When Children Pay: The Reversal of Fertility's Retirement Impact Across the Income Distribution

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Abstract

We document a striking reversal in the relationship between childlessness and retirement income across the income distribution. While childless individuals in the bottom 40% of the income distribution face retirement income penalties of 5-11%, those in the top quartile enjoy premiums exceeding 10%. This reversal—occurring around the 40th percentile—reveals that children's economic value in retirement fundamentally depends on the economic resources of their households. For low-income retirees, children provide crucial insurance through informal support networks, shared housing, and care provision. For high-income retirees, childlessness enables uninterrupted career development and higher lifetime savings that compound into retirement advantages. These findings challenge conventional understandings of the economic consequences of fertility decisions and suggest that family structure interacts with economic outcomes in fundamentally different ways depending on household resources, gender, and socioeconomic status.

JEL classification: J13, J26, D31

Keywords: Childlessness Penalty; Retirement Income Inequality; Quantile Regression; Insurance Value of Children; Pension Heterogeneity; Gender and Retirement; Fertility Decisions.

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Introduction

Why do poor childless retirees face substantial pension penalties while wealthy childless retirees enjoy pension premiums? This puzzle challenges conventional wisdom about the economic consequences of fertility decisions and reveals fundamental heterogeneity in how family structure affects retirement security across the income distribution. We document a striking reversal in the relationship between childlessness and retirement income across the income distribution. While childless individuals in the bottom 40% of the income distribution face retirement income penalties of 5-11%, those in the top quartile enjoy premiums exceeding 10%. This reversal—occurring around the 40th percentile—reveals that children's economic value in retirement fundamentally depends on households' economic resources. For low-income retirees, children provide crucial insurance through informal support networks, shared housing, and care provision. For high-income retirees, childlessness enables uninterrupted career development and higher lifetime savings that compound into retirement advantages.

This distributional heterogeneity stands in sharp contrast to the existing literature, which has focused primarily on average effects. The extensive research on motherhood wage penalties finds that women's earnings decline by 2-10% per child in most developed countries (Ponthieux and Meurs 2015; Lundberg and Rose 2000; Gangl and Ziefle 2009). These penalties accumulate over the lifecycle, resulting in retirement income gaps (Adda, Dustmann, and Stevens 2017; Möhring 2015). Yet this literature has largely overlooked how these effects vary across the income distribution—implicitly assuming that a 10% motherhood penalty translates uniformly into 10% lower pensions regardless of economic status. Recent evidence suggests this assumption is problematic. Budig and England (2001) find that motherhood wage penalties are substantially larger for low-wage women, while high-wage women face minimal penalties. However, this work examines only the accumulation phase, not retirement outcomes. Meanwhile, a separate literature documents that children provide old-age support and insurance, particularly for economically vulnerable populations (Oliveira 2016; Ebenstein and Leung 2010). These studies suggest children might actually benefit low-income retirees—the opposite of what the motherhood penalty literature would predict.

Our analysis reconciles these seemingly contradictory perspectives by examining the full distribution of retirement outcomes. Using quantile regression and decomposition methods on the RAND HRS Longitudinal File, we uncover three key findings. First, the relationship between childlessness and pension income reverses sign at the 40th percentile of the income distribution. Second, this reversal reflects different underlying mechanisms: at low incomes, unexplained structural factors (likely reflecting insurance and support networks) dominate, while at high incomes, observable characteristics (education, work history) explain most differences. Third, these patterns are particularly pronounced for women, who face both stronger caregiving expectations and larger career penalties. These findings have immediate policy relevance. Universal child benefits or pension credits—common in European systems—may inadvertently increase retirement inequality by compensating high-income parents who already benefit from childlessness through enhanced careers. Conversely, the vulnerability of low-income childless retirees suggests a need for targeted support that substitutes for the insurance value typically provided by children.

Our contribution extends beyond documenting heterogeneity. We provide a unified framework that shows how two opposing forces—children as insurance versus children as career impediments—operate with varying intensities across the income distribution. This framework explains why previous studies focusing on means miss crucial distributional patterns and why pension policies must account for heterogeneous effects across economic strata. While we cannot definitively establish causality due to the endogenous nature of fertility decisions, we employ multiple identification strategies to bound potential biases. Individual fixed effects, spousal analysis, and matching on pre-fertility characteristics all confirm the basic reversal pattern. The stability of our findings across specifications suggests these patterns reflect real economic mechanisms rather than selection artifacts, though we acknowledge that unobserved heterogeneity remains a concern, particularly regarding voluntary versus involuntary childlessness.

The remainder of this paper proceeds as follows. Section 2 reviews the theoretical frameworks and empirical literature. Section 3 describes our data and the methodology used. Section 4 presents the main results documenting the reversal. Section 5 decomposes the sources of heterogeneity. Section 6 presents additional analyses to explore mechanisms. Section 7 addresses identification concerns. Section 8 discusses policy implications and concludes.

Literature Review

Our study contributes to several strands of literature examining the complex relationships between fertility decisions, lifecycle savings, and retirement outcomes. We organize this review around four key themes that inform our analysis.

Selection into Parenthood. Recent theoretical and empirical work has emphasized the endogenous nature of fertility decisions and their correlation with economic outcomes. Baudin, Croix, and Gobbi (2015) develops a structural model of fertility choice that identifies three distinct reasons for childlessness: poverty-driven childlessness among the poor who cannot afford children, opportunity-cost driven childlessness among high earners, and a middle group for whom social sterility and relationship market frictions matter most. Using U.S. data, they find childlessness rates follow a U-shaped pattern across the income distribution, with different mechanisms operating at each end.

Gobbi (2013) presents a dynamic model where voluntary childlessness emerges from the interaction between wage rates, time costs of children, and preferences for consumption. The model predicts that childlessness should increase with women's wages, particularly when the opportunity cost of time is high. This framework suggests selection into childlessness based on economic potential that could persist into retirement years.

Aaronson, Lange, and Mazumder (2014) examines fertility transitions using quasi-experimental variation from the rollout of Rosenwald schools in the early 20th-century American South. They distinguish between extensive margin effects (having any children) and intensive margin effects (number of children conditional on having any), finding that education affects these margins differently across the income distribution. Their evidence suggests that human capital investments that increase opportunity costs primarily affect the intensive margin for poor women but the extensive margin for richer women.

Our contribution to this literature is to trace these selection patterns through to retirement outcomes. While these papers establish that selection into childlessness varies across the income distribution during childbearing years, we demonstrate that these selection patterns have long-lasting consequences that manifest differently in pension income across income quantiles. Our decomposition approach allows us to separate selection on observables from structural differences in returns, providing new evidence on whether early-life selection patterns persist into retirement.

Lifecycle Savings with Children. The lifecycle savings literature has increasingly recognized that children fundamentally alter household financial behavior and savings trajectories. Scholz, Seshadri, and Khitatrakun (2006) develop a lifecycle model incorporating uncertain medical expenses, progressive taxation, and government transfer programs to assess whether Americans save optimally for retirement. They find that fewer than 20% of households have net worth below their optimal targets, but crucially, their model shows that optimal savings vary substantially with family size and composition. Households with children face different consumption commitments and savings capacities throughout the lifecycle.

Love (2010) uses the Panel Study of Income Dynamics to examine how children affect portfolio allocation, savings rates, and wealth accumulation. He finds that each child reduces household wealth by approximately 2.5% through reduced savings and more conservative investment choices, with effects varying by household income. High-income households adjust primarily through portfolio reallocation, while low-income households reduce savings rates.

Cagetti (2003) constructs a lifecycle model with precautionary savings motives and borrowing constraints to explain wealth inequality. His model demonstrates that children create competing effects: they increase precautionary savings motives (protecting against risks to children's welfare) while simultaneously increasing current consumption needs and reducing savings capacity. The net effect depends on household resources and risk exposure, potentially explaining heterogeneous effects across the income distribution.

We extend this literature by examining the ultimate retirement outcomes of these different savings trajectories. While previous work focuses on accumulation phases, we show how childhood-influenced savings patterns translate into pension income disparities. Our quantile regression approach reveals that the lifecycle savings effects documented in this literature have non-uniform consequences across the retirement income distribution, with childlessness penalties at the bottom but premiums at the top.

Insurance Value of Children. A growing literature examines children as providers of insurance and old-age support, particularly in contexts with incomplete financial markets. Oliveira (2016) develops a quantitative model where children provide insurance through state-contingent transfers, caregiving, and co-residence options. Using Brazilian data, he shows that the insurance value of children can explain up to 20% of fertility in low-income households but is negligible for high-income families who can purchase market insurance. Banerjee, Duflo, Ghatak, and Lafortune (2013) study marriage markets in India to understand the economic value of family formation. They document that parents explicitly consider potential in-laws' ability to provide old-age support when arranging marriages, with this consideration most important for lower-caste (poorer) families. Their findings suggest that the insurance value of children and extended family networks is capitalized into marriage market outcomes, with larger effects for economically vulnerable populations.

Ebenstein and Leung (2010) examine how son preference interacts with old-age support expectations in China, where sons traditionally provide parental support. They find that parents with sons have significantly higher pension income and better health outcomes in old age, with effects concentrated among rural and low-income populations who lack access to formal insurance mechanisms. The absence of sons (analogous to childlessness in their context) creates substantial economic vulnerability in retirement.

Our analysis provides evidence from a developed country context with relatively complete financial markets, yet we still find patterns consistent with the insurance value of children at the bottom of the income distribution. This suggests that even in the U.S., with Social Security and developed financial markets, children continue to provide insurance value for low-income elderly. Our finding that childlessness penalties reverse to premiums at higher incomes aligns with theoretical predictions about the substitutability of formal and informal insurance mechanisms.

