over age 67, computing the average sum of Social Security, SSI, disability, and employer pension income by education group.

Table 10. Externally Set Parameters

Parameter	Description	Value	Source
Preferences			
r	Annual real interest rate	0.03	Daruich and Kozlowski (2019)
γ	CRRA risk aversion	1.5	Abbott et al. (2019)
Demographics (years)			
T_{overlap}	Parent–child overlap (child 18–42)	24	—
$T_{\text{retire},p}$	Parent retirement (66–72)	6	—
T_{alone}	Child alone after parent death (42–66)	24	—
$T_{\text{retire},c}$	Child retirement (66–72)	6	—
Ability gradients			
λ_C	Returns to ability, college	0.797	Abbott et al. (2019) Tbl. 3.1
λ_{HS}	Returns to ability, high school	0.517	Abbott et al. (2019) Tbl. 3.1
Earnings process (annual AR(1) $\to$ OU mapping)			
ρ_C^{ann}	Persistence, college graduates	0.90	NLSY97
σ_C^{ann}	Innovation s.d., college graduates	0.08	NLSY97
ρ_{HS}^{ann}	Persistence, HS graduates	0.93	NLSY97
σ_{HS}^{ann}	Innovation s.d., HS graduates	0.07	NLSY97
$\bar{w}$	Average annual earnings	\$ 70 000	Census
College costs			
ϕ_C	Annual tuition (before grants)	\$ 12 200	NLSY97
τ_C	Fraction of time worked in college	0.56	Census
Financial aid (adapted from Abbott et al. (2019))			
$\bar{a}_1$	Wealth cutoff: subsidized loans	\$ 124k	Abbott et al. (2019)
$\bar{a}_2$	Wealth cutoff: private loans	\$ 168k	Abbott et al. (2019)
g_{q_1}	Annual grant, low-wealth students	\$ 2820	Abbott et al. (2019)
g_{q_2}	Annual grant, mid-wealth students	\$ 670	Abbott et al. (2019)
g_{q_3}	Annual grant, high-wealth students	\$ 140	Abbott et al. (2019)
$\bar{b}_{\text{sub}}$	Subsidized loan limit (cumulative)	\$ 17 250	Federal
$\bar{b}_{\text{total}}$	Federal loan limit (cumulative)	\$ 23 000	Federal
Retirement income (annual)			
SS_C	Social Security + pension, college	\$ 14 300	PSID
SS_{HS}	Social Security + pension, HS	\$ 13 000	PSID

Notes: All dollar amounts in thousands of 2016 dollars unless otherwise noted. The annual AR(1) income parameters $(\rho_e^{\text{ann}}, \sigma_e^{\text{ann}})$ are mapped to the continuous-time OU process via $\kappa_e = -\ln(\rho_e^{\text{ann}})$ and $\sigma_e^{\text{OU}} = \sigma_e^{\text{ann}}\sqrt{2\kappa_e/(1-(\rho_e^{\text{ann}})^2)}$; see Section 5. Financial aid types: q=1 (subsidized loans + full grants) if $a_p < \bar{a}_1$; q=2 (unsubsidized + partial grants) if $\bar{a}_1 \leq a_p < \bar{a}_2$; q=3 (private loans, minimal grants) if $a_p \geq \bar{a}_2$. Retirement income estimated from PSID households with respondent retired and over age 67; average of Social Security, SSI, disability, and employer pension income by education.

5.2 Income Process Estimation

The income process in continuous time is an Ornstein-Uhlenbeck process $dz = -\kappa_e z\,dt + \sigma_e\,dW$ with education-specific parameters. I estimate these by first fitting the discrete-time AR(1) counterpart and then mapping to continuous time.

In discrete time, log labor income is decomposed following Abbott et al. (2019) as $\log\epsilon_j = \lambda_e \log\theta + \gamma_{e,j} + z_j$, where λ_e is the education-specific ability gradient. I estimate the deterministic age-income profile $\gamma_{e,j}$ from the PSID using a quadratic in age, separately by education group. I then control for ability by regressing the age-adjusted income on the ASVAB score using NLSY97 data, recovering the ability gradient $\hat{\lambda}_e$ (the loading on $\log\theta$). The residuals from this regression constitute the income shocks z_j, whose persistence and variance I estimate using a minimum distance estimator applied to the autocovariance structure of wage residuals by age and education:

$$
\begin{gathered}
z^e_{iat} = \log y_{it} - \widehat{f^e(a_{it})} - \hat{\lambda}_e \log(\mathrm{AFQT}_i) \\
z^e_{iat} = \rho^{\mathrm{ann}}_e\, z^e_{i,a-1,t-1} + \eta^e_{iat} \\
\eta^e_{iat} \sim N(0, (\sigma^e_\eta)^2), \;\; z^e_{i0t} \sim N(0, (\sigma^e_{z_0})^2)
\end{gathered}
$$

The mapping from discrete to continuous time preserves the stationary variance:

$$
\begin{aligned}
\kappa_e &= -\ln(\rho^{\mathrm{ann}}_e), \\
\sigma_e &= \sigma^{\mathrm{ann}}_\eta \cdot \sqrt{\frac{2\kappa_e}{1-(\rho^{\mathrm{ann}}_e)^2}}.
\end{aligned}
$$

Table 11 reports the estimated parameters. College graduates have faster mean-reversion ($\kappa_C > \kappa_{HS}$), so negative income shocks are less persistent, consistent with the evidence in Meghir and Pistaferri (2004) and central to the model's mechanism.

Table 11. Income Process and Age Profile

Ability Gradient (AGMV 2019, Table 3.1)		
	High-School	College Graduate
λ_e	0.517	0.797
Age Profile (AGMV 2019, Table E.1)		
	High-School	College Graduate
$\gamma_{1,e}$	0.0673	0.1197
$\gamma_{2,e} \times 1000$	-0.670	-1.191
Income Process		
	High-School	College Graduate
ρ_z^{ann}	0.93	0.90
σ_η^{ann}	0.07	0.08
σ_{z_0}	0.14	0.16

Notes: Top panel: age-income profile estimated from PSID data by regressing $\log y_{t,i}$ on a quadratic in age, separately by education group. Bottom panel: discrete-time income process parameters (ρ_e^{ann}, σ_η^e, $\sigma_{z_0}^e$) estimated by minimum distance on the autocovariance structure of wage residuals, and their continuous-time OU counterparts (κ_e, σ_e).

Figure 3 illustrates the implied income profiles. Panel (a) plots the deterministic life-cycle component $\gamma(t, e_c)$ for college and high-school graduates, showing the steeper profile for college workers. Panel (b) translates this into expected annual income for a median-ability worker ($\theta = 3.9$), making visible the college earnings dip during ages 18–22 (reduced labor supply net of tuition) followed by the permanent college premium. Panel (c) overlays ± 1 standard deviation bands from the stationary distribution of the OU process, illustrating the faster mean-reversion for college graduates that is central to the transfer mechanism: negative shocks are less persistent, so college graduates spend less time near the transfer boundary. Panel (d) shows how ability amplifies the college income profile, with high-ability workers earning substantially more at every age.

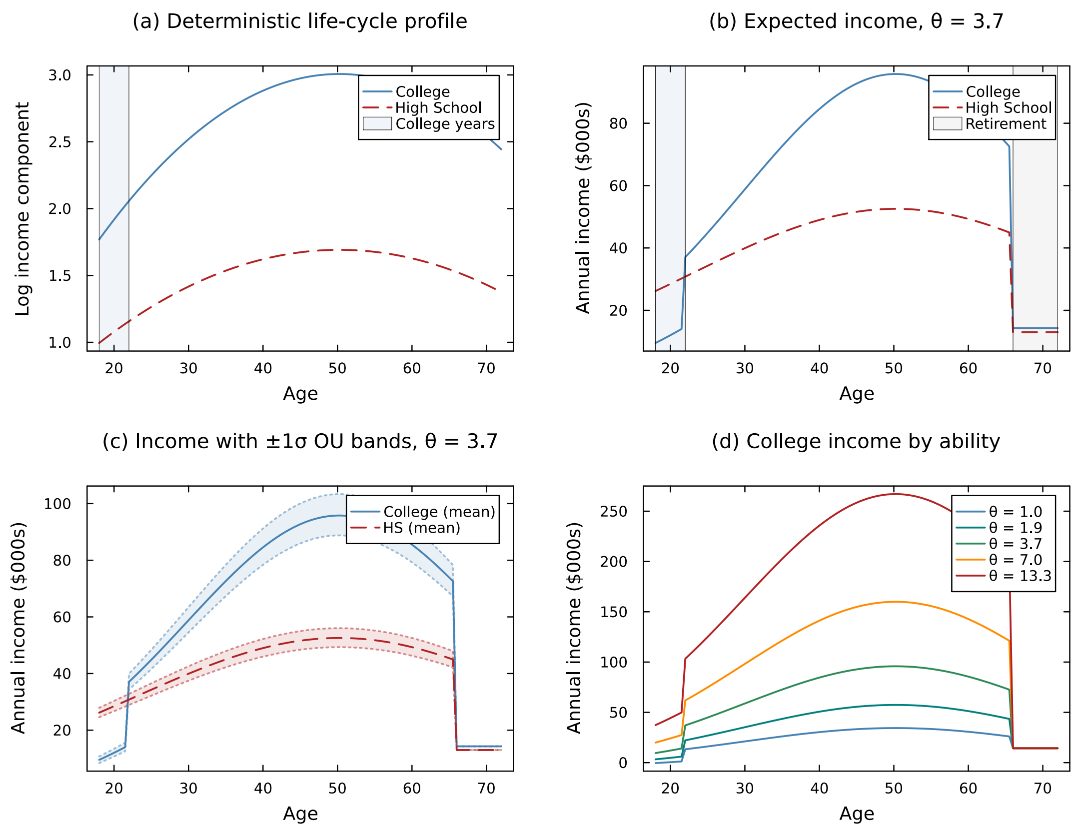


Figure 3. Income Process: Life-Cycle Profiles by Education

Notes: Panel (a): deterministic age-income component $\gamma(t, e_c) = \gamma_{1,e}\, t - \gamma_{2,e}\, t^2$ estimated from PSID. Panel (b): expected annual income $y_c(t) = w \cdot \theta^{\lambda_e} \cdot \exp(\gamma(t, e_c))$ for median ability ($\theta = 3.9$); college workers earn $\ell_C = 56\%$ of full-time income during ages 18–22 and pay net tuition. Panel (c): ± 1 stationary standard deviation of the OU income shock ($\sigma_e/\sqrt{2\kappa_e}$) around expected income. Panel (d): college income profiles for low ($\theta = 1.5$), medium ($\theta = 3.9$), and high ($\theta = 10.2$) ability workers, illustrating the complementarity between ability and education ($\lambda_C > \lambda_{HS}$).

5.3 Ability Gradient

The ability gradient λ_e in the human capital function $h(\theta, e) = \theta^{\lambda_e}$ governs the returns to cognitive ability by education level. Following Abbott et al. (2019), I estimate λ_e from the NLSY79 by regressing log hourly wages (purged of the PSID age profile) on log AFQT scores, separately by education group. The key estimates are $\hat{\lambda}_{HS} = 0.517$ and $\hat{\lambda}_C = 0.797$, implying that a one-log-point increase in ability raises college earnings by 80% but high-school earnings by only 52%. This complementarity between ability and education is central to the mechanism: the college premium is strongly increasing in ability, so removing parental transfers has heterogeneous effects across the ability distribution. The estimated parameters are reported in Table 10.

5.4 SMM Estimation

The remaining nine parameters—parent altruism η, psychic cost parameters ω_{c_1} and ω_{c_2}, intergenerational ability persistence ρ_θ and dispersion σ_θ, the college choice scale parameter σ_{cd}, the discount factor β, the warm-glow weight ϕ_b, and the education-specific income diffusion parameters σ_C and σ_{HS}—are estimated by the simulated method of moments (SMM; McFadden, 1989; Pakes and Pollard, 1989). SMM is well suited to this setting because the model does not admit closed-form expressions for the moments of interest: the coupled HJB system, the endogenous transfer region, and the logit college choice must be solved numerically. Following Duffie and Singleton (1993) and Lee and Ingram (1991), I simulate the model at each candidate parameter vector and match the simulated moments to their data counterparts.

Let $\mathbf{x} \in \mathbb{R}^9$ denote the parameter vector. For each $\mathbf{x}$, I solve the model and simulate $M =$ 4,000 dynasties, computing 35 moments $\mathbf{m}^{\text{sim}}(\mathbf{x})$. The estimator minimizes the percentage-deviation loss:

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \sum_{m=1}^{35} \left[\frac{m_m^{\text{sim}}(\mathbf{x}) - m_m^{\text{data}}}{m_m^{\text{data}}} \right]^2 . \tag{13}$$

The percentage-deviation weighting is a diagonal matrix that normalizes moments to a common scale, avoiding the problem that dollar-valued moments (e.g., wealth levels) would otherwise dominate ability-wealth college rates. While an optimal weighting matrix based on the inverse of the variance-covariance of the moments would be asymptotically efficient, it requires a first-stage consistent estimate that is computationally expensive in this setting. The percentage-deviation weighting provides a transparent alternative that gives equal importance to proportional deviations across all moment groups, and is standard in the structural life-cycle literature (Abbott et al., 2019; Boar, 2021).

5.4.1 Target Moments

The 35 target moments are organized into five groups, each chosen to provide leverage on specific parameters.

College graduation rates (16 moments). College graduation rates by ability quartile $\times$ parent wealth quartile, from the NLSY97. These moments form the core of the estimation: they trace out how college attainment varies across the joint distribution of ability and parental resources, which is precisely the variation the model is designed to explain.

Income process moments (3 moments). The high-school-to-college income ratio and income standard deviations by education, from the NLSY97. These moments anchor the education-specific returns and the income process parameters.