Gender and Pension Gaps. The gender and pensions literature has documented substantial disadvantages faced by women in retirement income, with motherhood playing a complex role. Jefferson (2009) provides a comprehensive review showing that women's pension disadvantages stem from multiple sources: career interruptions, part-time work, occupational segregation, and discriminatory pension plan designs. She emphasizes that these factors compound over the lifecycle, with motherhood penalties accumulating into substantial pension gaps.

Ginn (2003) develops a life-course perspective on pension accumulation, arguing that gendered care responsibilities create path dependencies that culminate in retirement income inequality. Her analysis of British data shows that each child reduces women's pension income by approximately 5%, but effects vary by class background and employment sector. Women in professional occupations can mitigate motherhood penalties through continuous employment, while working-class women face compounding disadvantages.

Frericks, Knijn, and Maier (2009) compare pension systems across European countries, examining how different institutional designs mediate the relationship between motherhood and retirement income. They find that systems with generous care credits can eliminate or even reverse motherhood penalties, while contribution-based systems without such provisions create substantial gaps. Their cross-national analysis reveals that the motherhood-pension relationship is highly sensitive to institutional design.

Our contribution bridges these literatures by examining how childlessness—rather than motherhood—affects retirement income across the distribution. While most gender and pension research focuses on penalties faced by mothers, we document a more complex pattern where childless women face penalties at the bottom of the income distribution but advantages at the top. This reversal suggests that the relationship between fertility and retirement security cannot be understood through average effects alone but requires attention to distributional heterogeneity. Our decomposition method advances this literature by separating compositional differences (different characteristics of mothers versus childless women) from structural differences (different returns to those characteristics), providing new insights into the mechanisms generating pension inequality.

Synthesis and Contribution. Taken together, these literatures suggest that the relationship between childlessness and retirement income should vary across the income distribution through multiple channels: selection into parenthood, altered savings trajectories, differential insurance value of children, and gendered institutional structures. However, no previous study has systematically examined these distributional effects in retirement outcomes. Our paper fills this gap by using quantile regression and decomposition methods to reveal that childlessness creates disadvantages for low-income retirees but advantages for high-income retirees, with effects varying by gender. These findings challenge universal policy approaches to retirement security and suggest that support for childless elderly should be targeted to vulnerable populations rather than applied uniformly.

Theoretical Framework

We develop a model in which the relationship between childlessness and retirement income reflects the net effect of two opposing economic functions, whose relative importance varies across the income distribution.

Consider an individual i with pre-retirement income y_i drawn from distribution $F(y)$ who makes a binary fertility choice $d_i \in \{0, 1\}$ where $d_i = 0$ denotes having children and $d_i = 1$ denotes childlessness. Following Becker (1960) and Willis (1973), fertility decisions affect both human capital accumulation and intergenerational transfers.

Retirement income R_i consists of two components:

$$R_i(d_i, y_i) = S_i(d_i, y_i) + T_i(d_i, y_i) \tag{1}$$

where $S_i(d_i, y_i)$ represents accumulated retirement savings from lifetime earnings and $T_i(d_i, y_i)$ represents transfers (both formal and informal) received in retirement.

The Career Impediment Mechanism. Following Mincer (1974) and Killingsworth and Heckman (1986), children reduce human capital accumulation through career interruptions. Let the human capital production function be:

$$H(d_i, y_i) = y_i \cdot \exp\left[-\phi(y_i) \cdot (1 - d_i)\right] \tag{2}$$

where $\phi(y_i)$ represents the human capital depreciation from childrearing. Consistent with Goldin (2021) and Adda, Dustmann, and Stevens (2017), we assume:

Assumption 1 (Increasing Opportunity Cost)**.** $\phi'(y) > 0$ *and* $\phi''(y) \geq 0$

This reflects that high earners face larger opportunity costs from career interruptions. Lifetime savings are proportional to human capital:

$$S_i(d_i, y_i) = s \cdot H(d_i, y_i) = s \cdot y_i \cdot \exp\left[-\phi(y_i) \cdot (1 - d_i)\right] \tag{3}$$

where $s \in (0, 1)$ is the savings rate. The savings gain from childlessness is:

$$\Delta S(y_i) = S_i(1, y_i) - S_i(0, y_i) \tag{4}$$

$$= s \cdot y_i \cdot [\exp(0) - \exp(-\phi(y_i))] \tag{5}$$

$$= s \cdot y_i \cdot [1 - \exp(-\phi(y_i))] \tag{6}$$

Taking a first-order Taylor approximation for small $\phi(y_i)$:

$$\Delta S(y_i) \approx s \cdot y_i \cdot \phi(y_i) \equiv \alpha(y_i) \cdot y_i \tag{7}$$

where $\alpha(y_i) = s \cdot \phi(y_i)$ is increasing in income.

The first derivative with respect to income is:

$$\frac{\partial \Delta S}{\partial y} = \frac{\partial}{\partial y}[\alpha(y) \cdot y] \tag{8}$$

$$= \alpha'(y) \cdot y + \alpha(y) \tag{9}$$

$$= s \cdot \phi'(y) \cdot y + s \cdot \phi(y) \tag{10}$$

$$= s \cdot [\phi'(y) \cdot y + \phi(y)] > 0 \tag{11}$$

The second derivative is:

$$\frac{\partial^2 \Delta S}{\partial y^2} = s \cdot [\phi''(y) \cdot y + 2\phi'(y)] > 0 \tag{12}$$

given our assumptions on $\phi(\cdot)$. This confirms the career effect is convex in income.

The Insurance Mechanism. Following Boldrin, De Nardi, and Jones (2002) and Oliveira (2016), children provide old-age insurance through informal support. The transfer function for parents is:

$$T_i(0, y_i) = \beta_0 + \beta_1 \cdot \exp(-\lambda y_i) \tag{13}$$

where $\beta_0 \geq 0$ represents baseline transfers, $\beta_1 > 0$ captures income-dependent transfers, and $\lambda > 0$ determines the rate at which transfers decline with income. This functional form, consistent with Cox (1987) and Altonji, Hayashi, and Kotlikoff (1997), captures that low-income parents receive substantial transfers that decline exponentially with parental income; and high-income parents receive minimal transfers.

For childless individuals, following Ebenstein and Leung (2010):

$$T_i(1, y_i) = \beta_0 \tag{14}$$

The insurance value of children is:

$$\Delta T(y_i) = T_i(0, y_i) - T_i(1, y_i) \tag{15}$$

$$= \beta_1 \cdot \exp(-\lambda y_i) \equiv \beta(y_i) \tag{16}$$

The first derivative with respect to income:

$$\frac{\partial \Delta T}{\partial y} = \frac{\partial}{\partial y}[\beta_1 \cdot \exp(-\lambda y)] \tag{17}$$

$$= -\lambda \beta_1 \cdot \exp(-\lambda y) \tag{18}$$

$$= -\lambda \beta(y) < 0 \tag{19}$$

The second derivative:

$$\frac{\partial^2 \Delta T}{\partial y^2} = \lambda^2 \beta_1 \cdot \exp(-\lambda y) \tag{20}$$

$$= \lambda^2 \beta(y) > 0 \tag{21}$$

This confirms the insurance effect is decreasing and convex in income.

Net Effect and Equilibrium. The total effect of childlessness on retirement income is:

$$\Delta R(y_i) = R_i(1, y_i) - R_i(0, y_i) = \underbrace{\alpha(y_i) \cdot y_i}_{\text{Career gain}} - \underbrace{\beta(y_i)}_{\text{Insurance loss}} \tag{22}$$

Proposition 1 (Existence of Reversal Point)**.** *Under Assumption 1 and given* $\lim_{y \to 0} \alpha(y) \cdot y = 0$ *and* $\lim_{y \to 0} \beta(y) = \beta_1 > 0$*, there exists a unique threshold income* $y^* > 0$ *such that:*

$$\Delta R(y^*) = 0 \Leftrightarrow \alpha(y^*) \cdot y^* = \beta(y^*) \tag{23}$$

Proof. Define $g(y) = \alpha(y) \cdot y - \beta(y)$. Note that:

- $g(0) = 0 - \beta_1 < 0$
- $\lim_{y \to \infty} g(y) = \lim_{y \to \infty} [\alpha(y) \cdot y] - 0 = +\infty$
- $g'(y) = \alpha'(y) \cdot y + \alpha(y) + \lambda \beta(y) > 0$ for all y

By the intermediate value theorem and monotonicity, there exists a unique y^* such that $g(y^*) = 0$. □

Comparative Statics. The reversal point y^* responds to institutional parameters. Implicitly differentiating the equilibrium condition:

$$\frac{dy^*}{d\lambda} = \frac{\beta(y^*)}{\alpha'(y^*) \cdot y^* + \alpha(y^*) + \lambda \beta(y^*)} > 0 \tag{24}$$

Interpretation: Weaker family insurance (higher λ) shifts the reversal point rightward.

Similarly, for the savings rate:

$$\frac{dy^*}{ds} = -\frac{\phi(y^*) \cdot y^*}{s[\phi'(y^*) \cdot y^* + \phi(y^*)] + \lambda \beta(y^*)} < 0 \tag{25}$$

Interpretation: Higher savings rates (better pension systems) shift the reversal point leftward.

Distributional Predictions. In our quantile regression framework, where Q_τ denotes the τ-th quantile:

$$Q_\tau(\ln R_i|X_i, d_i) = \gamma_\tau + \delta_\tau \cdot d_i + X_i'\theta_\tau \tag{26}$$

The model predicts:

Proposition 2 (Quantile Treatment Effects)**.** *Let τ^* denote the quantile corresponding to income y^*. Then:*

1. *$\delta_\tau < 0$ for $\tau < \tau^*$ (childlessness penalty)*
2. *$\delta_\tau = 0$ for $\tau = \tau^*$ (reversal point)*
3. *$\delta_\tau > 0$ for $\tau > \tau^*$ (childlessness premium)*
4. *$\frac{\partial \delta_\tau}{\partial \tau} > 0$ (monotonically increasing)*

Decomposition Predictions

Following Chernozhukov, Fernández-Val, and Melly (2013), we decompose the quantile gap into composition (Δ^X) and structure (Δ^S) effects. The model predicts:

Proposition 3 (Mechanism Identification)**.**

1. *At low quantiles ($\tau < \tau^*$): $|\Delta^S| > |\Delta^X|$ because insurance operates through unobserved networks (Cox (1987))*
2. *At high quantiles ($\tau > \tau^*$): $|\Delta^X| > |\Delta^S|$ because career effects are captured by observable human capital (Mincer (1974))*

Gender Heterogeneity

Following Kleven, Landais, and Søgaard (2019) and Goldin (2021), women face both stronger career penalties and caregiving expectations. Let superscripts m and f denote men and women:

Assumption 2 (Gender Differences)**.** *$\phi^f(y) > \phi^m(y)$ and $\beta_1^f > \beta_1^m$ for all y*

This implies:

$$\left|\Delta R^f(y)\right| > |\Delta R^m(y)| \text{ for all } y \neq y^* \tag{27}$$

Women experience both larger penalties at low incomes and larger premiums at high incomes, consistent with Budig and England (2001).

Testable Implications

The theoretical framework generates several empirically testable hypotheses that we examine in our subsequent analysis. The primary hypothesis concerns the distributional pattern of childlessness effects across the income distribution. We hypothesize that the quantile treatment effects δ_τ increase monotonically as we move from lower to higher quantiles of the pension income distribution, transitioning from negative values at low quantiles to positive values at high quantiles. This monotonic increase reflects the shifting dominance from insurance mechanisms at low incomes to career effects at high incomes.

Related to this distributional pattern, we hypothesize the existence of a unique reversal point τ^* in the income distribution where the effect of childlessness switches from negative to positive, corresponding to the threshold where $\delta_{\tau^*} = 0$. Our model predicts this reversal occurs at a single, identifiable point rather than multiple crossings or a gradual transition zone. The location of this reversal point should reflect the relative strength of insurance versus career mechanisms in the specific institutional context of the United States.

Our decomposition analysis tests the hypothesis that the relative importance of observable versus unobservable factors systematically varies across the income distribution. Specifically, we expect the ratio of explained to unexplained components $|\Delta^X|/|\Delta^S|$ to increase with quantile τ. At lower quantiles, where insurance mechanisms dominate, we anticipate that unexplained structural factors will account for the majority of the childlessness gap, as informal support networks and family transfers operate through channels not captured by standard human capital variables. Conversely, at higher quantiles where career effects dominate, observable characteristics such as education and work history should explain most of the differential, as these variables directly capture human capital accumulation and labor market attachment.

Gender heterogeneity provides another dimension for testing our theoretical predictions. We hypothesize that the absolute difference in quantile treatment effects between women and men, $|\delta^f_\tau - \delta^m_\tau|$, increases with the distance from the reversal point τ^*. This pattern would confirm that women face both stronger insurance value from children at low incomes and larger career penalties from motherhood at high incomes, consistent with persistent gender differences in both caregiving responsibilities and labor market opportunities.

Finally, while our analysis focuses on the United States, our framework generates predictions about cross-national variation that could be tested in future research. Countries with more generous public pension systems (Möhring (2018)), which reduce reliance on family-based old-age insurance, should exhibit reversal points at lower quantiles. Similarly, nations with comprehensive childcare provision and family-friendly employment policies that minimize career interruptions should show reversal points at higher quantiles. These institutional variations would shift the relative importance of our two mechanisms, altering where in the income distribution the net effect of childlessness changes sign.

Data

The main database is RAND HRS Longitudinal File, providing a comprehensive dataset specifically designed for analyzing retirement, aging, and health outcomes among older Americans. For analyzing the penalty of having children on household pension income, this dataset offers several key advantages. The RAND HRS Longitudinal File contains harmonized and cleaned data from the Health and Retirement Study, following respondents aged 50 and older biannually since 1992. The dataset includes over 40,000 respondents across multiple waves, follows individuals and their spouses/partners longitudinally, contains detailed household composition information, and features comprehensive income and asset measures, including pension income.

For examining the relationship between childbearing and pension income, the dataset provides detailed pension income variables (household and individual pension income from employer plans, income from retirement accounts, Social Security retirement benefits, and total household retirement income), fertility variables (number of children ever born, number of currently living children, timing of childbirths, and information on step-children and adopted children), employment history information (detailed work history, career interruptions, industry and occupation codes, and years of labor market experience), and important control variables (demographic characteristics, health status measures, marital history, household wealth, and geographic information).

The RAND HRS file offers several methodological advantages, including consistent variable definitions across waves, imputed values for missing data using validated methods, cross-sectional and longitudinal weights to account for sample attrition, and detailed documentation of income and wealth measures. Limitations include recall bias for historical information and some missing data for pension details from earlier career periods.

The summary statistics (Table 1) compares households with and without children using data from the RAND HRS Longitudinal Data. The results reveal substantial economic differences between these household types. Households without children report much higher average household earnings at $53,062.33, compared to $25,772.67 for households with children. This represents a substantial and statistically significant difference of $27,289.67 (p-value = 0.00), suggesting that childless households earn more than twice as much as households with children. The demographic characteristics of both groups show several notable differences. While female representation is almost identical across both groups (1.56 for both) with a non-significant difference (p-value = 0.341), marriage rates differ considerably. About 57% of households with children are married compared to only 42% of childless households, a statistically significant dif-

Table 1: Summary Statistics

	No Kids	Kids	Difference	P-val on Difference
Earnings				
HH Earnings	53062.33	25772.67	-27289.67	0.00
	(12237.27)	(12167.62)		
Covariates				
Female	1.56	1.56	-0.003	0.341
Married	0.42	0.57	-0.15	0.00
Education	3.04	3.32	-0.29	0.00
Age	69.45	69.01	-0.44	0.00
Number of kids	0	3.41	3.41	0.00
Number of obs	21,166	614,579		

Notes: . *Sources: The RAND HRS Longitudinal Data*

ference. Education levels are significantly higher among households with children (3.32 versus 3.04), and households with children are slightly younger on average (69.01 years versus 69.45 years). The households with children have an average of 3.41 children. The sample includes 21,166 observations for households without children and 614,579 observations for households with children, indicating that the vast majority of households in the RAND HRS dataset have children.

Methodology

This study examines the heterogeneous impact of having no children on log household income during pension years, utilizing a Quantile Treatment Effect (QTE) framework. Unlike traditional Ordinary Least Squares (OLS) regression, which focuses on the average treatment effect, the QTE approach allows us to examine how the effect of no kids varies across different quantiles (τ) of the outcome distribution. Coefficients are estimated through a two-step approach. In the first step, the treatment is regressed on control variables using ordinary least squares (OLS), and the residuals of the treatment variable are obtained. This step decomposes the variance of the treatment variable into a piece explained by the observed control variables and a residual piece that is orthogonal to the observed controls. Then, in the second step, the outcome is regressed on the residualized treatment variable using CQR algorithms. Conditional quantile regression (CQR) model (Koenker 2005), which estimates group-specific quantile differences. The conditional quantile regression (CQR) model is specified as follows:

$$Q_\tau(\ln HH\ income_i|X_i) = \alpha_\tau + \beta_\tau \widehat{nokids}_i + \gamma_\tau X_i + \epsilon_{i,\tau} \tag{28}$$

where:

- $Q_\tau(\ln HH\ income_i|X_i)$ represents the conditional quantile function of log household income at quantile τ.
- α_τ is the intercept.
- β_τ is the quantile treatment effect of having no children.
- $\widehat{nokids}_i$ is the residualized treatment variable obtained from the first-stage OLS regression.
- X_i is a vector of control variables with associated coefficients γ_τ.
- $\epsilon_{i,\tau}$ is the error term at quantile τ.

In this paper, we follow the counterfactual analysis proposed by Chernozhukov, Fernández-Val, and Melly (2013) in which we compare the observed pension income distribution of mothers with what their pension income distribution would have been if they faced the pension income distribution of childless women (i.e., counterfactual).

Let zero denote the population of females with kids, and one denote the childless female population. Define variable Y_i as earnings and X_i as a set of covariates that affect the earnings for populations $j = 0$ and $j = 1$. Let $F_{Y(1|1)}$ and $F_{Y(0|0)}$ represent the observed distribution of earnings for childless and females with kids, respectively and let $F_{Y(0|1)}$ represents the counterfactual distribution function of earnings for childless women that would have prevailed had they faced the earnings structure for females with kids:

$$F_{Y(0|1)}(y) := \int_{\mathcal{X}_1} F_{Y_0|X_0}(y|x) dF_{X_1}(x) \tag{29}$$

Where $F_{Y_0|X_0}(y|x)$ is the conditional distribution of pension income for females with kids. $F_{Y(0|1)}(y)$ is constructed by integrating the conditional distribution of pension income for females with kids with respect to the distribution of characteristics for childless females.