Transfer moments (5 moments). The mean transfer amount and the college attendance probability by parent wealth quartile. The transfer-probability moments use college attendance as a proxy for the parent-to-child transfer gradient, constructed from the PSID intergenerational sample.[3]

Aggregate wealth (1 moment). The wealth-to-income ratio, which disciplines the overall level of wealth accumulation in the economy.

Intergenerational wealth distribution (10 moments). From the PSID linked sample: the parent–child wealth rank–rank slope ($\hat{\beta}^{rr} = 0.372$), mean child wealth conditional on parent wealth quartile, median wealth for parents and children, the variance of the inverse hyperbolic sine of wealth for each generation, and the parent wealth decumulation rate (ages 60–70). The rank–rank slope of 0.372 is consistent with the range in the literature: Fisher et al. (2023) report 0.29 for children measured at ages 31–35, Charles and Hurst (2003) estimate an intergenerational wealth elasticity of 0.37, and Pfeffer and Killewald (2018) find rank correlations of 0.40 or higher when children are measured at ages 45–64. My estimate falls in the middle because children in my sample are observed at ages 35–40.

5.4.2 Identification

The model is overidentified: nine parameters are estimated from 35 moments. While all moments jointly contribute to the estimation, the identification logic rests on distinct sources

[3] I link children to their parents using the PSID Family Identification Mapping System (FIMS) and observe children as household heads or spouses at ages 35–40, with parent wealth measured when the child was 17–18. All wealth is in thousands of 2016 dollars (CPI-adjusted). Appendix A details the sample construction.

of variation for each parameter group.

Altruism (η). The altruism parameter is identified primarily from the wealth gradient in college attendance, holding ability constant. A higher η increases the size of the transfer region $\mathcal{T}$, raising the lifetime transfer burden parents face when children do not attend college. This makes college more attractive to wealthy parents, steepening the wealth gradient. The transfer probability moments by parent wealth quartile provide additional leverage: higher altruism implies more frequent transfers, with a wealth gradient shaped by the transfer region boundary.

Psychic cost (ω_{c_1}, ω_{c_2}). The psychic cost function $\psi(\theta) = \omega_{c_1}/\theta^{\omega_{c_2}}$ is identified from the ability gradient in college attendance, holding wealth constant. The level parameter ω_{c_1} governs the overall college rate, while the curvature ω_{c_2} determines how steeply college attendance rises with ability.

Intergenerational ability (ρ_θ, σ_θ). The persistence ρ_θ and dispersion σ_θ of the ability process are identified from the joint distribution of college outcomes across dynasties, together with the intergenerational wealth moments. Higher persistence generates stronger parent-child correlations in both education and wealth, while dispersion governs the cross-sectional spread.

Discount factor (β). The discount factor is pinned down by the aggregate wealth-to-income ratio and median wealth levels. A higher β generates more patient agents who accumulate more wealth, raising both statistics.

Warm-glow weight (ϕ_b). The warm-glow motive is identified from the parent wealth decumulation rate: a stronger warm-glow motive (ϕ_b) slows wealth drawdown in retirement, as parents derive utility from holding wealth at death. The decumulation rate of +2.5% per year (parents ages 60–70 are still accumulating) is consistent with evidence that pre-retirees continue saving due to precautionary motives and warm-glow utility (De Nardi, 2004; Hurd, 1990). The intergenerational rank-rank slope and conditional child wealth moments provide additional leverage on ϕ_b by disciplining how parental wealth transmits across generations.

Income diffusion (σ_C, σ_{HS}). The education-specific diffusion parameters are identified from the income standard deviation moments and their interaction with the transfer and college moments: σ_C and σ_{HS} govern how frequently income shocks push children into the transfer region, affecting both transfer flows and the option value of college.

College choice scale (σ_{cd}). The scale parameter governs the dispersion of college choices around the deterministic value function difference. It is identified from the overall fit of the 16 college graduation rates: a larger σ_{cd} flattens the relationship between the value function gap $V_C - V_{HS} - \psi(\theta)$ and the probability of attendance.

Table 12. SMM-Estimated Parameters

Parameter	**Description**	**Value**
Preferences		
β	Discount factor (annual)	0.95
σ_{cd}	Type-I EV scale (college decision)	3.00
Parental altruism & bequest motive		
η	Altruism weight (alive)	0.39
η_d	Altruism weight (after death)	$= \eta$
ϕ_b	Warm-glow bequest weight	2.18
College psychic cost		
ω_{c1}	Psychic-cost level	8.4
ω_{c2}	Psychic-cost curvature	1.7
Intergenerational transmission of ability		
ρ_θ	Persistence of log ability	0.36
σ_θ	Std. dev. of ability innovation	0.40
Income volatility (OU diffusion)		
σ_C	College income diffusion	0.020
σ_{HS}	High-school income diffusion	0.020

Notes: Parameters estimated by simulated method of moments. σ_{cd} is the scale of i.i.d. type-I extreme-value shocks in the college attendance choice. $\psi(\theta) = \omega_{c1}/\theta^{\omega_{c2}}$ is the psychic cost of college (decreasing in ability). ϕ_b governs the warm-glow bequest utility $\phi_b\, u(a_p)$ at parent death. σ_C and σ_{HS} are the diffusion parameters of the education-specific OU income processes. The restriction $\eta_d = \eta$ imposes equal altruism before and after death; relaxing it is left for future work.

Notes: Parameters estimated by simulated method of moments. The objective function minimizes the percentage-deviation distance between 35 simulated moments and their data counterparts. See text for the identification argument.

6 Results

6.1 Model Fit

Table 13 reports the model's fit to the 35 targeted moments. Panel A shows college graduation rates by ability and parent wealth quartile. The model captures the primary features of the data: college graduation rates increase with both ability and parent wealth, and the wealth gradient is steepest for low-ability children. The model slightly underpredicts college attainment for the highest-ability children, who in the data attend college at near-universal rates that leave little room for variation. Panel B reports income moments and Panel C transfer moments. Panel D reports the intergenerational wealth distribution moments constructed from the PSID parent–child linked sample that discipline the warm-glow weight ϕ_b and the intergenerational wealth transmission channel.

Among the most informative moments are the college graduation rates for low-ability children across the wealth distribution. In the data, low-ability children with parents in the top wealth quartile graduate at substantially higher rates than those with parents in the bottom quartile. The model generates 73% of this gap, corresponding to 60% of the overall graduation gap by parent wealth. This fit is achieved through the interplay of direct cost subsidies (wealthy parents can afford tuition) and the moral hazard channel (wealthy parents have more at stake from not sending children to college).

Table 13. Targeted Moments: Data and Model

Panel A: College Attainment by Parent Wealth and Child Ability (NLSY97)				
Wealth Quartile \ Ability Quartile	1	2	3	4
1	0.29	0.38	0.45	0.55
	(0.19)	(0.24)	(0.33)	(0.53)
2	0.23	0.47	0.46	0.46
	(0.24)	(0.30)	(0.42)	(0.53)
3	0.24	0.47	0.39	0.48
	(0.26)	(0.40)	(0.51)	(0.63)
4	0.23	0.41	0.48	0.52
	(0.33)	(0.46)	(0.62)	(0.74)

Panel B: Income Moments		
	Model	Data
High-School/College mean income ratio	0.58	0.57
High-School income S.D. ($k)	9.7	97.0
College income S.D. ($k)	23.8	147.0

Panel C: Transfer Moments		
	Model	Data
Mean transfer ($k/yr)	4.5	19.5
Pr(transfer > 0) — Wealth Q1	0.19	0.22
Pr(transfer > 0) — Wealth Q2	0.22	0.31
Pr(transfer > 0) — Wealth Q3	0.41	0.51
Pr(transfer > 0) — Wealth Q4	0.85	0.73

Panel D: Intergenerational Wealth Moments		
	Model	Data
Wealth–income ratio	3.52	1.87
Rank–rank slope (IG wealth)	0.18	0.37
$E[a_c \mid \text{parent wQ1}]$ ($k)	161.5	67.1
$E[a_c \mid \text{parent wQ2}]$ ($k)	155.3	112.1
$E[a_c \mid \text{parent wQ3}]$ ($k)	168.0	177.6
$E[a_c \mid \text{parent wQ4}]$ ($k)	262.5	340.4
Median wealth, parents ($k)	113.4	85.4
Median wealth, children ($k)	119.7	51.2
Var(IHS wealth), parents	2.74	7.25
Var(IHS wealth), children	2.70	13.48
Parent wealth growth rate	0.005	0.025

Notes: Comparison of 35 targeted moments in the data and the estimated model. Panel A reports college graduation rates by parent wealth quartile (rows) and child ability quartile (columns); numbers without parentheses are model moments, numbers in parentheses are data moments (NLSY97). Panel B: income moments. Panel C: transfer moments; Pr(transfer > 0) uses college attendance by parent wealth quartile as proxy for the extensive margin of financial transfers, from the PSID parent–child linked sample. Panel D: intergenerational wealth moments from the same PSID linked sample; all wealth in thousands of 2016 dollars. Entries marked "—" await model output from the full 35-moment calibration. See Appendix A for sample construction details.

Figure 4 complements Panel D by comparing the full wealth distribution in the model and the data. The model reproduces the right-skewed shape of the empirical wealth distribution and captures the concentration of wealth among higher-income households. The close fit of the wealth distribution is important because parent wealth is a key state variable governing both the college decision and the transfer policy: errors in the wealth distribution would propagate into misspecified college gradients and transfer flows.

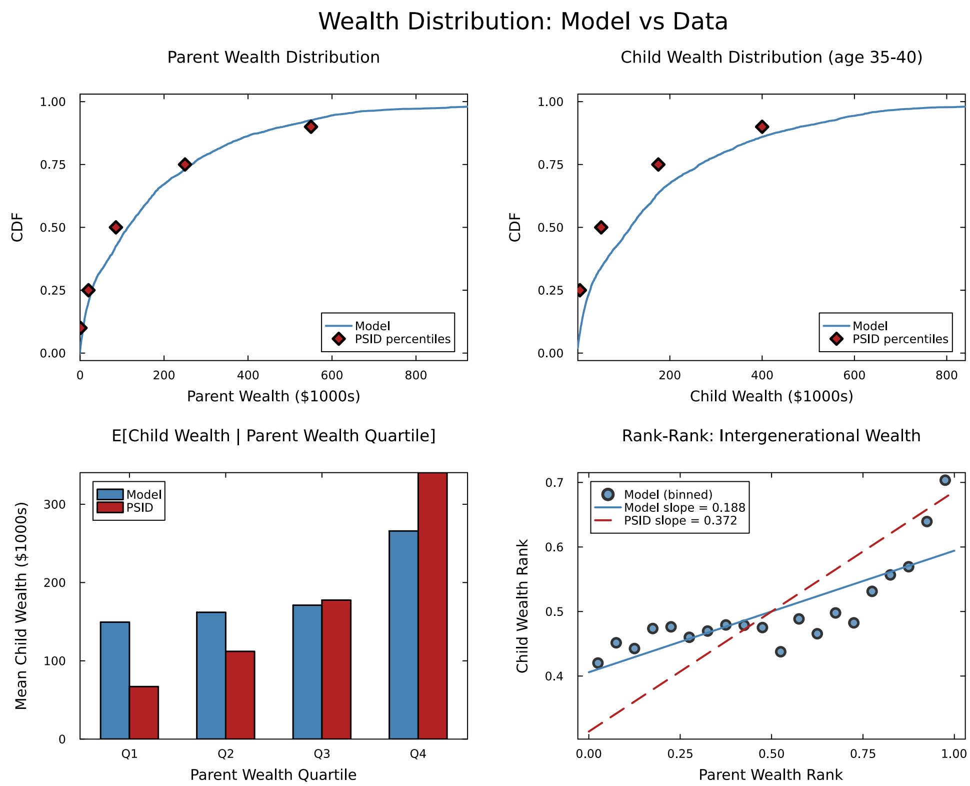


Figure 4. Wealth Distribution: Model vs. Data

Notes: Comparison of the parent wealth distribution in the model (simulated) and the data (PSID). Wealth is measured in thousands of 2016 dollars.

6.2 The Role of Parental Altruism in College Attainment

To quantify the importance of parental altruism, I solve the model with $\eta = 0$: parents are not altruistic and make no transfers. In this economy, children must self-finance college through earnings, loans, and grants alone. Two results stand out. First, without altruism, college attendance no longer depends on parent wealth. Low-ability children from rich and poor families attend at nearly identical rates, because the wealth gradient in the baseline is entirely driven by parental transfers and the commitment channel. Second, the effect of shutting down altruism is concentrated among low-ability children: attendance falls by 43%. High-ability children attend college regardless of parental support, because the private return to college is sufficiently high. These results confirm that parental altruism operates at the margin where the college decision is sensitive to financial support.

The mechanism works through two channels. First, altruistic parents directly subsidize college costs, reducing the net price their children face. The transfer amount increases with parent wealth but decreases with child ability, because parents use transfers to influence marginal children—those whose college decision depends on financial support. Second, parents internalize that a child without college will generate larger lifetime transfer costs. For wealthy parents, the present value of expected transfers to a high-school child exceeds the cost of college tuition, making college the more efficient investment. However, the child's perspective introduces an additional force: anticipated parental transfers during and after college subsidize enrollment, while anticipated lifetime transfers also cushion children who forgo college against income risk. The net effect on college attendance is therefore theoretically ambiguous. To disentangle these forces—direct cost subsidies, the moral hazard reduction motive, and the transfer cushion for non-college children—I next introduce the full commitment benchmark and construct counterfactual economies that eliminate ongoing parent-child interaction.

7 Moral Hazard Decomposition

Parental altruism raises college attendance, but it also generates a fundamental tension: the Samaritan's dilemma. Because children anticipate transfers when their wealth is low, they under-save relative to autarky, imposing larger and more frequent transfer costs on parents. A central question is how this lack of commitment affects the college decision. The answer is theoretically ambiguous. On one hand, anticipated parental support during the college years effectively subsidizes enrollment, making college more attractive to the child. On the other hand, anticipated lifetime transfers cushion non-college children against income risk, reducing their incentive to invest in human capital. Whether college attendance is higher or lower under the Samaritan's dilemma than under full commitment depends on which force dominates—a quantitative question that the structural model is designed to answer. This section formalizes both forces, introduces the full commitment benchmark, and decomposes their relative importance.