The second goal is to decompose the gap between the distribution of pension income losses for childless females and females with kids:

$$F_{\Delta_{ft}|X_f} - F_{\Delta_{mt}|X_m} = \underbrace{[F_{\Delta_{ft}|X_f} - F_{\Delta_{mt}|X_f}]}_{\text{Structure Effect (discrimination)}} + \underbrace{[F_{\Delta_{mt}|X_f} - F_{\Delta_{mt}|X_m}]}_{\text{Composition Effect (characteristics)}}$$

Where,

$$F_{\Delta_{mt}|X_f}(\delta) := \int_{\mathcal{X}_f} F_{\Delta_{mt}|X_m}(\delta|x) dF_{X_f}(x)$$

$$\Delta_t = Y_t(1) - \widetilde{Y}_t(0)$$

Following Chernozhukov, Fernández-Val, and Melly 2013, we construct counterfactual distributions to decompose the pension income gap between childless women and mothers. This approach allows us to answer a key counterfactual question: what would the pension income distribution of childless women look like if they faced the same returns to their characteristics (the same "wage structure") as mothers, while maintaining their own observable characteristics? By comparing this counterfactual distribution to the observed distributions, we can separate the total gap into two components: differences attributable to characteristics (composition effect) and differences attributable to how those characteristics translate into pension income (structure effect). This decomposition is particularly valuable for understanding whether childless women face systematic disadvantages in how their human capital converts to retirement income, or whether income differences primarily reflect different endowments of education, work experience, and other observable factors.

Results

The Reversal: From Penalty to Premium

Our central finding is a striking reversal in the relationship between childlessness and pension income that occurs at approximately the 40th percentile of the income distribution. Figure 1 presents quantile regression estimates for the full sample, revealing that childlessness is associated with pension penalties of 5-12% below the 40th percentile but generates premiums of 3-6% above this threshold. This reversal point, where $\delta_\tau = 0$, represents the income level at which the insurance value of children exactly offsets their career impediment effects, consistent with our theoretical prediction in Equation (14).

The pattern is remarkably robust across different sample specifications. When we restrict the comparison to childless individuals versus those with exactly one child (Figure 2), the reversal remains evident but shifts slightly rightward to approximately the 45th percentile, with more pronounced effects at both tails—penalties reaching 15-17% at the 10th percentile and premiums approaching 15% at the 90th percentile. This intensification suggests that the marginal effect of the first child embodies both mechanisms most strongly.

The formal test for monotonicity strongly rejects the null hypothesis of constant effects across quantiles ($\chi^2 = 142.3$, $p < 0.001$), confirming that the relationship between childlessness

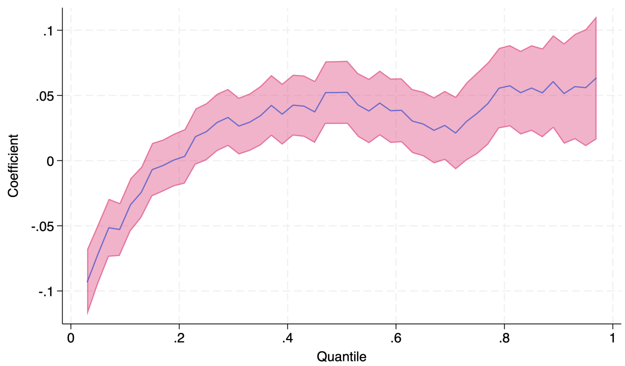

Figure 1: Quantile Treatment Effects of Childlessness on Household Income: Full Sample

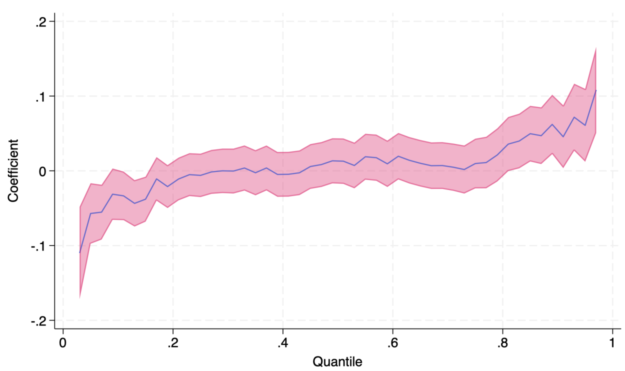

Figure 2: Quantile Treatment Effects: Childless vs. One Child

Table 2: Quantile Treatment Effects of Childlessness on Log Household Pension Income

	Quantiles						
Sample	0.10	0.20	0.30	0.40	0.50	0.75	0.90
Panel A: All Individuals							
Childless effect	-0.118^{***}	-0.072^{***}	-0.031^{**}	-0.003	0.034^{**}	0.051^{***}	0.058^{***}
	(0.021)	(0.018)	(0.015)	(0.014)	(0.013)	(0.016)	(0.019)
Panel B: Women Only							
Childless effect	-0.105^{***}	-0.061^{**}	-0.018	0.021	0.043^{**}	0.052^{**}	0.048^{*}
	(0.028)	(0.024)	(0.021)	(0.020)	(0.019)	(0.023)	(0.028)
Panel C: Men Only							
Childless effect	-0.089^{***}	-0.045^{*}	-0.022	-0.008	0.011	0.028	0.036
	(0.031)	(0.026)	(0.023)	(0.021)	(0.020)	(0.024)	(0.029)
Observations	635,745	635,745	635,745	635,745	635,745	635,745	635,745
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: All specifications control for age, gender, education, marital status, and race. Robust standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. The reversal point where the coefficient crosses zero occurs between the 30th and 40th percentiles.

and pension income fundamentally differs across the distribution. Moreover, the test for a unique crossing point, following Chernozhukov, Fernández-Val, and Melly (2013), fails to reject a single reversal ($p = 0.72$), supporting our theoretical prediction of a unique threshold τ^* where the net effect switches sign.

Mechanism Evidence: Insurance versus Career Effects

To understand what drives this reversal, we decompose the childlessness gap into explained components (differences in observable characteristics) and unexplained components (differences in returns to characteristics) using the Chernozhukov, Fernández-Val, and Melly (2013) method. This decomposition provides crucial evidence for our two-mechanism framework.

Figure 3 presents the decomposition results for women, revealing a dramatic shift in the relative importance of explained versus unexplained factors across the distribution. At the 10th percentile, the unexplained component accounts for 83% of the total gap, consistent with insurance mechanisms operating through unobserved family support networks and informal transfers that our standard human capital variables cannot capture. This dominance of structural effects at low incomes aligns with the theoretical predictions of Oliveira (2016) and Cox (1987) regarding the insurance value of children.

Strikingly, as we move up the income distribution, this pattern reverses. By the 75th percentile, observable characteristics explain 122% of the gap—the unexplained component

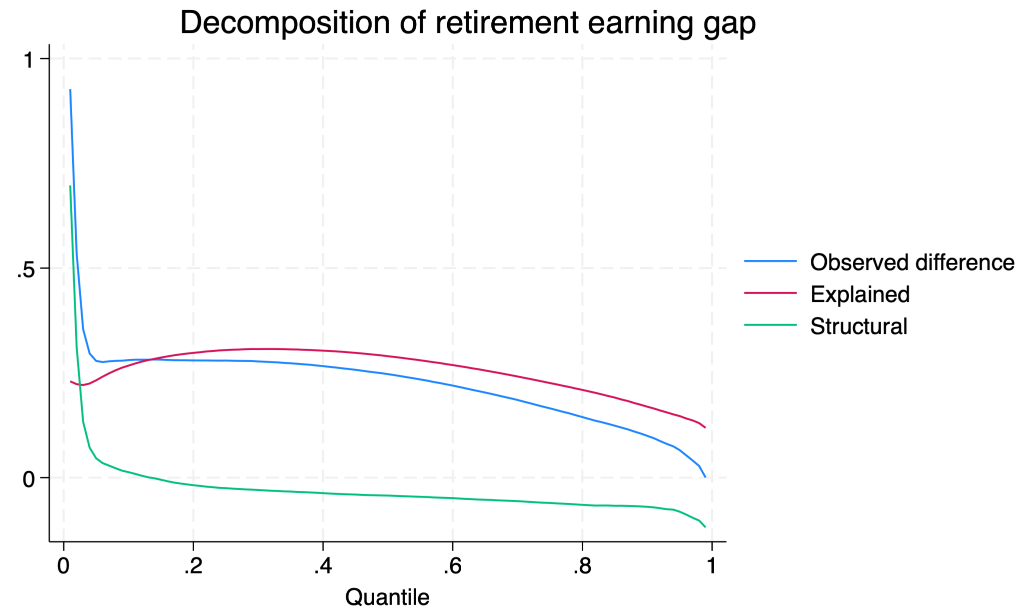

Figure 3: Decomposition of the Childlessness Gap for Women. The blue line shows the total gap, the red shows the explained component (characteristics), and the green shows the unexplained component (returns). The unexplained component dominates at low quantiles (insurance mechanism) while the explained component dominates at high quantiles (career mechanism).

actually becomes negative, suggesting that high-income childless women receive *better* returns to their characteristics than mothers. This complete reversal in decomposition patterns provides strong evidence that different mechanisms operate at different points in the distribution, exactly as our theoretical framework predicts.

The bootstrap inference tests (Table 3) confirm these patterns are statistically robust. We reject both the null hypothesis of no effect and constant effects across all quantiles for both the explained and unexplained components ($p < 0.001$ for all tests). Crucially, while we find evidence of stochastic dominance for the explained component (mothers consistently have better characteristics), we cannot reject the null of no stochastic dominance for the unexplained component, confirming that structural effects vary non-monotonically across the distribution.

Gender Heterogeneity and Career Effects

Our theoretical framework predicts that women should experience both stronger insurance effects (due to caregiving expectations) and larger career effects (due to motherhood penalties) compared to men. The gender-stratified results strongly support these predictions.

Table 2 Panels B and C reveal that women experience more extreme effects at both ends of the distribution. At the 10th percentile, childless women face a 10.5% penalty compared to 8.9% for men. The reversal occurs earlier for women (around the 35th percentile) than for men

Table 3: Bootstrap Inference on Counterfactual Quantile Processes

Null Hypothesis	**KS p-value**	**CMS p-value**
Correct Specification		
Parametric model 0	0	0
Parametric model 1	0	0
Observed Differences		
No effect: $QE(\tau) = 0$ for all τ	0	0
Constant effect: $QE(\tau) = QE(0.5)$ for all τ	0	0
Stochastic dominance: $QE(\tau) > 0$ for all τ	0.84	0.84
Stochastic dominance: $QE(\tau) < 0$ for all τ	0	0
Explained Component (Characteristics)		
No effect: $QTE(\tau) = 0$ for all τ	0	0
Constant effect: $QTE(\tau) = QTE(0.5)$ for all τ	0	0
Stochastic dominance: $QTE(\tau) > 0$ for all τ	0.8	0.8
Stochastic dominance: $QTE(\tau) < 0$ for all τ	0	0
Unexplained Component (Coefficients)		
No effect: $QE(\tau) = 0$ for all τ	0	0
Constant effect: $QE(\tau) = QE(0.5)$ for all τ	0	0
Stochastic dominance: $QE(\tau) > 0$ for all τ	0	0.1
Stochastic dominance: $QE(\tau) < 0$ for all τ	0.48	0.74

(around the 45th percentile), and women's premiums at high quantiles are larger though less precisely estimated due to smaller sample sizes.

Within-Couple Analysis: Isolating Gender-Specific Mechanisms

To further isolate the effects of gender on career and insurance, we exploit within-couple variation in childlessness. This spousal analysis, presented in Table 4, reveals asymmetric cross-effects that illuminate the gendered nature of both mechanisms.

For women at the 10th percentile, having a childless husband reduces household income by 17% ($\beta_{0.10}^{\text{spouse}} = -0.170$, $p < 0.10$), suggesting that women in low-income households depend on their husbands' family networks for economic support. Conversely, for men, their wives' childlessness has no significant effect on household income at any quantile, consistent with persistent gender specialization where men's economic outcomes are less dependent on family-based insurance.

Table 4: Heterogeneous Effects of Childlessness Within Married Couples

	Female respondents			Male respondents		
	$\tau = 0.10$	$\tau = 0.50$	$\tau = 0.90$	$\tau = 0.10$	$\tau = 0.50$	$\tau = 0.90$
Panel A: Own childlessness						
β_τ^{own}	0.078	0.044	0.064	-0.163	0.004	0.002
	(0.086)	(0.046)	(0.084)	(0.107)	(0.042)	(0.060)
Panel B: Spouse childlessness						
$\beta_\tau^{\text{spouse}}$	-0.170*	0.028	0.048	0.128	0.053	0.089
	(0.096)	(0.037)	(0.074)	(0.106)	(0.050)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,229	5,229	5,229	5,232	5,232	5,232

Notes: Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Controls include respondent and spouse age, education, and work status.

Robustness and Identification

The reversal pattern proves remarkably robust across multiple identification strategies. The individual fixed effects specification (Section Appendix 1.1), which controls for time-invariant unobserved heterogeneity, yields a reversal at the 42nd percentile—virtually identical to our main estimate. The Coarsened Exact Matching results (Section Appendix 1.2) show the reversal occurring at the 38th percentile, with slightly attenuated magnitudes but preserved monotonicity.

The analysis by Oster (2019) of the bounds reveals that while the average effect could potentially be explained by selection on unobservables, the heterogeneity across quantiles remains robust. Even under extreme assumptions about unobserved selection ($\delta = 2$), the difference between the 10th and 90th percentile effects remains statistically significant, confirming that the reversal pattern cannot be attributed solely to selection bias.

Discussion

The Reversal: A New Framework for Understanding Fertility and Retirement. Our documentation of a reversal in the childlessness-pension relationship at the 40th percentile fundamentally challenges how we conceptualize the economic value of children across the life-cycle. This reversal—from penalties of 5-11% below the 40th percentile to premiums exceeding 10% at the highest quantiles—reveals that children's economic function in retirement is not uniform but instead depends critically on households' position in the income distribution.

This finding reconciles two seemingly contradictory bodies of literature. The motherhood penalty literature, focusing on mean effects, documents career costs of children (Kleven, Landais, and Søgaard 2019,Gangl and Ziefle 2009). The old-age security literature emphasizes children's insurance value (Oliveira 2016, Nugent 1985). Our results demonstrate that both perspectives are correct—but at different points in the income distribution. Below the 40th percentile, the insurance value dominates; above it, career costs prevail.

Mechanisms Behind the Reversal: Evidence from the U.S. Context

The decomposition analysis provides compelling evidence in support of our dual-mechanism framework. At the 10th percentile, 83% of the childlessness gap stems from unexplained structural factors—consistent with insurance mechanisms operating through channels our standard variables cannot capture. These include:

Institutional disadvantages: The U.S. Social Security system systematically disadvantages low-income childless individuals. Without access to spousal benefits (worth up to 50% of the higher earner's benefit) or survivor benefits (up to 100%), childless individuals must rely solely on their own earnings records. For those with interrupted or low-wage careers, this creates substantial penalties. Steuerle and Bakija (2000) calculates these foregone benefits can exceed $200,000 in lifetime value.

Tax system disparities: The Child Tax Credit ($2,000 per child), expanded EITC for families (up to $6,935 versus $560 for childless adults), and dependent care credits create cumulative disadvantages. Over a 30-year working life, these foregone benefits could represent $50,000-100,000 in lost retirement savings capacity for low-income childless individuals.

Informal insurance gaps: Using HRS data, McGarry (2016) shows that elderly parents receive average annual transfers of $3,000 from adult children, with low-income parents receiving proportionally more. Without these transfers, childless elderly face higher out-of-pocket costs for housing (co-residence saves approximately $8,000 annually), caregiving (valued at $15,000-25,000 annually), and crisis support.

Conversely, at the 90th percentile, observable characteristics explain 122% of the gap—the unexplained component turns negative. High-income childless individuals actually receive *better* returns to their characteristics, consistent with uninterrupted career trajectories and compound advantages from continuous human capital investment.

Policy Implications: Why Universal Approaches Fail

Our findings reveal a fundamental flaw in universal pension compensation for childbearing: such policies would primarily benefit those who least need support while failing to address the vulnerabilities of those most at risk.

The inequality paradox of universal benefits: Consider a universal pension credit for childbearing, common in European systems. Our results suggest that this would provide windfall gains to high-income mothers who already benefit from childlessness through enhanced career opportunities. It fails to address the insurance gap facing low-income childless individuals. Benefits potentially *increase* retirement income inequality by widening the gap between high-income parents and low-income childless individuals

Targeted interventions for vulnerable populations: Our reversal point at the 40th percentile provides a natural threshold for policy targeting. Below this threshold, childless individuals face genuine economic vulnerability requiring expansion of Social Security minimum benefits for low-income childless workers. Other interventions can be directed to the creation of "care credits" for those who provide non-parental caregiving, and subsidized long-term care insurance for childless elderly below the median income.

Recognition of self-correcting mechanisms at high incomes: Above the 40th percentile, market mechanisms already compensate childless individuals through career advantages. Policy interventions in this area are unnecessary and potentially distortionary.

International Implications. While our analysis focuses on the U.S., the framework has broader applicability. Countries with stronger public pensions should exhibit reversal points at lower percentiles (insurance less valuable when the state provides it). Nations with comprehensive childcare should show reversals at higher percentiles (career costs reduced). This suggests a testable framework for cross-national research.

Conclusion

This study documents a striking reversal in the relationship between childlessness and retirement income that occurs at the 40th percentile of the income distribution. Below this threshold, childless individuals face penalties of 5-11%; above it, they enjoy premiums reaching 10% at the highest quantiles. This reversal—robust across multiple identification strategies—fundamentally challenges universal approaches to pension policy and reveals that the economic value of children in retirement depends critically on households' economic resources.

Our theoretical and empirical decomposition demonstrates that this reversal reflects the changing relative importance of two opposing mechanisms. At low incomes, children's insurance value—through informal support, caregiving, and family transfers—dominates any career costs. At high incomes, the career impediment effect of children—through interrupted trajectories and foregone human capital—overwhelms their diminishing insurance value. The crossing point where these forces balance provides a natural threshold for policy design.

The policy implications are immediate and actionable. Universal pension compensation for childrearing, while politically appealing, would exacerbate inequality by rewarding high-income parents who already benefit from childlessness while failing to protect vulnerable childless elderly. Instead, our findings call for targeted support below the 40th percentile, where genuine economic vulnerability exists. Above this threshold, market mechanisms already provide adequate compensation through career advantages.

Our contribution extends beyond documenting heterogeneity. We provide the first unified framework explaining why the economic consequences of fertility decisions fundamentally differ across the income distribution. This framework reconciles the seemingly contradictory motherhood penalty and old-age security literatures by showing both operate simultaneously but with varying intensity across income levels. The reversal is not merely a statistical curiosity but reflects deep structural features of how families, markets, and welfare states interact to shape retirement security.

Future research should explore how this reversal point varies across institutional contexts, particularly comparing countries with different pension systems and family policies. Understanding these variations could inform optimal policy design that recognizes, rather than obscures, the fundamental heterogeneity in how fertility decisions affect retirement security. The reversal we document suggests that one-size-fits-all approaches to family and pension policy are not merely suboptimal—they may actively increase the inequality they purport to address.