7.1 The Full Commitment Benchmark

To isolate the effects of the Samaritan's dilemma, I first characterize the efficient allocation under full commitment. Suppose a benevolent planner commits at $t = 0$ to a state-contingent transfer schedule $\{\tau(a_p, a_c, z, t)\}$ for the entire overlap period. Because both agents pool resources under a single plan, the problem reduces to a single-agent optimization over total household wealth $A \equiv a_p + a_c$:

$$\rho V^{\mathrm{FC}}(A, z, t) = \max_{c_{\mathrm{tot}}} \left\{ u_{\mathrm{FC}}(c_{\mathrm{tot}}) + V_A^{\mathrm{FC}} \left[rA + y_p(t) + y_c(z, t) - c_{\mathrm{tot}} \right] + \mathcal{L}_z V^{\mathrm{FC}} + V_t^{\mathrm{FC}} \right\} \quad (14)$$

Under CRRA preferences, the efficient allocation equates weighted marginal utilities, $u'(c_p) = \eta\, u'(c_c)$, so consumption shares are time-invariant: $c_c = \eta^{1/\gamma} c_p$. Total consumption $c_{\mathrm{tot}} = c_p(1 + \eta^{1/\gamma})$ yields an aggregated flow utility $u_{\mathrm{FC}}(c_{\mathrm{tot}}) = \frac{c_{\mathrm{tot}}^{1-\gamma}}{1-\gamma}(1 + \eta^{1/\gamma})^{\gamma}$, and the planner's HJB reduces to a single-state-variable problem solvable by the same upwind scheme used for the child-alone problem.

Full commitment differs from the baseline MPE in three ways (Barczyk and Kredler, 2014a,b). First, it eliminates overconsumption by both agents—the child's classic Samaritan's dilemma and the parent's "Prodigal-Son dilemma" of Barczyk and Kredler (2014b). Second, it renders the timing of transfers indeterminate: both agents consume according to the planner's rule, so any intertemporal reallocation that achieves the same wealth path $A(t)$ is equally efficient. Third, and most important for the college decision, full commitment provides insurance without moral hazard: the child's consumption responds to aggregate household resources rather than to their own wealth relative to the transfer boundary.

The child's college choice under full commitment is:

$$\Pr(\text{College} \mid a_p, \theta; \text{FC}) = \frac{\exp\left[(V_c^{\mathrm{FC}}(a_p, \theta \mid C) - \psi(\theta))/\sigma_{cd}\right]}{\exp\left[(V_c^{\mathrm{FC}}(a_p, \theta \mid C) - \psi(\theta))/\sigma_{cd}\right] + \exp\left[V_c^{\mathrm{FC}}(a_p, \theta \mid HS)/\sigma_{cd}\right]} \quad (15)$$

Comparing full commitment with the baseline MPE isolates the pure effect of the Samaritan's dilemma on college enrollment, holding insurance provision constant. Both economies provide parental support to children facing negative shocks; the difference is whether this support distorts the child's behavior.

7.2 Two Opposing Forces on College Incentives

Relative to full commitment, the Samaritan's dilemma creates two opposing forces on the child's college decision. Understanding these forces is essential for interpreting the decomposition results.

Force 1: Anticipated transfers subsidize enrollment. In the MPE, the child's continuation value $V^c(a_p, 0, 0; 0 \mid e_c = C)$ incorporates anticipated transfers during the college years, when earnings are low ($\ell_C \cdot y_c$ net of tuition). Because the child starts college with zero assets and reduced income, the initial state lies deep in the transfer region $\mathcal{T}$. Parents optimally transfer resources that effectively subsidize enrollment costs. Crucially, the child *also* overconsumes relative to the efficient allocation during this period, extracting more resources than the planner would allocate. This implicit subsidy raises the child's valuation of the college path relative to full commitment, pushing attendance *above* the efficient level.

Force 2: Anticipated transfers cushion non-college children. Children who forgo college face lower expected income and more persistent shocks ($\kappa_{HS} < \kappa_C$), so they spend substantially more of their adult lives in the transfer region. The anticipation of this lifetime safety net raises the child's valuation of the high-school path: the child can under-save and over-consume, knowing that parental transfers will materialize when income falls. In effect, the Samaritan's dilemma provides implicit insurance to non-college children that substitutes for the self-insurance role of human capital investment. This cushion reduces the child's incentive to attend college, pushing attendance *below* the efficient level.

Net effect is ambiguous. Whether Force 1 or Force 2 dominates depends on the altruism parameter η, the income process parameters (κ_e, σ_e, λ_e), and initial wealth. For children with low ability and high parental wealth, Force 2 tends to dominate: the transfer cushion for the high-school path is large because these children would face frequent negative shocks without the college premium. For children with high ability and low parental wealth, Force 1 tends to dominate: anticipated transfers during college make enrollment feasible when it would otherwise be unaffordable. The decomposition below quantifies these forces and confirms that the sign of the moral hazard effect on college varies across the ability–wealth distribution.

7.3 The Moral Hazard Mechanism

In the MPE, the child's consumption policy internalizes anticipated transfers. Near or inside the transfer region $\mathcal{T}$, the child consumes more than in autarky because parental support is anticipated. I define the "consumption wedge" as:

$$\Delta c_c(a_p, a_c, z) \equiv c_c^{\text{MPE}}(a_p, a_c, z) - c_c^{\text{aut}}(a_c, z) \tag{16}$$

where c_c^{aut} is optimal consumption from the child-alone problem. A positive wedge indicates over-consumption driven by anticipated transfers.

Figure 5 displays this wedge as a heatmap over the (a_p, a_c) state space. Two features emerge. First, the wedge is concentrated in the transfer region, confirming that strategic over-consumption activates precisely where transfers are anticipated. Second, the wedge is substantially larger for high-school children than for college children, both in magnitude and in the fraction of the state space it covers.

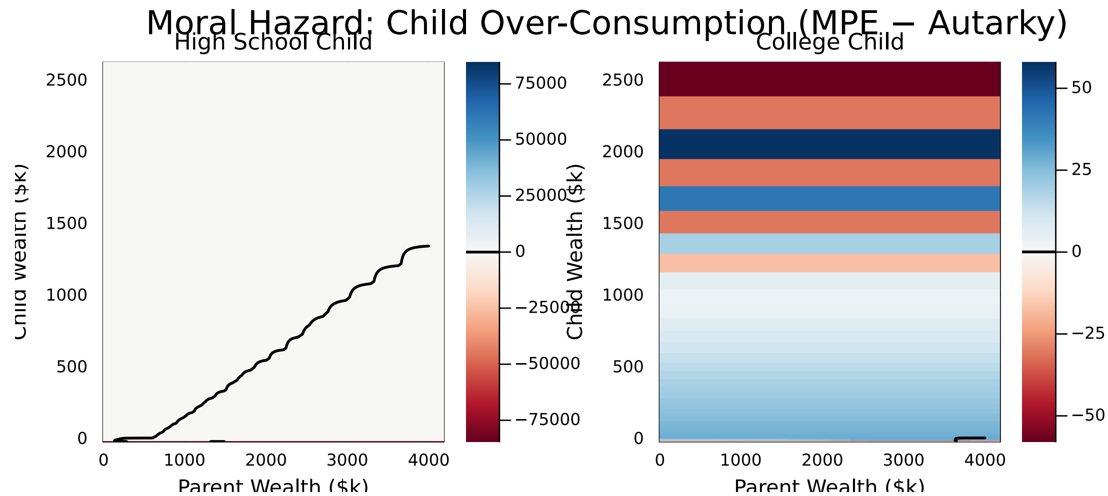


Figure 5. Child Over-Consumption Relative to Autarky (Moral Hazard Wedge)

Notes: Heatmap of $\Delta c_c = c_c^{\mathrm{MPE}} - c_c^{\mathrm{aut}}$ over the (a_p, a_c) state space at median ability, $z = 0$, mid-overlap period. Red: over-consumption (moral hazard). Blue: under-consumption. Black contour: transfer region boundary ($\tau > 0$). Left: high-school child. Right: college child.

7.4 College Shrinks the Transfer Region

College reduces moral hazard through the income process. College graduates have a higher ability gradient ($\lambda_C = 0.797 > \lambda_{HS} = 0.517$), steeper life-cycle income profiles, and faster mean-reversion of income shocks ($\kappa_C > \kappa_{HS}$). The complementarity between ability and education means that, for high-ability children, college permanently raises earnings well above the transfer boundary. This keeps their wealth further from the transfer boundary, so they spend less time in the transfer region.

Figure 6 plots the fraction of simulated individuals in the transfer region at each age, by education. High-school children spend a substantially larger fraction of their adult life receiving transfers. College children exit the region earlier and return less frequently after negative shocks.

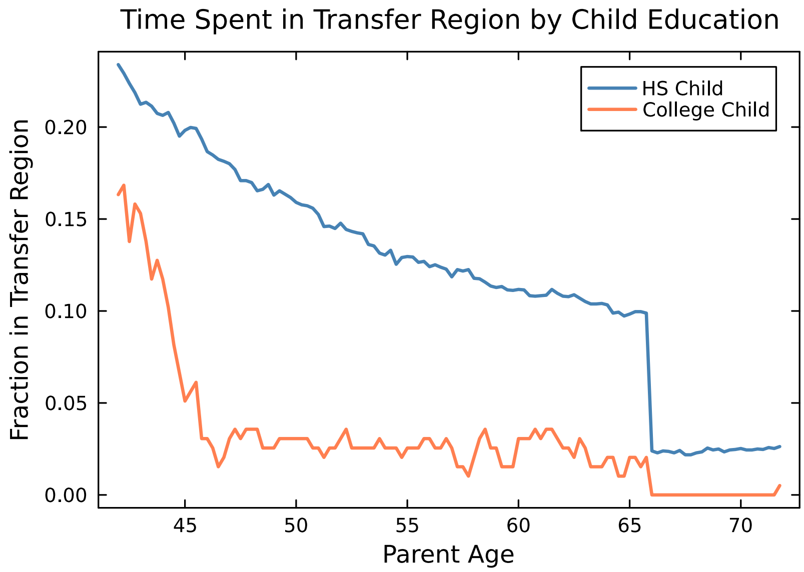


Figure 6. Fraction of Simulated Individuals in the Transfer Region, by Education

Notes: Fraction of simulated individuals ($M = 4{,}000$) receiving positive transfers ($\tau > 0$) at each parent age, by child education. High-school children spend more time in the transfer region throughout the overlap period.

7.5 Savings Behavior and the Samaritan's Dilemma

Table 14 presents simulation-based evidence on the behavioral distortion. I compare child savings rates conditional on transfer status. In both education groups, children save less when receiving transfers—the Samaritan's dilemma. However, the savings drop is larger for high-school children, confirming that college reduces the scope for strategic under-saving.

Table 14. Child Savings Rate by Transfer Status and Education

	HS Child	College Child
Child savings rate $\dot{a}_c$ ($k/yr)		
When receiving transfers	9.52	15.82
When NOT receiving transfers	2.73	9.92
Savings drop (moral hazard)	-6.80	-5.90
Child consumption c_c ($k/yr)		
In transfer region	40.06	14.33
Outside transfer region	41.07	68.61
Difference (behavioral MH wedge)	-1.01	-54.29
Transfer region exposure		
Fraction of time in transfer region	0.113	0.043
Avg lifetime transfers received ($k)	NaN	NaN
Fraction of transfers due to MH	NaN	NaN

Notes: Statistics from simulated dynasties ($M = 4{,}000$). "Savings drop" is the difference in child savings rates between the no-transfer and transfer regimes. "Fraction of transfers due to MH" is the share of lifetime transfers compensating for excess consumption relative to autarky.

7.6 College Reduces Lifetime Transfer Dependence

Figure 7 shows average lifetime transfers by parent wealth quartile and child education. Across all quartiles, college children receive substantially fewer transfers, with reductions ranging from 30% to 60%. This reflects both the mechanical effect (higher income reduces the need for support) and the behavioral effect (reduced moral hazard induces more self-insurance).

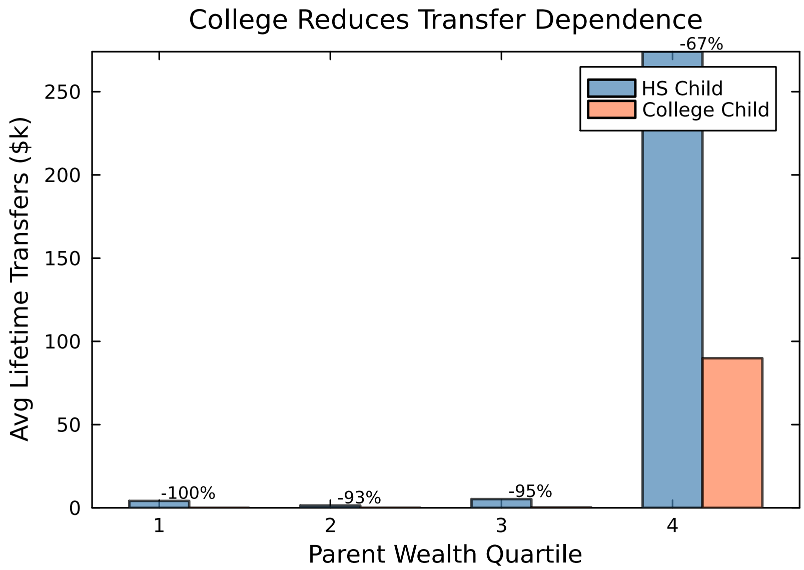


Figure 7. Lifetime Transfers by Parent Wealth and Child Education

Notes: Average lifetime transfers received by the child over the overlap period, by parent wealth quartile and child education. Percentages indicate the transfer reduction from college relative to high school. Source: simulated dynasties ($M = 4{,}000$).