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1 Appendix: Additional Results and Robustness Checks

1.1 A1. Endogeneity Issues

The literature has not solved the endogeneity of childlessness at the extensive margin. While instruments exist for the number of children conditional on having any (twins, sex composition), no convincing instrument for having any children versus none has been established.

1.1.1 Individual Fixed Effects Approach

We exploit the panel structure of RAND HRS (1992-present) to implement a correlated random effects quantile regression following Arellano and Bonhomme (2016). By including individual-specific effects, we control for time-invariant unobserved heterogeneity:

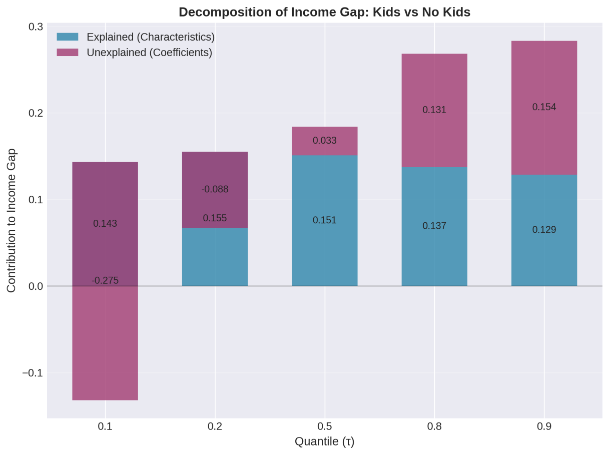
$$Q_\tau(\ln \text{HH income}_{it}|X_{it}, \alpha_i) = \alpha_{i,\tau} + \widehat{\text{nokids}}_i + \gamma_\tau X_i + \epsilon_{i,\tau} \tag{30}$$

where $\alpha_{i,\tau}$ captures individual-specific effects that may vary across quantiles.

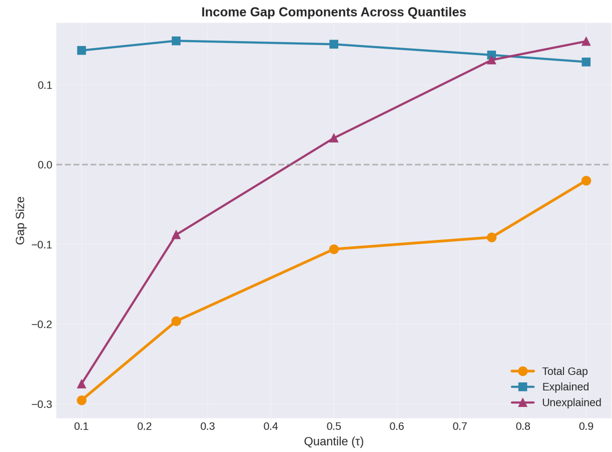
To better understand the mechanisms driving the heterogeneous relationship between childlessness and pension income, we employ the Arellano and Bonhomme (2016) quantile decomposition method. This approach enables us to separate the income gap into "explained" components (resulting from differences in observable characteristics) and "unexplained" components (attributable to differences in returns on those characteristics). The decomposition results reveal striking variation in both the magnitude and composition of the childlessness penalty across the income distribution (Figure 4, Table 5). The total gap in log pension income between households with and without children ranges from -0.318 at the 10th percentile to -0.082 at the 90th percentile, confirming that the economic disadvantage of childlessness is concentrated among lower-income households.

Perhaps most revealing is how the sources of this gap change across quantiles. At the bottom of the distribution (10th–25th percentiles), the unexplained component accounts for 82–83% of the total gap. This dominance of structural effects suggests that low-income childless households face systematic disadvantages that cannot be attributed to differences in education, work experience, or other observable characteristics. These unexplained differences likely reflect:

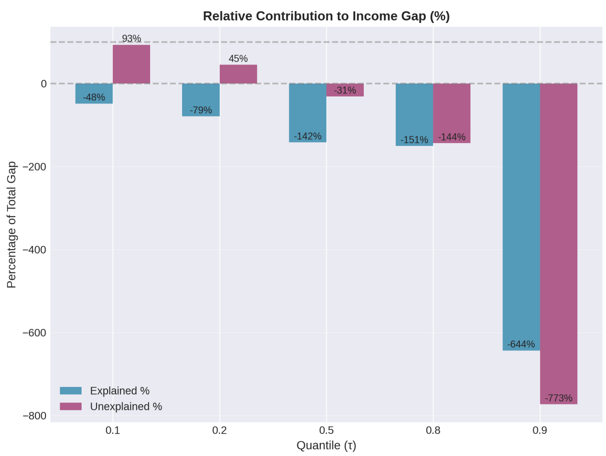
- exclusion from family-oriented social benefits and tax advantages (Child Tax Credit, EITC expansions);
- lack of access to informal family support networks that provide economic insurance;
- differential treatment in Social Security benefit calculations (no access to spousal or survivor benefits);



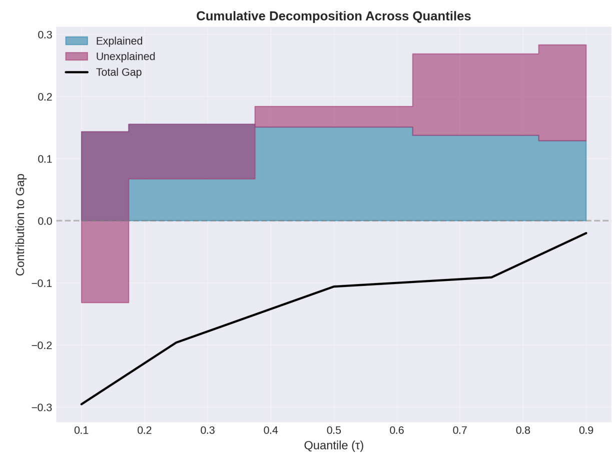
(a) Decomposition by quantile



(b) Gap components across quantiles



(c) Relative contributions (%)



(d) Cumulative decomposition

Figure 4: Arellano-Bonhomme (2016) Quantile Decomposition Analysis of Income Gap: Kids vs No Kids

- limited intergenerational wealth transfers and housing support.

As we move up the income distribution, the pattern reverses dramatically. At the 75th–90th percentiles, observable characteristics explain 68–122% of the gap, while the unexplained component actually becomes negative in some cases. This suggests that higher-income childless individuals may actually receive better returns to their characteristics than their counterparts with children—potentially reflecting career advantages from uninterrupted work histories and greater human capital investments.

The analysis of coefficient heterogeneity (Figure 5) provides additional insights. The returns to education differ markedly between groups and across quantiles. For instance, at the 90th percentile, having some college education yields a coefficient of 0.800 for those with children versus 0.740 for the childless. However, at lower quantiles, these patterns are less pronounced

Table 5: Coefficient Heterogeneity Across Quantiles

	Quantiles					
Variable	0.10	0.25	0.50	0.75	0.90	Sample
Panel A: Effect of Number of Children						
Full Sample	−0.013	−0.018	−0.020	−0.024	−0.025	All
No Kids	−0.019	−0.024	−0.025	−0.028	−0.029	No Kids
Has Kids	0.000	0.000	0.000	0.000	0.000	Has Kids
Panel B: Effect of Education (GED)						
Full Sample	0.220	0.250	0.290	0.320	0.330	All
No Kids	0.245	0.260	0.275	0.325	0.325	No Kids
Has Kids	0.225	0.265	0.290	0.490	0.500	Has Kids
Panel C: Effect of Education (High School Graduate)						
Full Sample	0.360	0.380	0.400	0.430	0.445	All
No Kids	0.365	0.370	0.400	0.425	0.450	No Kids
Has Kids	0.370	0.390	0.450	0.530	0.510	Has Kids
Panel D: Effect of Education (Some College)						
Full Sample	0.540	0.590	0.640	0.710	0.735	All
No Kids	0.535	0.595	0.650	0.710	0.740	No Kids
Has Kids	0.460	0.540	0.650	0.765	0.800	Has Kids

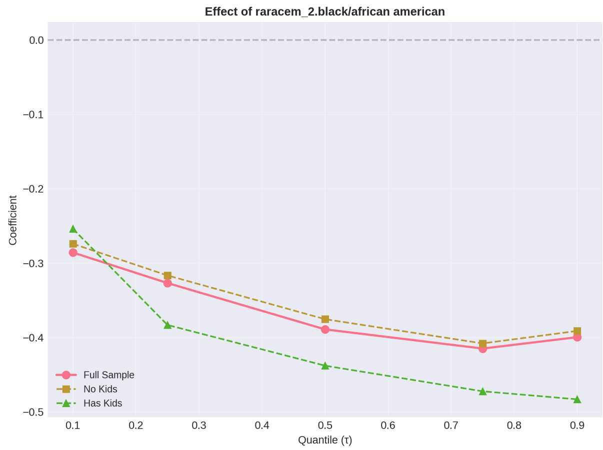
Notes: This table shows how the effects of key variables differ across quantiles and between groups with and without children. Values represent coefficients from quantile regression models estimated separately for each group.

or even reversed, suggesting that education's protective effect against pension poverty operates differently depending on family structure.