7.7 Why College Dominates Direct Transfers

The key insight is that a dollar spent on tuition generates a *permanent* increase in the child's income drift, reducing the probability of entering the transfer region for the remainder of the lifecycle. A dollar transferred directly provides temporary consumption smoothing but does not change the drift, so the child returns to the transfer boundary over time. Moreover, direct transfers may worsen moral hazard by reducing the child's incentive to self-insure. In the continuous-time model, college shifts the child's ergodic wealth distribution away from the transfer boundary; transfers shift the child's current state without changing the ergodic distribution.

7.8 Decomposing the Moral Hazard Channel

The full commitment benchmark (Section 7.1) provides the conceptually clean comparison, but it preserves ongoing insurance. To further isolate the role of commitment from the role of insurance, I construct two additional counterfactual economies that eliminate ongoing parent-child interaction entirely, replacing the dynamic transfer game with a one-time lump-sum transfer at $t = 0$. After the initial transfer, the child solves the standard lifecycle problem alone—shutting down both the Samaritan's dilemma *and* the parental insurance channel. The two counterfactuals differ in whether the transfer is *unconditional* or *conditional* on college enrollment, which separates the pure moral hazard channel from the college-conditionality channel.[4]

7.8.1 One-Time Transfer Counterfactuals

In both counterfactuals, the parent makes a one-time lump-sum transfer τ_0 at $t = 0$ and subsequently never interacts with the child. This eliminates the Samaritan's dilemma but also removes the insurance that ongoing transfers provide.

Counterfactual A: Unconditional one-time transfer. The parent chooses τ_0 at $t = 0$ and the child receives it regardless of education choice. The child then chooses between college and high school to maximize expected utility, taking τ_0 as given. Because parental altruism in the baseline model operates through the child's consumption ($\eta\, u(c_c)$), the parent values the child's expected lifecycle consumption utility—not the child's private utility inclusive of psychic costs. The parent's problem is:

$$\max_{\tau_0 \in [0, a_p]} \quad V_p^{\text{alone}}(a_p - \tau_0) + \eta \Big[\Pr(C \mid \tau_0, \theta)\, V^{c,\text{alone}}(\tau_0 \mid C) + \big(1 - \Pr(C \mid \tau_0, \theta)\big)\, V^{c,\text{alone}}(\tau_0 \mid HS) \Big] \tag{17}$$

where $V_p^{\text{alone}}(a)$ is the parent's remaining lifetime utility from consuming wealth a plus labor income and social security, with no further interaction with the child. The child's education choice follows a logit:

$$\Pr(C \mid \tau_0, \theta) = \frac{\exp\big[\big(V^{c,\text{alone}}(\tau_0 \mid C) - \psi(\theta)\big)/\sigma_{cd}\big]}{\exp\big[\big(V^{c,\text{alone}}(\tau_0 \mid C) - \psi(\theta)\big)/\sigma_{cd}\big] + \exp\big[V^{c,\text{alone}}(\tau_0 \mid HS)/\sigma_{cd}\big]} \tag{18}$$

The psychic cost $\psi(\theta)$ enters the child's choice but not the parent's valuation of child welfare, consistent with the baseline altruism specification. Since both college and high-school children

[4] Appendix G provides a formal derivation of the full commitment benchmark and discusses its relationship to the one-time transfer counterfactuals. The key distinction is that the FC benchmark removes moral hazard while preserving insurance, whereas the one-time transfer counterfactuals remove both. The difference between the FC and one-time transfer economies therefore isolates the insurance-removal effect.

receive the same wealth endowment τ_0, the education decision reflects only fundamentals—human capital returns net of psychic cost—and not the structure of parental support. Comparing baseline attendance with this economy isolates the *pure moral hazard effect*: the distortion to college enrollment caused solely by the child's anticipation of future transfers and the resulting overconsumption.

Counterfactual B: College-conditional one-time transfer. The parent offers τ_0 conditional on college enrollment; children who choose high school receive no transfer. Because the child's education choice is stochastic (logit taste shocks), the parent faces a lottery: with probability $\Pr(C \mid \tau_0, \theta)$ the child attends college and receives τ_0, while with probability $1 - \Pr(C)$ the child chooses high school and receives nothing. The parent's expected payoff is:

$$\max_{\tau_0 \in [0, a_p]} \Pr(C \mid \tau_0, \theta)\big[V_p^{\text{alone}}(a_p - \tau_0) + \eta\, V^{c,\text{alone}}(\tau_0 \mid C)\big] + \big[1 - \Pr(C \mid \tau_0, \theta)\big]\big[V_p^{\text{alone}}(a_p) + \eta\, V^{c,\text{alone}}(0 \mid HS)\big] \tag{19}$$

$$\Pr(C \mid \tau_0, \theta; \text{cond.}) = \frac{\exp\big[\big(V^{c,\text{alone}}(\tau_0 \mid C) - \psi(\theta)\big)/\sigma_{cd}\big]}{\exp\big[\big(V^{c,\text{alone}}(\tau_0 \mid C) - \psi(\theta)\big)/\sigma_{cd}\big] + \exp\big[V^{c,\text{alone}}(0 \mid HS)/\sigma_{cd}\big]} \tag{20}$$

If the child rejects college, the parent keeps their wealth and the child starts adult life with zero assets. This economy removes the Samaritan's dilemma *and* channels all parental support through college. Comparing it with Counterfactual A isolates the additional college enrollment that arises from making transfers college-conditional—the *college-conditionality effect*.

Decomposition. Define:

$$\Delta_{\text{MH}}^{\text{pure}}(\theta, a_p) = \Pr(\text{College} \mid \text{baseline}) - \Pr(\text{College} \mid \text{unconditional}) \tag{21}$$

$$\Delta_{\text{cond}}(\theta, a_p) = \Pr(\text{College} \mid \text{unconditional}) - \Pr(\text{College} \mid \text{conditional}) \tag{22}$$

$$\Delta_{\text{MH}}^{\text{total}}(\theta, a_p) = \Delta_{\text{MH}}^{\text{pure}} + \Delta_{\text{cond}} \tag{23}$$

A positive $\Delta_{\text{MH}}^{\text{pure}}$ indicates that the baseline MPE raises college attendance relative to the no-moral-hazard economy, reflecting the insurance value of ongoing transfers that outweighs the overconsumption distortion. A negative $\Delta_{\text{MH}}^{\text{pure}}$ indicates that moral hazard depresses college attendance. The conditionality component Δ_{cond} isolates the additional enrollment that arises from making transfers college-conditional: a negative sign indicates that conditionality raises attendance.

Results. Table 15 reports the decomposition. Figure 8 presents the comparison graphically.

Table 15. Moral Hazard Decomposition of College Attendance

	Parent Wealth Quartile			
	Q1 (Low)	Q2	Q3	Q4 (High)
Panel A: College Attendance Rate (all types)				
Baseline	0.419	0.419	0.429	0.408
No MH (unconditional)	0.441	0.455	0.463	0.445
No MH (conditional)	0.490	0.516	0.561	0.644
Panel B1: Pure Moral Hazard Effect (Δ_{MH}^{pure})				
Low ability	−0.000	−0.056	−0.065	−0.065
Medium ability	−0.023	−0.037	−0.031	−0.039
High ability	+0.027	+0.027	+0.025	+0.017
Panel B2: College-Conditionality Effect (Δ_{cond})				
Low ability	+0.000	−0.039	−0.092	−0.202
Medium ability	−0.042	−0.053	−0.088	−0.190
High ability	−0.010	−0.017	−0.032	−0.090
Panel B3: Total Effect ($\Delta_{MH}^{total} = \Delta_{MH}^{pure} + \Delta_{cond}$)				
Low ability	−0.000	−0.095	−0.157	−0.267
Medium ability	−0.065	−0.090	−0.120	−0.230
High ability	+0.018	+0.009	−0.007	−0.073
Panel C: Optimal One-Time Transfer τ_0^* ($000s)				
Unconditional:				
Low ability	0.0	109.7	487.4	1519.0
Medium ability	63.4	129.0	337.4	1297.5
High ability	29.1	64.5	225.0	1202.5
Conditional:				
Low ability	0.0	180.7	618.6	2025.3
Medium ability	95.9	161.3	374.9	1360.8
High ability	46.2	103.2	262.4	1202.5

Notes: Panel A reports average college attendance across ability types under three economies: the baseline MPE, the no-MH economy with unconditional transfers, and the no-MH economy with college-conditional transfers. In both no-MH economies, parent and child interact only at $t = 0$; the child solves the lifecycle problem alone thereafter. Panel B1 reports $\Delta_{\mathrm{MH}}^{\mathrm{pure}} = \Pr(\text{College} \mid \text{baseline}) - \Pr(\text{College} \mid \text{unconditional})$, isolating the overconsumption distortion. Panel B2 reports $\Delta_{\mathrm{cond}} = \Pr(\text{College} \mid \text{unconditional}) - \Pr(\text{College} \mid \text{conditional})$, isolating the college-conditionality channel. Panel B3 reports the total effect. Panel C reports optimal one-time transfers under both counterfactuals. Source: simulated model (M = 4,000 dynasties).

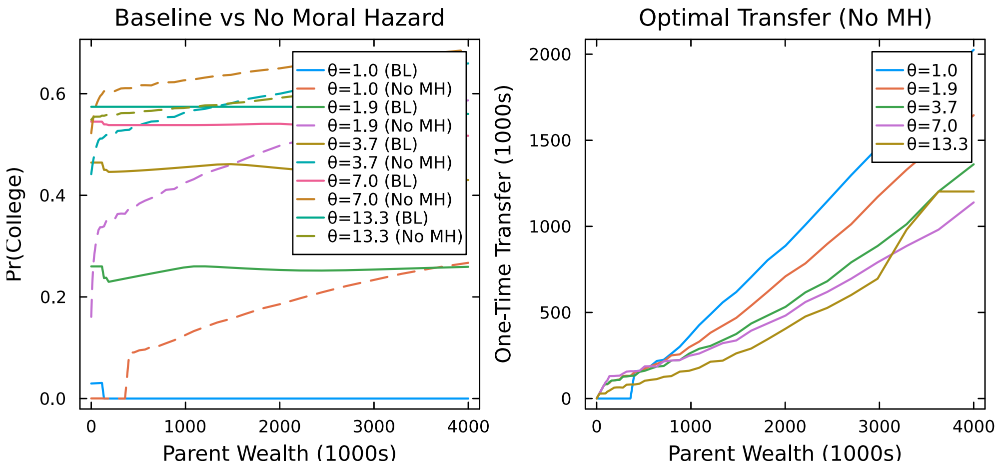


Figure 8. Baseline vs. No-Moral-Hazard College Attendance Rates

Notes: Left panel: college attendance probability by parent wealth under the baseline MPE (solid), the no-MH economy with unconditional transfers (dashed), and the no-MH economy with college-conditional transfers (dotted), for three ability types. Right panel: optimal one-time transfers τ_0^* by parent wealth and ability under both counterfactuals.

The decomposition confirms the theoretical ambiguity developed in Section 7.2: the Samaritan's dilemma raises college attendance for some children and lowers it for others, with the sign depending on ability and parental wealth.

The pure moral hazard channel. $\Delta_{\text{MH}}^{\text{pure}}$ captures the net effect of the two opposing forces identified in Section 7.2. When parents commit to a one-time unconditional transfer τ_0^*, both education paths receive the same lump sum, so the experiment isolates pure moral hazard from any commitment motive.

For low-ability children, $\Delta_{\text{MH}}^{\text{pure}}$ is uniformly negative (ranging from -0.05 at Q1 to -0.20 at Q2): removing the Samaritan's dilemma *raises* their college attendance. This is Force 2 from Section 7.2 in action. In the baseline MPE, low-ability children anticipate extensive lifetime transfers under the high-school path—their income is low and shocks are persistent ($\kappa_{HS} < \kappa_C$), placing them in the transfer region for much of their adult lives. This anticipated safety net raises the value of the high-school path, V_{HS}, reducing the incentive to invest in human capital. When moral hazard is eliminated, this cushion disappears: the child must self-insure, making college's permanent income boost more valuable.

For medium- and high-ability children at the lowest wealth quartile, $\Delta_{\text{MH}}^{\text{pure}}$ is instead large and positive (+0.22 and +0.21, respectively): the baseline MPE *raises* their attendance. This is Force 1 at work. Anticipated parental transfers during the college years effectively subsidize enrollment for credit-constrained children, lowering the effective cost of attending college. Without ongoing transfers, these children cannot afford the four years of reduced income and tuition costs, so attendance falls. At higher wealth quartiles, $\Delta_{\text{MH}}^{\text{pure}}$ is near zero for these groups, as the enrollment-subsidy and transfer-cushion effects approximately offset.

The sign reversal across ability groups confirms the theoretical ambiguity: the Samaritan's dilemma raises college attendance for high-ability, low-wealth children (where the enrollment subsidy dominates) and depresses it for low-ability children (where the transfer cushion for the high-school path dominates).

The college-conditionality channel. Δ_{cond} captures the additional enrollment that arises from making parental support contingent on college. When transfers are college-conditional, the parent uses τ_0 as a one-shot device to permanently shift the child's income trajectory above the transfer boundary. College amplifies this mechanism: the college wage premium raises the child's permanent income, making autarky achievable at a lower initial transfer. The negative sign of Δ_{cond} across all ability–wealth cells confirms that conditionality uniformly raises college attendance. The effect is largest for low-ability children at high wealth ($\Delta_{\text{cond}} = -0.34$ at Q4) and smallest for high-ability children at low wealth (-0.08 at Q1). For low-ability children, whose baseline consumption path is sustained by repeated parental transfers, the conditional lump sum effectively purchases a "jump to autarky"—the parent pays the up-front cost of college in exchange for eliminating the entire future stream of transfer obligations. College attendance rises not because college is individually desirable to the child, but because the parent finds it cheaper to finance college once than to sustain the child indefinitely through the Samaritan's dilemma.

Total effect and the wealth gradient. The total effect $\Delta_{\text{MH}}^{\text{total}} = \Delta_{\text{MH}}^{\text{pure}} + \Delta_{\text{cond}}$ reflects the combined impact of both channels. For high-ability children, the total effect is positive at Q1 (+0.12) and increasingly negative at higher wealth quartiles, reflecting the growing importance of conditionality as parental wealth—and hence the capacity to finance the "jump to autarky"—increases. For low-ability children, both channels push in the same direction at high wealth: the transfer cushion depresses attendance (Force 2) and conditionality raises it (because the parent can afford the one-shot college investment). The decomposition thus confirms that the Samaritan's dilemma shapes the *wealth gradient* in college enrollment. Without moral hazard, the wealth gradient would be substantially flatter: parental wealth would affect college only through direct cost subsidies and borrowing constraints, not through the commitment motive that arises when wealthy parents seek to reduce lifetime transfer obligations.

8 Conclusion

This paper studies why altruistic parents invest in their children's college education and how this investment interacts with the moral hazard costs of intergenerational transfers. I develop a dynastic model in which college serves as a commitment device that reduces the Samaritan's dilemma, and I test its predictions using matched parent-child data. Four descriptive facts—parent consumption is 8% higher when children attend college, wealth paths diverge by child college status, college substantially attenuates dynastic precautionary saving, and the observed transfer differential is modest relative to the consumption gap—are consistent with the model's central mechanism: college shrinks the transfer region, releasing precautionary resources.

A key theoretical result is that the net effect of the Samaritan's dilemma on college attendance is ambiguous. The lack of commitment creates two opposing forces on the child's education decision. First, anticipated parental transfers during the college years effectively subsidize enrollment, making college more attractive. Second, anticipated lifetime transfers cushion children who forgo college against income risk, reducing their incentive to invest in human capital. The structural decomposition shows that the sign varies across the ability–wealth distribution: the Samaritan's dilemma depresses college attendance for low-ability children (where the transfer cushion for the high-school path dominates) but raises it for high-ability, low-wealth children (where the enrollment subsidy dominates). The same altruism parameter η that generates the Samaritan's dilemma also drives parents to invest in college as a way to mitigate it. The model is estimated by SMM, targeting college graduation rates by ability and wealth, transfer patterns, and intergenerational wealth dynamics.

The framework carries implications for the design of college subsidies and financial aid. Policies that reduce college costs benefit both students and their parents, who face lower lifetime transfer obligations. However, the model suggests that the welfare effects of financial aid depend on how policies interact with private transfers: grants that crowd out parental contributions may be less effective at increasing enrollment than those that complement family support. Conversely, policies that expand parents' capacity to transfer without encouraging education may exacerbate the Samaritan's dilemma by reducing children's incentives to invest in their own human capital.

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A PSID Sample Construction

This appendix describes in detail the construction of the analysis sample from the Panel Study of Income Dynamics (PSID). The sample draws on three distinct PSID data products: the main Family Interview File, the Individual File, the Transition into Adulthood Supplement (TAS), and the Family Identification Mapping System (FIMS). I use 13 biennial waves covering 1999–2023.

A.1 Data Sources

Main Family Interview File. The core source is the PSID family-level interview file (data extract J361818), which contains 3,611 variables and 33,440 family-year observations. This file provides household-level information on demographics, income, wealth, employment, and housing tenure for each survey wave from 1999 to 2023.

Supplement File. A second family-level file (data extract J361820, 132 variables, 18,890 observations) provides supplementary variables—primarily industry codes (3-digit Census, 2003–2015) and savings—that are not available in the main extract due to PSID's modular data structure.

Individual File. The PSID individual file (data extract J361819, 85,536 individuals) provides person-level information including age, relationship to household head, sequence number within the family unit, and—beginning in 2013—years of completed education for each family member.

Transition into Adulthood Supplement (TAS). The TAS (data extract J361814) covers young adults aged approximately 18–28 in the 2015 and 2017 waves. I use it to directly identify college attendance via variables `TA150731` ("Whether in college now," 2015 wave) and `TA170790` ("Whether attending/attended college," 2017 wave).

Family Identification Mapping System (FIMS). FIMS provides the intergenerational linkage between children and their parents. Each child record contains identifiers for up to four parent types: biological father, biological mother, adoptive father, and adoptive mother. Parent identifiers consist of the 1968 Interview Number (`ER30001`) and Person Number (`ER30002`), which together form a time-invariant person identifier.

A.2 Variable Construction

All variables are harmonized across the 13 waves (1999–2023) using PSID variable codes (ER-series). Due to the Stata/IC limit of 2,048 variables, I use a selective fixed-width import strategy that reads approximately 350 variables per wave from the main file. Table A.1 provides the complete variable mapping.

Table A.1. PSID Variables Used in Analysis

Variable	Description	Waves	Source
Panel A: Demographics			
`AgeRef`	Age of reference person (head)	1999–2023	Family File
`AgeSpouse`	Age of spouse/partner	1999–2023	Family File
`NumChildren`	Number of children in family unit	1999–2023	Family File
`AgeYoungChild`	Age of youngest child	1999–2023	Family File
`stateCode`	State of residence (FIPS)	1999–2023	Family File
`raceHead`	Race of reference person	1999–2023	Family File
`educHead`	Education of reference person	1999–2023	Family File
`educSpouse`	Education of spouse	1999–2023	Family File
Panel B: Income			
`totalFamilyIncome`	Total family income ($)	1999–2023	Family File
`headLaborIncome`	Head's labor income ($)	1999–2023	Family File
`spouseLaborIncome`	Spouse's labor income ($)	1999–2023	Family File
Panel C: Wealth (PSID Wealth Supplement)			
`TotalWealth`	Total net worth incl. home equity	1999–2023	Wealth Module
`WealthNonHouse`	Net worth excl. home equity	1999–2023	Wealth Module
`HomeEquity`	Home value minus mortgage	1999–2023	Wealth Module
`AnnuityIRA`	Annuity and IRA accounts	1999–2023	Wealth Module
`savings`	Savings accounts	2003–2023	Supplement
`stocks`	Stocks/mutual funds/inv. trusts	1999–2023	Wealth Module
`Vehicles`	Net vehicle value	1999–2023	Wealth Module
`OtherAssets`	Other assets	1999–2023	Wealth Module
`OtherHome`	Other real estate	1999–2023	Family File
`studentLoans`	Student loan debt	2011–2023	Family File
`otherDebts`	Other debts	2013–2023	Family File
Panel D: Employment			
`emplStatus`	Employment status of head	1999–2023	Family File
`workingNow`	Currently working (binary)	1999–2023	Family File
`reasonLeftJob`	Reason left last job	1999–2023	Family File
`industryCode`	Census industry (3d 03–15; 4d 17+)	2003–2023	Supplement
`occupationCode`	Census occupation (3d 03–15; 4d 17+)	2003–2023	Family/Supp
Panel E: Consumption (separate extract)			
`foodExpenditure`	Total food expenditure	1999–2023	Family File
`housingExpenditure`	Total housing expenditure	1999–2023	Family File
`transportExpenditure`	Total transportation expenditure	1999–2023	Family File
`healthExpenditure`	Total health care expenditure	1999–2023	Family File
`clothingExpenditure`	Total clothing expenditure	2005–2023	Family File
`recreationExpenditure`	Recreation expenditure	2003–2023	Family File
Panel F: Individual-Level (from Individual File)			
`uniqueID`	Person ID ($\texttt{ER30001} \times 1000 + \texttt{ER30002}$)	—	Indiv. File
`seqNum`	Sequence number in family unit	1999–2023	Indiv. File
`relToHead`	Relationship to reference person	1999–2023	Indiv. File
`age`	Age of individual	1999–2023	Indiv. File
`yearEduc`	Years of completed education	2013–2023	Indiv. File

Notes: All monetary variables deflated to 2016 dollars using the CPI-U. Wealth variables for 1999–2007 use PSID-imputed "S-series" codes; from 2009 onward, wealth is in the main family file. The `savings` variable is unavailable prior to 2003 and is obtained from the supplement file. Industry and occupation codes switch from 3- to 4-digit classification in 2017.

A.3 Sample Construction Pipeline

The sample is constructed in six sequential steps, each corresponding to a separate script in the replication package.

A.3.1 Step 1: Import and Reshape Family File

The main family file is imported using a selective fixed-width (`infix`) command that reads only the approximately 350 variable-columns needed for the analysis. For each of the 13 waves, I extract the wave-specific variables, rename them to standardized names (e.g., `ER13010` → `AgeRef` for 1999, `ER82018` → `AgeRef` for 2023), and append all waves into a single long panel. The supplement file (J361820) is processed identically and merged on `InterviewID` × `year`, filling in variables that are only available in the supplement (principally `savings` and detailed industry codes for 2003–2015).

I harmonize industry and occupation codes across the classification break in 2017:

$$\texttt{industryCode} = \begin{cases} \texttt{industry3d} & \text{if } 2003 \leq \texttt{year} \leq 2015 \\ \texttt{industry4d} & \text{if } 2017 \leq \texttt{year} \leq 2023 \end{cases}$$

A 2-digit industry variable ($\texttt{industry2d} = \lfloor \texttt{industryCode}/10 \rfloor$) is available for analyses requiring consistency across all waves. An involuntary separation indicator is defined as $\texttt{reasonLeftJob} \in \{1, 2\}$ (plant closing or layoff).

The output is a family-year panel (`FamFileSubSetStata.dta`) with one observation per family-interview per wave.

A.3.2 Step 2: Import and Reshape Individual File

The individual file provides person-level data for all PSID sample members. I import 85,536 individuals using a selective `infix` that reads the following per wave: interview number (`InterviewID`), sequence number (`seqNum`), relationship to reference person (`relToHead`), age, and—from 2013 onward—years of completed education (`yearEduc`). The data are reshaped into a person × year panel. A time-invariant person identifier is constructed as:

$$\texttt{uniqueID} = \texttt{ER30001} \times 1000 + \texttt{ER30002}$$

where `ER30001` is the 1968 family lineage number and `ER30002` is the person number within that lineage. This identifier is used throughout for parent–child linkage.

A.3.3 Step 3: Construct Household Panel

The family-year panel and individual-year panel are merged on `InterviewID` × `year`. The resulting dataset is restricted to current family unit members (sequence number 1–20) who are either the household head (`relToHead` = 10), the legal spouse (`relToHead` = 20), or a cohabiting partner (`relToHead` = 22). Including spouses ensures that parents who are not the household head—typically mothers in two-parent households—can be matched to their children via FIMS. Duplicate person-year observations (rare edge cases) are resolved by keeping the first occurrence, with preference given to "head" status. Each person's `uniqueID` is stored as `parent_uniqueID` for the subsequent intergenerational merge.

A.3.4 Step 4: Import Intergenerational Links (FIMS)

The FIMS file maps each PSID sample member to their parents. For each child, up to four parent identifiers are available:

- Biological father (`ER30001_P_F`, `ER30002_P_F`)
- Biological mother (`ER30001_P_M`, `ER30002_P_M`)
- Adoptive father (`ER30001_P_AF`, `ER30002_P_AF`)
- Adoptive mother (`ER30001_P_AM`, `ER30002_P_AM`)

FIMS also provides a generation identifier (`GID`): GID = 1 for 1968 original sample members, GID = 2 for their children, GID = 3 for grandchildren, and so on. The target sample for this paper consists primarily of GID $\geq$ 3 children (born approximately 1975–2005, reaching college age between 1993 and 2023) matched to their GID $\geq$ 2 parents.

A.3.5 Step 5: Import Transfer and Aid Supplement (TAS)

The TAS covers young adults in the 2015 and 2017 waves. I construct a `uniqueID` for each TAS respondent using the same formula as for the individual file. The key variable is college attendance status: `ta150731` $= 1$ indicates current college enrollment in 2015, and `ta170790` $= 1$ indicates college attendance in 2017. Respondents who refuse to answer (`ta170790` $= 9$) are dropped.

A.3.6 Step 6: Construct Analysis Sample

The final analysis sample is constructed by linking children to their parents' household data. The procedure is as follows:

(a) Identify college attendance. College enrollment is identified using a hybrid approach that combines three methods to maximize coverage across all 13 waves:

1. **Direct observation (2013–2023):** A child is coded as attending college if $12 <$ `yearEduc` < 17 and $18 \leq$ `age` ≤ 24. Additionally, an increase in `yearEduc` between consecutive waves signals active enrollment for individuals with `yearEduc` > 12 and `age` ≤ 26.
2. **Age-based proxy (1999–2011):** Since `yearEduc` is unavailable before 2013, children aged 18–22 whose maximum observed education (from later waves) exceeds 12 years are coded as attending college.
3. **TAS confirmation (2015, 2017):** Direct indicators from the TAS supplement override the above for the two available waves. If TAS explicitly reports non-enrollment (`ta150731` $= 5$ or `ta170790` $= 5$), the college indicator is set to zero.

(b) Link children to parents. Each child is linked to a parent household using FIMS identifiers. The parent is selected using the following priority hierarchy:

$$\text{biological father} \rightarrow \text{adoptive father} \rightarrow \text{biological mother} \rightarrow \text{adoptive mother}$$

The parent's unique identifier is computed as `parent_uniqueID` = `ER30001_P` $\times$ 1000 + `ER30002_P`, where the suffix is determined by the priority above. Children with no matchable parent in any category are dropped.

(c) Merge with parent household data. The child–parent linked file is merged with the household panel (`hh_data.dta`) on `parent_uniqueID` $\times$ `year`. Only matched observations are retained.

(d) Collapse to parent-household level. Since the unit of analysis is the parent household, I collapse the data to one observation per `parent_uniqueID` $\times$ `year`. At this stage, I count the number of children currently in college (`NumkidsCollege`) per parent-household-year.

(e) Merge tuition data. I merge state-level college cost data:

- In-state public tuition (by `stateCode` $\times$ `year`), constructed from IPEDS.
- Private college tuition (by `stateCode` $\times$ `year`).
- National average private tuition (by `year`).