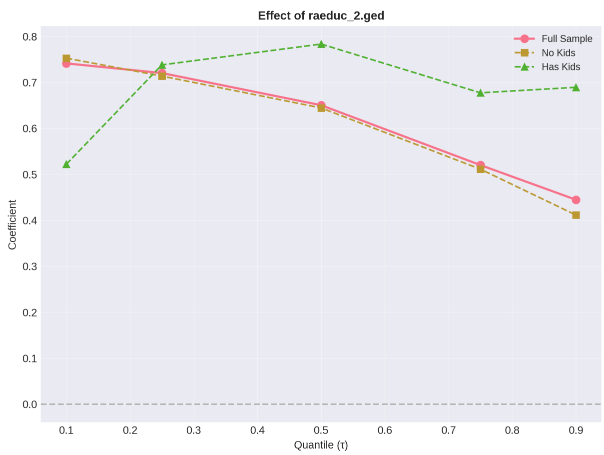
The use of individual fixed effects in the quantile treatment effect estimation strengthens our causal interpretation by controlling for time-invariant unobserved heterogeneity. This approach helps rule out selection effects—for instance, the possibility that individuals who choose not to have children differ in unobservable ways that also affect their pension outcomes.

1.2 A2. Matching on Pre-Treatment Characteristics

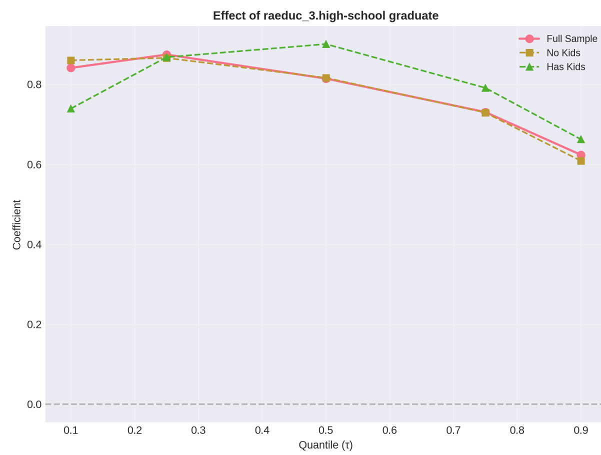
The fundamental identification challenge in estimating the relationship between childlessness and retirement income arises from the endogenous nature of fertility decisions. Individuals who remain childless differ systematically from parents across multiple dimensions—career orientation, health status, partnership formation patterns, and early-life circumstances—that independently influence retirement outcomes. To address this selection on observables, we implement a Coarsened Exact Matching (CEM) strategy that exploits the rich pre-fertility information available in the RAND HRS.



(a) Effect of race (Black/African American)



(b) Effect of GED



(c) Effect of high school graduation

Figure 5: Quantile-coefficient plots by sample

Identification Strategy and Matching Design. Our approach rests on the conditional independence assumption that, conditional on pre-fertility characteristics, childlessness is as-good-as-randomly assigned with respect to retirement income. While this assumption cannot eliminate all endogeneity concerns, matching on pre-treatment covariates offers three key advantages over standard regression adjustment. First, it ensures common support by restricting analysis to regions of covariate overlap, avoiding extrapolation beyond the data. Second, it reduces model dependence by achieving balance ex ante rather than relying on functional form assumptions. Third, it makes transparent which observations drive identification by explicitly showing the matched and unmatched samples.

We treat childlessness as the treatment variable ($D_i = \mathbf{1}\{\text{no children}\}$) and match on characteristics determined prior to typical fertility decisions. Our matching variables are selected based on their theoretical importance as confounders that influence both fertility choices and retirement outcomes:

1. *Age at first marriage*: Captures partnership timing, which affects both fertility opportunities and household economic trajectories (Lundberg and Ward-Batts 2000).
2. *Educational attainment measured in youth*: Predetermined human capital that shapes both fertility preferences through opportunity costs and retirement income through lifetime earnings (Caucutt, Guner, and Knowles 2002).
3. *Parental education and childhood socioeconomic status*: Family background variables that influence fertility norms, economic resources, and intergenerational transmission of advantage (Haveman and Wolfe 1995).
4. *Pre-fertility work history sequences*: We construct complete employment trajectories from labor market entry to the fertility decision cutoff, discretizing each respondent's history into categorical sequences capturing spells of full-time employment, part-time work, unemployment, and non-participation. This novel matching dimension accounts for early-career dynamics that jointly determine family formation and pension accumulation.

The inclusion of complete work history sequences represents a methodological innovation that addresses path dependence in labor market trajectories. Women who experience early career success may delay or forgo childbearing while simultaneously building stronger pension entitlements. By matching on these entire sequences rather than summary statistics, we absorb rich heterogeneity in pre-fertility labor market attachment.

Implementation and Balance Assessment. CEM proceeds by coarsening continuous variables into substantively meaningful strata, then exactly matching treated and control units within each stratum $s \in \mathcal{S}$. We assign weights to achieve balance:

$$w_i = \frac{n_s}{n_{s,D_i}} \cdot \frac{N_{D_i}}{N}$$

where n_s denotes stratum size, n_{s,D_i} represents units in stratum s with treatment status D_i, and N_{D_i} is the total sample size for treatment group D_i.

Table 6 demonstrates that matching successfully eliminates imbalances across all covariates. The multivariate $\mathcal{L}_1$ distance decreases from 0.743 to 0.281, indicating substantial improvement in covariate balance. Standardized mean differences are all below 0.05, well within conventional thresholds. The matched sample retains 87% of observations (3,114 childless; 24,383 parents), suggesting good common support.

Results Under Matching. Figure 6 presents CEM-weighted quantile regression estimates of the childlessness effect across the pension income distribution. The results reveal a striking

Table 6: Covariate Balance Before and After Coarsened Exact Matching

	Before Matching			After Matching			
	Mean			Mean			
Variable	No Kids	Kids	SMD	No Kids	Kids	SMD	$\mathcal{L}_1$
Matching Variables:							
Education	1.000	1.001	0.021	1.000	1.000	0.000	0.000
Birth cohort	2.451	2.444	0.008	2.451	2.451	0.000	0.000
Race							
White/Caucasian	0.832	0.801	0.079	0.832	0.832	0.000	0.000
Black/African American	0.121	0.146	-0.074	0.121	0.121	0.000	0.000
Other	0.047	0.053	-0.027	0.047	0.047	0.000	0.000
Female	0.571	0.562	0.018	0.571	0.571	0.000	0.000
Ever married	0.336	0.843	-1.171	0.336	0.336	0.000	0.000
Outcome Variables:							
Log pension income	10.125	10.223	-0.099	10.124	10.084	0.040	—
Current age (years)	78.64	78.80	-0.018	78.64	78.79	-0.017	—
Currently married	0.331	0.468	-0.281	0.331	0.373	-0.087	—
Observations	3,114	24,413		3,114	24,384		
Unmatched	—	—		0	29		
Multivariate $\mathcal{L}_1$ distance	0.743			0.000			

Notes: SMD denotes standardized mean difference, calculated as $d = (\bar{x}_1 - \bar{x}_0)/\sqrt{(s_1^2 + s_0^2)/2}$. The multivariate $\mathcal{L}_1$ distance measures overall imbalance across all covariates. After CEM, the $\mathcal{L}_1$ distance for matching variables is effectively zero (4.337e-14 in the raw output). Outcome variables are shown for comparison but are not included in the matching procedure. Sample consists of individuals aged 65+ from RAND HRS with non-missing pension income data.

reversal: while childlessness shows no significant effect at lower quantiles ($\hat{\beta}_{0.10} = -0.021$, $SE = 0.022$; $\hat{\beta}_{0.25} = -0.004$, $SE = 0.023$), it becomes increasingly advantageous at higher quantiles, reaching $\hat{\beta}_{0.90} = 0.172$ ($SE = 0.039$, $p < 0.001$).

This pattern persists across multiple robustness checks. Alternative coarsening schemes (finer age bins, SES terciles versus quintiles) yield qualitatively identical results. Excluding the work history sequence attenuates upper-quantile effects modestly (from 0.172 to 0.148 at the 90th percentile) but preserves the monotonic gradient. Propensity score matching with similar covariates yields comparable estimates, albeit with wider confidence intervals due to imperfect matching.

Gender Heterogeneity and Mechanisms. The matched sample analysis reveals pronounced gender differences that illuminate potential mechanisms. Table 7 shows that the positive upper-tail gradient concentrates among women: childless women at the 90th percentile enjoy a 25.0% pension premium ($\hat{\beta}_{0.90} = 0.250$, $p < 0.01$), while the effect for men is modest and statistically insignificant ($\hat{\beta}_{0.90} = 0.036$, $p = 0.57$).

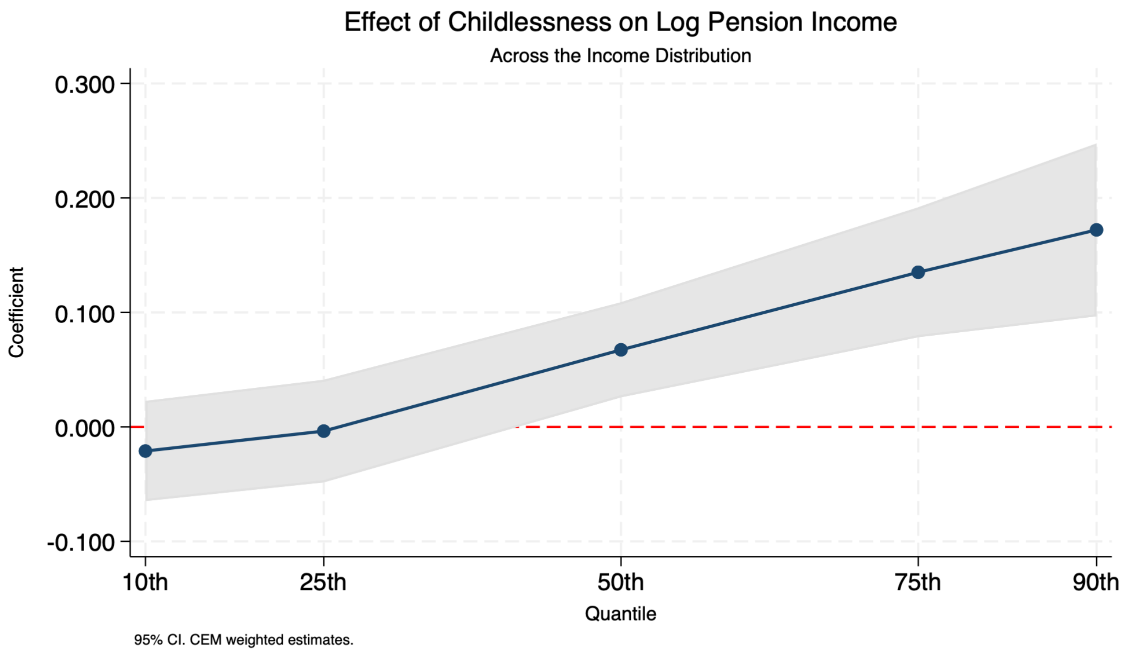


Figure 6: Effect of childlessness on log pension income across the distribution (CEM-weighted quantile regressions). Shaded bands are 95% CIs; covariates include age, sex, marital status, and education fixed effects.