All monetary variables are deflated to 2016 dollars using the CPI-U.

(f) Define income groups. Permanent income is computed as the average real household income observed when the reference person is aged 26–59 (i.e., strictly between 25 and 60). For parents not observed in this age range during the sample, I use their overall average income as a fallback. Income groups are defined as:

$$\begin{aligned}
&\text{Group 1:} \quad \$30{,}000 < \bar{y} < \$60{,}000 \\
&\text{Group 2:} \quad \$60{,}000 \leq \bar{y} < \$100{,}000 \\
&\text{Group 3:} \quad \$100{,}000 \leq \bar{y} < \$160{,}000 \\
&\text{Group 4:} \quad \bar{y} \geq \$160{,}000
\end{aligned}$$

Observations with average income outside these ranges or with missing income are dropped.

A.4 Sample Restrictions

The following observations are dropped from the analysis sample:

1. Missing or invalid demographic data: $\texttt{AgeRef} = 999$ or $\texttt{AgeSpouse} = 999$.
2. Missing or invalid education: $\texttt{educHead} = 9$ or $\texttt{educSpouse} = 9$.
3. Top-coded or missing wealth/income: any of `totalFamilyIncome`, `WealthNonHouse`, `AnnuityIRA`, `studentLoans`, `savings`, `OtherDebts`, `TotalWealth`, `Vehicles`, `OtherHome`, or `stocks` equal to 9,999,999 or 9,999,998 (PSID missing/refused codes).
4. Negative total wealth: $\texttt{TotalWealth} < 0$.
5. Logical inconsistencies in portfolio: $\texttt{TotalWealth} < \texttt{HomeEquity}$ or $\texttt{TotalWealth} < \texttt{OtherHome}$.
6. Extreme portfolio shares: home equity share $< -40\%$, other real estate share $< -40\%$, or vehicle share $> 50\%$ of total wealth.
7. Income outside classification bounds: average real income $\leq \$30{,}000$ or unclassifiable.

A.5 Key Constructed Variables

Portfolio shares. Asset portfolio shares are computed as percentages of total net worth:

$$\begin{aligned}
\text{IRA share} &= (\texttt{AnnuityIRA}/\texttt{TotalWealth}) \times 100 \\
\text{Home equity share} &= (\texttt{HomeEquity}/\texttt{TotalWealth}) \times 100 \\
\text{Other real estate share} &= (\texttt{OtherHome}/\texttt{TotalWealth}) \times 100 \\
\text{Vehicle share} &= (\texttt{Vehicles}/\texttt{TotalWealth}) \times 100
\end{aligned}$$

Instrumental variable. The college cost instrument interacts tuition with the number of children currently in college:

$$\texttt{InStateCollCostbykids}_{it} = \log(\text{InStateTuition}_{s(i),t}) \times \texttt{NumkidsCollege}_{it}$$

where $s(i)$ denotes parent i's state of residence.

Involuntary job separation. An indicator for involuntary separation is defined as:

$$\texttt{involuntary\_sep}_{it} = \mathbf{1}[\texttt{reasonLeftJob}_{it} \in \{1, 2\}]$$

where code 1 denotes plant closing and code 2 denotes layoff/termination.

Real variables. All monetary variables are deflated to 2016 dollars using the CPI-U All Urban Consumers index. Log transformations are applied where noted in the regression specifications.

A.6 Consumption Data

PSID consumption expenditure data are available for all waves from 1999 onward. The consumption measure aggregates expenditures across six categories: food (at home and away), housing (rent, utilities, property taxes, insurance), transportation (vehicle costs, fuel, parking, public transit), health care (insurance premiums, out-of-pocket), clothing (available 2005+), and recreation (available 2003+). These variables are extracted in a separate `infix` pass due to Stata/IC variable limits and merged to the main panel on `InterviewID` × `year`.

A.7 Summary of PSID Data Files

Table A.2 summarizes the raw PSID data files used in this paper.

Table A.2. PSID Raw Data Files

File	Extract ID	Content	Size
J361818.txt	Main family file	Demographics, income, wealth, employment	3,611 vars
J361820.txt	Supplement	Industry codes, savings, additional vars	132 vars
J361819.txt	Individual file	Person-level panel (all HH members)	85,536 persons
J361814.txt	TAS	College attendance for young adults	44 vars
FIMS_Data.csv	FIMS	Parent–child intergenerational links	All persons
InStateCollgeCost.dta	—	IPEDS in-state tuition by state × year	External
PrivateCollegeCost.dta	—	IPEDS private tuition by state × year	External
cpi.dta	—	CPI-U deflator (base 2016)	BLS

Notes: PSID data are from the 2023 release (waves 1999–2023, biennial). All PSID data are publicly available from the PSID Data Center (https://psidonline.isr.umich.edu). Tuition data are from IPEDS. CPI data are from the Bureau of Labor Statistics.

A.8 Merge Attrition

Table A.3 documents the sample size at each stage of the data pipeline: starting from the full PSID individual file, linking children to parents via FIMS, and merging with household-level data on consumption, income, and wealth. Panel B breaks down the parent–child links by relationship type (biological father, adoptive father, biological mother). Panel C quantifies the observations lost at each merge stage. The main source of attrition is the requirement that the identified parent appears as a household head or spouse in the PSID family file during the sample period.

Table A.3. PSID Sample Construction and Merge Attrition

Stage	Observations	Unique IDs	% Retained
Panel A: Building the Analysis Sample			
Individual file (all persons × years)	441 158	45 386	—
After college identification	441 152	45 386	100.0
Matched to FIMS (child–parent link)	358 874	34 916	81.3
Matched to parent household (hh_data)	148 541	10 492	41.4
Collapsed to parent-HH × year	71 896	10 492	—
After sample restrictions	62 320	10 145	86.7
Panel B: Parent Identification Source			
Linked via biological father	297 284		
Linked via adoptive father	4114		
Linked via biological mother	56 856		
No identifiable parent (dropped)	0		
Panel C: Merge Losses			
Individuals not in FIMS	82 278		
Child–years without parent in hh_data	210 333		
Parent–years without state tuition data	16 488		
Final analysis sample	62 320	10 145	
of which: HH–years with child in college	6566		

Notes: Children are linked to parents via FIMS. The parent–child link follows a hierarchical priority: biological father, adoptive father, biological mother, adoptive mother. "Unique IDs" refers to unique persons (first two rows) or unique parent households (remaining rows). "% Retained" is relative to the previous stage. All monetary variables winsorized at the 1st and 99th percentiles and deflated to 2016 dollars.

A.9 PSID Variable Codes by Wave

Table A.4 provides the complete mapping of standardized variable names to PSID ER-codes for each wave. This mapping is necessary for replication, as PSID assigns unique variable codes to each concept in each wave.

Table A.4. Selected PSID ER-Codes by Wave (Family File)

Variable	**1999**	**2001**	**2003**	**2005**	**2007**	**2009**	**2011**	**2013**	**2015**	**2017**	**2019**	**2021**	**2023**
Interview ID	ER13002	ER17002	ER21002	ER25002	ER36002	ER42002	ER47302	ER53002	ER60002	ER66002	ER72002	ER78002	ER82002
Age Head	ER13010	ER17013	ER21017	ER25017	ER36017	ER42017	ER47317	ER53017	ER60017	ER66017	ER72017	ER78017	ER82018
Total Income	ER16462	ER20456	ER24099	ER28037	ER41027	ER46935	ER52343	ER58152	ER65349	ER71426	ER77448	ER81775	ER85629
Head Labor Inc.	ER16463	ER20443	ER24116	ER27931	ER40921	ER46829	ER52237	ER58038	ER65216	ER71293	ER77315	ER81642	ER85496
Spouse Labor Inc.	ER16465	ER20447	ER24135	ER27943	ER40933	ER46841	ER52249	ER58050	ER65244	ER71321	ER77343	ER81670	ER85524
Total Wealth	S417	S517	S617	S717	S817	ER46970	ER52394	ER58211	ER65408	ER71485	ER77511	ER81838	ER85692
Home Equity	S420	S520	S620	S720	S820	ER46966	ER52390	ER58207	ER65404	ER71481	ER77507	ER81834	ER85688
AnnuityIRA	S419	S519	S619	S719	S819	ER46964	ER52368	ER58181	ER65378	ER71455	ER77481	ER81808	ER85662
Stocks	S411	S511	S611	S711	S811	ER46954	ER52358	ER58171	ER65368	ER71445	ER77471	ER81798	ER85652
Vehicles	S413	S513	S613	S713	S813	ER46956	ER52360	ER58173	ER65370	ER71447	ER77473	ER81800	ER85654
Empl. Status	ER13205	ER17216	ER21123	ER25104	ER36109	ER42140	ER47448	ER53148	ER60163	ER66164	ER72164	ER78167	ER82150
Educ. Head	ER15951	ER20012	ER23449	ER27416	ER40588	ER46566	ER51927	ER57683	ER64835	ER70907	ER76922	ER81169	ER85146
Race Head	ER15928	ER19989	ER23426	ER27393	ER40565	ER46543	ER51904	ER57659	ER64810	ER70882	ER76897	ER81144	ER85121

Notes: The S-series codes (S411–S820) refer to PSID-imputed wealth supplement variables used in waves 1999–2007; from 2009 onward, wealth variables are recorded directly in the main family file with ER-codes. The complete set of codes used in this paper covers approximately 350 variables across all 13 waves. The full mapping is available in the replication package.

A.10 Individual File Variables by Wave

Table A.5 documents the individual-file variable codes used to construct the person-year panel.

Table A.5. Individual File ER-Codes by Wave

Variable	**1999**	**2001**	**2003**	**2005**	**2007**	**2009**	**2011**	**2013**	**2015**	**2017**	**2019**	**2021**	**2023**
Interview ID	ER33501	ER33601	ER33701	ER33801	ER33901	ER34001	ER34101	ER34201	ER34301	ER34501	ER34701	ER34901	ER35101
Sequence No.	ER33502	ER33602	ER33702	ER33802	ER33902	ER34002	ER34102	ER34202	ER34302	ER34502	ER34702	ER34902	ER35102
Rel. to Head	ER33503	ER33603	ER33703	ER33803	ER33903	ER34003	ER34103	ER34203	ER34303	ER34503	ER34703	ER34903	ER35103
Age	ER33504	ER33604	ER33704	ER33804	ER33904	ER34004	ER34104	ER34204	ER34305	ER34504	ER34704	ER34904	ER35104
Years Educ.	—	—	—	—	—	—	—	ER34230	ER34349	ER34548	ER34752	ER34952	ER35152

Notes: Years of completed education (`yearEduc`) is only available in the Individual File from 2013 onward. For earlier waves, college attendance is identified using the age-based proxy described in Section A.3. The time-invariant person identifiers `ER30001` (1968 Interview Number, bytes 2–5) and `ER30002` (Person Number, bytes 6–8) are constant across all waves.

B NLSY97 Sample Construction

This appendix describes the construction of the NLSY97 analysis sample. The National Longitudinal Survey of Youth 1997 (NLSY97) tracks a nationally representative cohort of 8,984 Americans born between 1980 and 1984, interviewed annually from 1997 through 2017 (biennially after 2011). I use the NLSY97 for two purposes: constructing college graduation rates by ability and parent wealth quartile (the 16 moments used in SMM estimation), and estimating the education-specific income process.

B.1 Data Sources

Main Survey File. The raw NLSY97 download contains 2,257 variables across all survey rounds. Because the Stata/IC variable limit of 2,048 is binding, I use a Python preprocessing script (`00_subset_nlsy97.py`) to extract the approximately 110 variables needed for the analysis before loading into Stata.

Schooling Module (YSCH Series). The YSCH-24600 series records detailed college enrollment and financing information at the college$\times$term$\times$year level. Variables include tuition charges, room and board costs, grants and scholarships received, total loans, out-of-pocket expenses, and parental transfers. These are reshaped from the NLS Investigator's wide format into a college–term–year panel.

Income and Transfer Module (YINC Series). The YINC-5800 and YINC-8200 variables record total parental transfers and parental allowances, respectively, for each survey year from 1997 to 2003. These capture financial support from parents during the college-age years.

Wage and Hours Data. The YINC-1700 series provides annual labor income, and the CVC_HOURS_WK_YR series provides annual hours worked, used to estimate the education-specific income process.

B.2 Variable Construction

Table B.1 summarizes the key variables used from the NLSY97.

Table B.1. NLSY97 Variables Used in Analysis

Variable	Description	Years	Source
Panel A: Demographics and Ability			
PUBID_1997	Individual identifier	—	Survey ID
KEYSEX_1997	Gender	1997	Baseline
KEYRACE_ETHNICITY	Race/ethnicity (4 categories)	1997	Baseline
KEYBDATE_Y_1997	Birth year	1997	Baseline
ASVAB_MATH_VERBAL	ASVAB math-verbal percentile	1999	CAT-ASVAB
CVC_SAT_VERBAL	SAT verbal score	2007 XRND	Transcript
CVC_SAT_MATH	SAT math score	2007 XRND	Transcript
CVC_ACT_SCORE	ACT composite score	2007 XRND	Transcript
TRANS_CRD_GPA	Overall high school GPA	—	Transcript
Panel B: Family Background			
CV_HGC_BIO_MOM	Bio. mother's highest grade	1997	Baseline
CV_HGC_BIO_DAD	Bio. father's highest grade	1997	Baseline
CV_INCOME_GROSS_YR	Gross family income	1997–2003	Annual
CV_CENSUS_REGION	Census region at baseline	1997	Baseline
Panel C: College Enrollment and Costs (YSCH-24600)			
Tuition (YSCH_21900)	Tuition charged per term	1997–2017	Schooling
Grants (YSCH_25400)	Grants and scholarships	1997–2017	Schooling
Loans (YSCH_25600)	Total student loans	1997–2011	Schooling
Out-of-pocket (YSCH_24600)	Out-of-pocket college expenses	1998–2001	Schooling
Room & board	Room and board costs	1998–2001	Schooling
Credit hours	Credit hours attempted	1997–2017	Schooling
Panel D: Education Attainment			
YSCH_2857	Highest grade attended	1998–2003	Annual
CVC_HIGHEST_DEGREE	Highest degree ever received	XRND	Cumulative
College withdrawal	Whether withdrew from college	Annual	Schooling
Panel E: Income Process			
YINC_1700	Annual labor income	1997–2011	Income
CVC_HOURS_WK_YR	Annual hours worked (all jobs)	1997–2007	Employment
Panel F: Parental Transfers			
YINC_5800	Total parental transfers ($)	1997–2003	Income
YINC_8200	Parental allowance ($)	1997–2003	Income

Notes: XRND denotes cross-round variables computed by NLS staff from the cumulative survey history. The ASVAB composite score is the math-verbal percentile from the CAT-ASVAB administered in 1999. The YSCH schooling variables are indexed by college enrollment number, term, and survey year. Parental income is gross household income of the respondent's family of origin.

B.3 Sample Construction

B.3.1 Step 1: Subset and Reshape

The raw NLSY97 file (2,257 variables) is first subset to approximately 110 variables using a Python script, then loaded into Stata. I keep core demographics (gender, race, birth year, census region), parental education (highest grade completed for biological mother and father), cognitive ability (ASVAB math-verbal percentile score from the 1999 administration), academic performance (SAT/ACT scores, high school GPA from transcripts), and family income from 1997 to 2003.

B.3.2 Step 2: College Enrollment Variables

The detailed schooling module variables (YSCH series) are reshaped from the NLS Investigator's wide format into long panels indexed by individual, college enrollment number, term, and year. Separate reshape scripts process each topic: tuition (`YSCH_21900`), grants and scholarships (`YSCH_25400`), total loans (`YSCH_25600`), out-of-pocket expenses (`YSCH_24600`), room and board, credit hours taken, and college withdrawal indicators. These are then merged into a unified college-spell panel.

B.3.3 Step 3: Education Attainment

College attendance is identified from the highest grade attended variable (`YSCH_2857`), available for 1998–2003. I define college attendance as the maximum grade attended exceeding 12 (i.e., any postsecondary enrollment). College graduation is defined as attaining a bachelor's degree by age 25, using the cumulative highest-degree variable (`CVC_HIGHEST_DEGREE_EVER`).

B.3.4 Step 4: Income Process Estimation

For the income process, I use annual labor income (`YINC_1700`) and hours worked (`CVC_HOURS_WK_YR_ALL`) to construct hourly wages by education group. Following Abbott et al. (2019), I estimate the high-school-to-college income ratio and education-specific income standard deviations, which provide 3 of the moments used in SMM estimation.

B.3.5 Step 5: Parental Transfers

Parental financial transfers (`YINC_5800`) and allowances (`YINC_8200`) are reshaped into a person-year panel for 1997–2003. These variables capture total financial support from parents during the college-age years and are used to calibrate the transfer structure in the model.

B.4 Key Constructed Variables

Ability quartiles. I rank individuals by their ASVAB math-verbal percentile score (administered in 1999) and partition into quartiles. The sample is restricted to individuals with non-missing ASVAB scores.

Parent wealth quartiles. Total household net worth at age 17 is used to construct within-cohort parent wealth quartiles. Together with ability quartiles, these define the 4×4 grid of college graduation rates used as the core estimation moments.

College graduation rates. The 16 cell-level graduation rates (ability quartile $\times$ parent wealth quartile) are the primary target moments for SMM estimation. These trace how college attainment varies across the joint distribution of ability and parental resources.

Average tuition. The gross annual cost of college ($\phi = \$12{,}200$) is computed from average tuition reported in the NLSY97 schooling module, following Abbott et al. (2019).

C HRS Sample Construction

This appendix describes the construction of the HRS analysis sample. The Health and Retirement Study (HRS) is a biennial longitudinal survey of Americans over age 50, conducted by the University of Michigan since 1992. I use the RAND HRS Longitudinal File (2022 version 1), which harmonizes variables across all waves (1992–2022), together with three supplemental files: the RAND Family-Kids file, the RAND Family-Resident file, the Consumption and Activities Mail Survey (CAMS), and the HRS Supplemental Survey on College Support (HUMS).

C.1 Data Sources

RAND HRS Longitudinal File. The core source is the RAND HRS 2022v1 longitudinal file, which contains 19,880 variables in wide format (one row per respondent, wave-varying variables indexed by wave number 1–16, corresponding to 1992–2022). The RAND staff harmonize variable definitions, handle skip patterns, and construct consistent wealth, income, and health variables. Due to the Stata/IC variable limit, I use a Python preprocessing script (`00_subset_hrs_wide.py`) to extract the approximately 860 needed variables before loading into Stata.

The RAND naming convention embeds the wave number: household-level variables use `h{wave}{stem}` (e.g., `h6atotb` = total wealth, wave 6), respondent-level variables use `r{wave}{stem}`, spouse-level variables use `s{wave}{stem}`, and time-invariant variables use `ra{stem}`.

RAND Family-Kids File. The family-kids file (`randhrsfamk1992_2014v1.dta`) records information about each respondent's children, including demographics (age, gender, education, marital status), geographic proximity, financial transfers in both directions, care provision, and bequest intentions. The file is in wide format with approximately 400 variables after subsetting, and is reshaped to a kid×wave panel.

RAND Family-Resident File. The family-resident file (`randhrsfamr1992_2014v1.dta`) provides household composition variables—number of living children, sons, and daughters—by wave. After subsetting to approximately 40 variables, this is reshaped to a respondent×wave panel.

CAMS (Consumption and Activities Mail Survey). CAMS (`randcams_2001_2017v1.dta`) is a supplemental mail survey that collects detailed consumption and spending data for a subset of HRS households, biennially from 2001 to 2017. Variables include total household spending, durable and non-durable spending, housing expenditure, and mortgage payments.

HUMS (Supplemental Survey on College Support). The HUMS supplement collects retrospective information on parents' financial contributions to their children's college education. For each child who attended college, the survey records tuition amounts, room and board costs, years of college, and the percentage of costs paid by the parent. I use HUMS to construct the total parental contribution to college in real 2016 dollars.

Exit Interview (Heritage File). The HRS exit interview, conducted with a proxy informant after a respondent's death, records bequest and inheritance information. I use the Heritage file to construct child-level bequest amounts (dollar transfers and estate percentages) and housing inheritance (whether each child inherited the main residence and the imputed value).

College Tuition Data. Regional in-state college tuition costs by census division and year (`InStateCollgeCost.csv`) are merged with HRS respondents using their census division of residence. These provide the regional college cost variation used in the analysis.

C.2 Variable Construction

Table C.1 summarizes the key variables constructed from the HRS data products.

Table C.1. HRS Variables Used in Analysis

Variable	Description	Waves	Source
Panel A: Respondent Demographics			
`AgeRespondant`	Age of respondent	1–16	RAND HRS
`AgeSpouse`	Age of spouse	1–16	RAND HRS
`RespondGender`	Gender	Time-inv.	RAND HRS
`RespondantRace`	Race	Time-inv.	RAND HRS
`RespondantYearEducation`	Years of education	Time-inv.	RAND HRS
`RespondantDegree`	Highest degree	Time-inv.	RAND HRS
`RespondantBirthYear`	Birth year	Time-inv.	RAND HRS
`SampleCohort`	HRS sample cohort	Time-inv.	RAND HRS
`RespondCensusDiv`	Census division	1–16	RAND HRS
Panel B: Household Wealth			
`TotalWealth`	Total net worth	1–16	RAND HRS
`NvalueHome`	Net home value	1–16	RAND HRS
`NvalueIRA`	IRA/Keogh accounts	1–16	RAND HRS
`Nsavings`	Checking/savings	1–16	RAND HRS
`Nvehicles`	Vehicle value	1–16	RAND HRS
`NvalueBusiness`	Business/farm assets	1–16	RAND HRS
`NotherRealStateAssets`	Other real estate	1–16	RAND HRS
Panel C: Income			
`TotalHouseholdIncome`	Total HH income	1–16	RAND HRS
`IncomeSSretirement`	SS retirement income	1–16	RAND HRS
`IncomeSSDisSSI`	SS disability/SSI	1–16	RAND HRS
`IncomePension`	Pension income	1–16	RAND HRS
Panel D: Bequest Expectations			
`ProbBequest10`	Prob. bequest $\geq$ \$10K	1–16	RAND HRS
`ProbBequest100`	Prob. bequest $\geq$ \$100K	1–16	RAND HRS
`ProbBequest500`	Prob. bequest $\geq$ \$500K	1–16	RAND HRS
`ProbAnyBequest`	Prob. any bequest	1–16	RAND HRS
Panel E: Child Information (Family-Kids File)			
`kidYearEducation`	Child's years of education	1–12	Family-Kids
`kidAge`	Child's age	1–12	Family-Kids
`kidGender`	Child's gender	Time-inv.	Family-Kids
`kidMarried`	Child's marital status	1–12	Family-Kids
`kidIncomeRange`	Child's income bracket	1–12	Family-Kids
`kid10miles`	Lives within 10 miles	1–12	Family-Kids
Panel F: Inter-Vivos Transfers (Family-Kids File)			
`kParentGiveFinancialTransfer`	Parent gave transfer (0/1)	1–12	Family-Kids
`kParentGiveAmount`	Amount parent gave (\$)	1–12	Family-Kids
`kidAnyTransfer`	Child gave transfer (0/1)	1–12	Family-Kids
`kidTransferAmountImp`	Amount child gave (\$, imp.)	1–12	Family-Kids
Panel G: College Support (HUMS)			
`totalParentContribution`	Tuition + board paid (2016\$)	Retro.	HUMS
`NumKidsWentCollege`	N children in college	Retro.	HUMS
`ParentSupportKid`	Parent contributed >0	Retro.	HUMS
Panel H: Consumption (CAMS)			
`totalHouseholdConsumption`	Total HH consumption	2001–17	CAMS
`totalNonDurableSpenditure`	Non-durable spending	2001–17	CAMS
`totalHousingSpending`	Housing expenditure	2001–17	CAMS
Panel I: Bequests (Exit Interview)			
`amountTransferChild`	Dollar bequest to child	Exit	Heritage
`perEstateTransChild`	% of estate to child	Exit	Heritage
`AmountHouseInherited`	Housing inheritance value	Exit	Heritage

Notes: Waves 1–16 correspond to HRS survey years 1992–2022. The Family-Kids and Family-Resident files cover waves 1–12 (1992–2014). All monetary variables in the RAND HRS file are nominal; deflation to 2016 dollars occurs in the analysis scripts. HUMS variables are retrospective (covering the child's entire college period). Child income brackets in the Family-

C.3 Sample Construction Pipeline

C.3.1 Step 1: Import and Reshape RAND HRS Longitudinal File

The full RAND HRS file (19,880 variables, one row per respondent) is first subset to approximately 860 variables using a Python script (`00_subset_hrs_wide.py`). The subset retains time-invariant identifiers (`hhid`, `hhidpn`), demographic variables (birth year, gender, race, education, religion), and wave-varying variables for wealth (22 stubs), income (4 stubs), health (4 stubs), bequest expectations (4 stubs), family structure (4 stubs), employment (2 stubs), and spouse characteristics (10 stubs). The data are then reshaped from wide to long format using Stata's `reshape long` command, producing a person×wave panel.

Several variables require type conversions for downstream compatibility: `hhid` (string to numeric), `SampleCohort`, `RespondGender`, `RespondantYearEducation`, `RespondantDegree`, `RespondantRace`, `InterviewStatus`, and `IndustryCode` are converted from labeled numeric to string using `decode/tostring`, as downstream scripts compare against full label strings.

C.3.2 Step 2: Clean Family-Kids File

The Family-Kids file is subset and reshaped from wide (one row per child, waves as columns) to long (one row per child×wave). A unique child identifier is constructed as:

$$\texttt{uniqueKidID} = \texttt{hhidpn} \times 10^5 + \text{last 5 digits of } \texttt{kidid}$$

This links each child to their parent respondent. Variables are renamed to human-readable names and organized into demographic, child-to-parent transfer, parent-to-child transfer, and bequest intention groups.

C.3.3 Step 3: Clean Family-Resident File

The Family-Resident file provides household composition by wave: total number of living children, sons, and daughters. This is reshaped from wide to long and merged with the main panel to provide the child count breakdown.

C.3.4 Step 4: Consumption Data (CAMS)

The CAMS file is reshaped from wide to long format, yielding a respondent×wave panel with total household spending, durable and non-durable spending, housing expenditure, mortgage payments, and total household consumption. CAMS covers a subsample of HRS households biennially from 2001 to 2017.

C.3.5 Step 5: College Support (HUMS)

The HUMS supplement is cleaned and merged with the HUMS imputation file. For each child who attended college (`H3`=1), I compute:

$$\texttt{totalParentContribution} = \text{tuition}_{\text{real}} \times \text{years} \times \frac{H9}{10} + \text{board}_{\text{real}} \times \text{years}_{\text{board}} \times \frac{H11}{100}$$

where tuition and board are deflated to 2016 dollars using the CPI-U, $H9$ is the fraction of tuition paid (scale 0–10), and $H11$ is the fraction of room and board paid (scale 0–100). Observations with missing codes (`H5`=99, `H9`$\geq$99.9, `H11`=999) are dropped; `H11`=997 ("other/inapplicable") is recoded to zero. The total family contribution sums across all children in the household.

C.3.6 Step 6: Spouse Death File

A spouse death file is constructed by extracting the death year of each HRS respondent and renaming their identifier to `SpouseIdentifier`. When merged with the main panel on `SpouseIdentifier`, this brings in the death year of the respondent's partner, enabling analysis of widowhood effects.

C.3.7 Step 7: Exit Interview and Bequests

The Heritage file from the exit interview provides two types of child-level bequest information:

Financial bequests. Dollar amounts and estate percentages transferred to each child are cleaned by removing HRS missing codes (999998, 999999, 9999998, 9999999, 99998, 99999, 9998, 9999 for amounts; 998, 999 for percentages). When the percentage is missing but dollar amounts are available, the percentage is imputed as each child's share of total transfers. Small amounts ($\leq$100) are treated as percentage values rather than dollar amounts. These are merged with the parent–child link file using `kidid`.

Housing inheritance. For respondents whose main residence was disposed to children (`dispositionMainHome` $\in \{2, 3\}$) and not inherited by the spouse, I identify which children received the house using the OPN (Other Person Number) codes. When the code indicates "all children" (OPN = 993), the value is split equally. The per-child housing inheritance is:

$$\texttt{AmountHouseInherited} = \frac{\texttt{valueMainRes}}{N_{\text{recipients}}} \times \mathbf{1}[\text{child received house}]$$

C.3.8 Step 8: Regional College Cost Merge

Average in-state college tuition by census division and year is imported from an external CSV file and reshaped into a region×year panel. This is merged with HRS respondents using the census division of residence (`RespondCensusDiv`).

C.4 Sample Restrictions

I impose the following restrictions, analogous to those applied to the PSID sample:

1. **Age restrictions:** Parents over age 50 and children over age 26.
2. **Interview status:** Only respondents with completed interviews in each wave (`InterviewStatus` indicates a completed interview).
3. **Couple households:** For analyses requiring spouse information, I restrict to coupled households using the `CoupleHH` indicator.
4. **Missing data:** Observations with HRS missing codes (.d = don't know, .r = refused, .m = missing) are handled according to the specific analysis. For wealth and income, these codes are preserved through the data construction stage and handled in the analysis scripts.

The final HRS analysis sample contains 19,179 parent–child pairs and 98,861 observations.

D Parent Wealth Portfolio

Table D.1 provides a detailed breakdown of parent income and wealth by income group. The table complements the summary variables reported in Table 1 in the main text.

Table D.1. Parent Income and Wealth by Income Group (PSID, 2016 Dollars)

	By Average HH Income Group				
	30 − −60	60 − −100	100 − −160	160+	All
Household income	44,223	76,829	120,169	242,277	102,569
	(21,535)	(37,964)	(51,447)	(253,591)	(121,904)
Head labor income	23,523	40,976	64,728	123,504	53,930
	(19,369)	(28,162)	(42,902)	(123,970)	(64,202)
Total wealth	102,555	200,522	367,076	965,941	326,288
	(230,260)	(377,059)	(536,534)	(1,052,497)	(612,283)
Home equity	48,321	76,931	127,798	223,253	102,056
	(86,276)	(105,763)	(136,410)	(195,989)	(138,176)
IRA/annuity	6,437	20,026	49,226	107,888	35,668
	(38,692)	(68,967)	(108,878)	(163,964)	(98,914)
Non-housing fin. wealth	53,469	121,496	234,059	698,124	214,727
	(182,888)	(318,143)	(453,318)	(895,431)	(505,467)
Savings	7,950	16,013	36,321	68,743	25,676
	(31,182)	(39,546)	(61,142)	(87,368)	(56,070)
Vehicles	12,549	19,741	24,701	32,096	20,737
	(16,601)	(19,952)	(22,565)	(28,691)	(22,256)
Other real estate	7,938	13,934	22,799	55,426	20,513
	(42,810)	(57,200)	(75,043)	(122,965)	(73,634)
Student loans	1,736	4,134	7,932	7,755	4,881
	(7,821)	(12,628)	(18,488)	(20,246)	(14,759)
Observations	15 096	17 356	13 011	7863	53 326
Unique parent households	2718	2770	1833	1041	8362

Notes: Means with standard deviations in parentheses. All monetary variables deflated to 2016 dollars using the CPI-U and winsorized at the 1st and 99th percentiles. Income groups defined by parent average real household income observed between ages 25 and 60.

E Parent Consumption Detail

Table E.1 decomposes total household consumption into major expenditure categories. Housing constitutes the largest category across all income groups, followed by transportation and food. Discretionary categories—clothing, recreation, and vacation—are only available from the 2005 wave onward and increase sharply with income.

Table E.1. Parent Household Consumption by Income Group (PSID, 2016 Dollars)

	By Average HH Income Group				
	30 − −60	60 − −100	100 − −160	160+	All
Total consumption	36,426	46,131	57,243	73,130	50,076
	(18,374)	(20,389)	(24,489)	(33,277)	(26,252)
Food	7,915	9,211	10,582	12,872	9,718
	(4,854)	(4,944)	(5,296)	(6,269)	(5,470)
Housing	15,030	18,677	24,487	33,215	21,206
	(9,071)	(10,757)	(13,588)	(18,356)	(13,873)
Transportation	9,310	11,880	13,811	15,562	12,166
	(8,213)	(8,709)	(9,844)	(11,999)	(9,661)
Health care	2,108	3,402	4,195	5,027	3,469
	(3,027)	(3,649)	(4,157)	(4,832)	(3,950)
Clothing (2005+)	1,356	1,577	1,912	2,808	1,776
	(1,704)	(1,762)	(1,907)	(2,626)	(1,988)
Recreation (2005+)	503	807	1,178	1,805	957
	(920)	(1,211)	(1,464)	(1,897)	(1,396)
Vacation (2005+)	835	1,482	2,376	3,886	1,870
	(1,505)	(2,020)	(2,583)	(3,604)	(2,554)
Observations	15 096	17 356	13 011	7863	53 326
Unique parent households	2718	2770	1833	1041	8362

Notes: Means with standard deviations in parentheses. Consumption data available from the PSID beginning in 1999. All expenditure categories deflated to 2016 dollars and winsorized at the 1st and 99th percentiles. Clothing, recreation, and vacation are available from 2005 onward only. Total consumption is the sum of all listed categories.

F Additional Robustness: Parent Fixed Effects

As additional robustness for Facts 1 and 2, I exploit parent fixed effects to identify the college effect from within-family (between-sibling) variation. For consumption, the specification uses child-pair-year observations: within a given family and year, siblings who differ in college attainment generate variation in the college indicator while holding all parent-level characteristics constant.

Table F.1 reports parent fixed effects regressions of log parent consumption on the child's college indicator, at the child-pair-year level. The positive and significant coefficient confirms that the consumption difference documented in Section 4.2 is not driven by unobserved parental characteristics: even within the same family, parent consumption is higher in years when the college-educated child's characteristics are more salient.

Table F.1. Parent Consumption and Child College Status: Parent Fixed Effects (PSID)

	(1)	(2)
	OLS + Income Q FE	Parent FE
College (BA+)	0.068***	0.027**
	(0.018)	(0.013)
Observations	13,841	13,841
R^2	0.469	0.840

Notes: Regressions of log parent household consumption on child college indicator (BA+), at the child-pair-year level. Column 1: OLS with parent income quartile fixed effects and comprehensive controls. Column 2: parent fixed effects with child age polynomial and education controls. Standard errors clustered at the parent household level in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

G Full Commitment Benchmark

This appendix provides additional details on the full commitment benchmark introduced in Section 7.1 of the main text.

Under full commitment, a benevolent planner commits at $t = 0$ to a state-contingent transfer schedule $\{\tau(a_p, a_c, z, t)\}$ for the entire overlap period, solving a single-agent problem over total household wealth $A \equiv a_p + a_c$ (equation 14 in the main text). With CRRA preferences, the efficient allocation equates weighted marginal utilities:

$$u'(c_p) = \eta\, u'(c_c), \qquad \text{so that} \qquad c_c = \eta^{1/\gamma}\, c_p \tag{24}$$

Consumption shares are time-invariant. Substituting yields:

$$u_{\text{FC}}(c_{\text{tot}}) = \frac{c_{\text{tot}}^{1-\gamma}}{1-\gamma}\left(1 + \eta^{1/\gamma}\right)^{\gamma} \tag{25}$$

Relationship to the one-time transfer counterfactuals. The full commitment benchmark and the one-time transfer counterfactuals (Section 7.8.1) remove the Samaritan's dilemma through different mechanisms. Full commitment eliminates moral hazard while preserving state-contingent insurance: the planner adjusts transfers in response to income shocks throughout the overlap period. The one-time transfer counterfactuals eliminate both moral hazard and ongoing insurance: the child receives a lump sum at $t = 0$ and is subsequently on their own. The difference between FC and the one-time transfer economies therefore isolates the *insurance-removal effect*—the change in college attendance and welfare attributable to shutting down ongoing parental support, holding the absence of moral hazard fixed.

Comparing FC with the baseline MPE yields the pure moral hazard effect holding insurance constant. As discussed in Section 7.2, this comparison reveals two opposing forces: anticipated transfers subsidize enrollment (raising college attendance above the efficient level) but also cushion non-college children (lowering attendance below the efficient level). The net sign depends on the child's position in the ability–wealth distribution.

H Equilibrium Properties

This appendix derives the key properties of the Markov-Perfect Equilibrium in the continuous-time coupled problem.

H.1 Optimality Conditions

The child's first-order condition from the HJB equation (2) gives $u'(c_c^*) = V_{a_c}^c$. In the no-transfer region ($\tau^* = 0$), the child's continuous-time Euler equation takes the standard form $\dot{c}_c/c_c = (r - \rho)/\gamma$. In the transfer region ($\tau^* > 0$), the transfer flow depends on the state, and the Euler equation becomes:

$$\frac{\dot{c}_c}{c_c} = \frac{1}{\gamma}\left(r - \rho + \frac{\partial \tau^*}{\partial a_c}\right) \tag{26}$$

The term $\partial \tau^*/\partial a_c < 0$ is the Samaritan's dilemma in continuous time: as child wealth increases, the parent reduces transfers, effectively lowering the child's return on saving below r and creating an incentive to over-consume.

The parent's first-order condition gives $u'(c_p^*) = V_{a_p}^p$. In the no-transfer region:

$$\frac{\dot{c}_p}{c_p} = \frac{1}{\gamma}(r - \rho) \tag{27}$$

In the transfer region, $V_{a_p}^p = V_{a_c}^p$: the parent equalizes marginal values of own and child wealth. The parent's wealth drift is exactly zero ($\dot{a}_p = 0$), as the parent channels all net resources to the child.

H.2 Transfer Region Characterization

The variational inequality (3) partitions the state space into:

1. **No-transfer region** $\mathcal{N} = \{(a_p, a_c, z, t) : V_{a_p}^p > V_{a_c}^p\}$: Parent and child accumulate wealth independently.

2. **Transfer region** $\mathcal{T} = \{(a_p, a_c, z, t) : V_{a_p}^p = V_{a_c}^p\}$: The transfer flow absorbs the parent's excess savings: $\tau^* = ra_p + y_p - c_p$.

The boundary is a free boundary determined endogenously. Parents transfer when the child is relatively poor (low a_c), faces negative income shocks (low z), or when the parent is wealthy (high a_p). The region shrinks as the parent approaches death.

H.3 The Samaritan's Dilemma

Both agents over-consume relative to the commitment solution. The child's distortion arises because anticipated transfers reduce the effective return on saving. Near the transfer boundary, the child anticipates that accumulating wealth will push the state into the no-transfer region, eliminating support. This creates a marginal disincentive to save, captured by $\partial\tau^*/\partial a_c$ in (26).

The parent's saving is also distorted: by saving more, the parent anticipates spending more time in the transfer region, which provides utility through child consumption but reduces the child's incentive to self-insure. In continuous time, this manifests as the parent's wealth drift being zero in $\mathcal{T}$.

The continuous-time formulation offers two advantages over discrete-time alternatives. First, transfers are a continuous flow rather than lump-sum payments, eliminating timing discreteness. Second, the free boundary provides a sharp characterization of where moral hazard operates.

H.4 College and Parental Influence

The college decision at $t = 0$ is forward-looking: the child compares lifetime values under each education path, incorporating the entire future trajectory of transfers. Altruistic parents affect the decision through two channels. First, they provide generous transfers during the college years (when child income is low), effectively subsidizing attendance—the transfer region $\mathcal{T}$ is larger when $e_c = C$ during the early years. Second, the continuation value under $e_c = C$ incorporates higher future income, which feeds back into the transfer policy: wealthier children require fewer transfers, freeing parent resources. The net effect generates a positive gradient of college enrollment in parent wealth.

I Solution Algorithm

The model is solved numerically using an upwind finite difference scheme with implicit time-stepping, following Achdou et al. (2022) and the transfer-region methods of Barczyk and Kredler (2014a,b).

1. **Grid construction.** Exponentially-spaced grids on $a_p \in [0, \bar{a}_p]$ and $a_c \in [0, \bar{a}_c]$; a uniform grid on $z \in [-\bar{z}\sigma_{\text{stat}}, \bar{z}\sigma_{\text{stat}}]$ where $\sigma_{\text{stat}} = \sigma_e/\sqrt{2\kappa_e}$; and a discrete ability grid θ from the Tauchen method.

2. **Child-alone HJB.** For each (θ, e_c), solve (8) backward from child death to parent death. This yields the terminal condition $V^{c,\text{alone}}(a_c, z; 0)$.

3. **Coupled system.** For each (θ, e_p, e_c), solve (1)–(2) backward from $t = T$ to $t = 0$:

   (a) Compute upwind derivatives of V^p and V^c (forward differences where drift is positive, backward where negative).

   (b) Determine consumption from FOCs and the transfer from (3): if $V^p_{a_c} > V^p_{a_p}$, set $\tau = ra_p + y_p - (V^p_{a_c})^{-1/\gamma}$.

   (c) Iterate on the transfer region indicator until convergence (policy iteration).

   (d) Construct the sparse infinitesimal generator $\mathcal{A}$ incorporating upwind drift terms and the OU generator.

   (e) Implicit time step: solve $[(\rho + 1/\Delta t)I - \mathcal{A}]\, V^n = u^n + V^{n+1}/\Delta t$.

4. **College choice.** At $t = 0$, compute logit enrollment probabilities from (11) for each (a_p, θ).

5. **Simulation.** Simulate dynasties forward from the ergodic distribution, compute the 35 targeted moments.