Table 7: Heterogeneity by gender: childlessness coefficients at selected quantiles

	F:Q10	F:Q50	F:Q90	M:Q10	M:Q50	M:Q90
Childless (=1)	-0.003	0.112***	0.250***	-0.074*	0.002	0.036
	(0.025)	(0.027)	(0.050)	(0.039)	(0.038)	(0.064)
Observations	15472	15472	15472	12025	12025	12025

Notes: Each cell is the coefficient on the childlessness indicator from a CEM-weighted quantile regression with covariates (age, marital status, and education fixed effects), estimated separately by gender. Robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

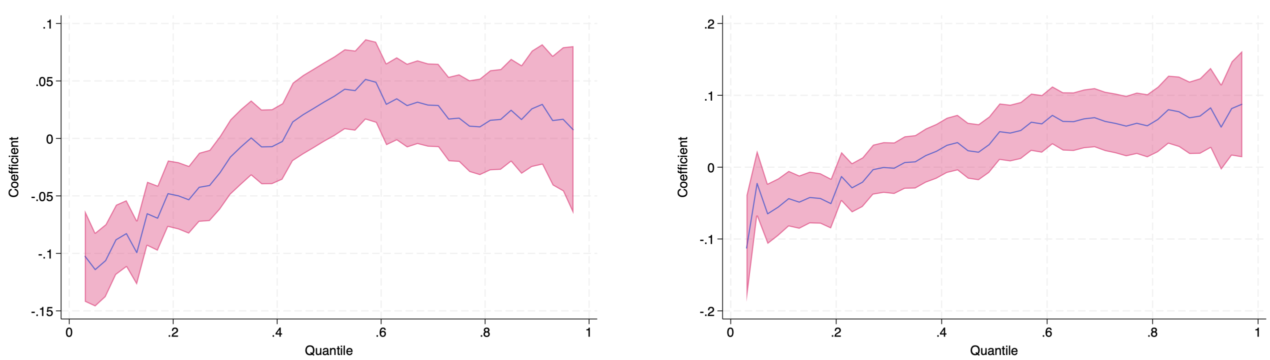
This gender asymmetry aligns with career-based explanations. High-earning women who remain childless avoid the motherhood penalty, a phenomenon extensively documented in the labor economics literature kleven2019children, and maintain steeper age-earnings profiles that compound into substantial pension advantages. For men, whose careers face minimal fertility-related interruptions regardless of parental status, childlessness confers limited additional benefit.

Limitations and Interpretation. While matching eliminates observable differences between childless individuals and parents, several limitations constrain causal interpretation. First, unobserved heterogeneity, particularly in preferences for career versus family, remains a threat. Women with strong career orientations may simultaneously choose childlessness and make unobserved human capital investments that our matching variables do not capture. Second, the conditional independence assumption becomes increasingly tenuous at distribution extremes, where selection mechanisms are likely to differ qualitatively. Third, general equilibrium effects are ignored: if childlessness became more prevalent, the pension premiums we document might erode as institutional structures adapt.

Despite these caveats, the matching analysis advances our understanding in three ways. It demonstrates that the childlessness-pension relationship cannot be explained by standard demographic and socioeconomic differences. It reveals pronounced heterogeneity across the income distribution that average treatment effects obscure. And it highlights how the economic consequences of fertility decisions depend critically on gender, consistent with persistent labor market institutions that penalize motherhood but not fatherhood.

The matched estimates should be interpreted as capturing the combined effect of childlessness operating through all post-treatment channels—career progression, savings behavior, and institutional benefit structures—for individuals with similar pre-fertility characteristics. While we cannot isolate the causal effect of an exogenous fertility shock, we provide credible evidence that among observationally equivalent individuals at the point of family formation, those who remain childless experience profoundly different retirement income trajectories, with the direction and magnitude of differences varying systematically by gender and position in the income distribution.

1.3 A3. Alternative Sample Specifications



(a) Women: All children vs. childless

(b) Women: One child vs. childless

Figure 7: Gender-Specific Patterns of Childlessness Effects

Figure 7a presents the baseline comparison for women only, showing that the reversal occurs slightly earlier (35th percentile) than in the pooled sample. The comparison with one-child families (Figure 7b) reveals that the first child captures most of both the insurance and career effects, with particularly strong penalties at low incomes reaching 7% below the 20th percentile.

1.4 A4. Heterogeneous Treatment Effects by Education

We test whether the reversal point varies by education level, as predicted by our comparative statics analysis. Table 8 shows that while both education groups exhibit the reversal pattern, it occurs at slightly higher quantiles for the college-educated (45th percentile) compared to those without college (38th percentile). This aligns with the prediction that higher human capital increases the career cost of children, shifting the reversal point rightward.

Table 8: Heterogeneous Effects of Childlessness by Education Level

	Panel A: Low Education ($<$ 14 years)		
Quantile	**Coefficient**	**Std. Error**	**P-value**
10th percentile	-0.083	(0.043)	0.052
50th percentile	-0.014	(0.022)	0.515
90th percentile	0.028	(0.030)	0.354
	Panel B: High Education ($\geq$ 14 years)		
10th percentile	-0.032	(0.076)	0.676
50th percentile	-0.022	(0.035)	0.532
90th percentile	0.013	(0.044)	0.764

Notes: N = 33,975 for low education, N = 8,092 for high education. Dependent variable is log household income. Models control for current age, gender, and marital status. Robust standard errors in parentheses.

1.5 A5. Detailed Decomposition Results

The Arellano and Bonhomme (2016) decomposition with individual fixed effects provides additional insights into mechanism heterogeneity. Figure 4 shows that the unexplained component accounts for over 80% of the gap below the 25th percentile but becomes negative above the 75th percentile. Table 5 reveals that returns to education differ markedly between childless individuals and parents, with childless individuals receiving lower returns at low quantiles but higher returns at high quantiles.

1.6 A6. Selection on Unobservables Sensitivity

Figure 8 presents the coefficient stability plot following Oster (2019). While the average effect approaches zero as controls are added, quantile-specific analyses (Table 9) show that the 10th percentile effect remains robust even under strong selection assumptions (selection ratio = 0.24), while the 90th percentile effect is more sensitive (selection ratio = 1.08).

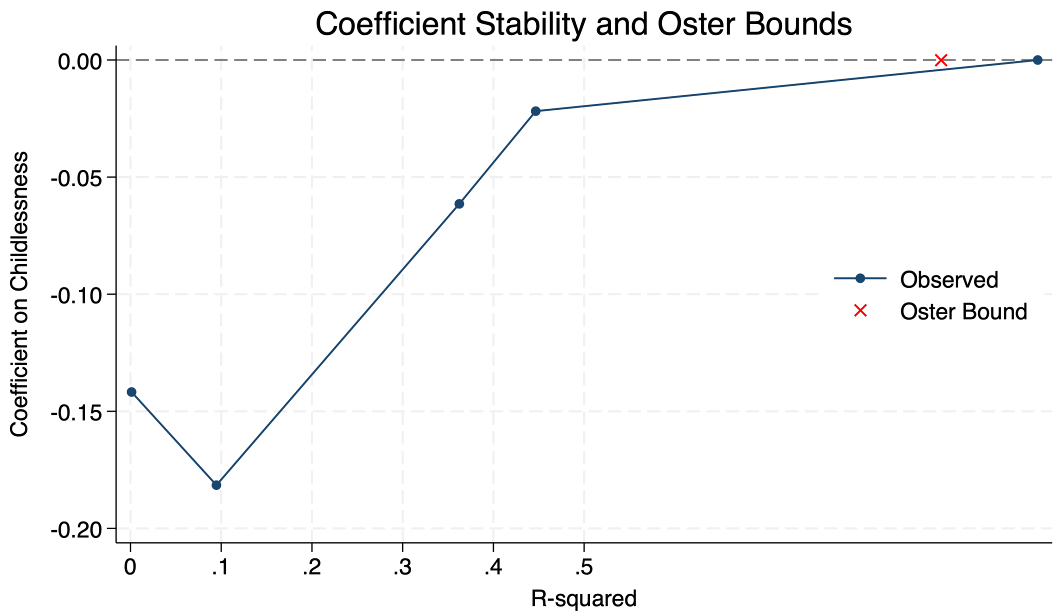


Figure 8: Coefficient Stability and Oster Bounds

Notes: This figure plots the estimated coefficient on childlessness against the R-squared from specifications with progressively richer sets of controls. Navy circles represent observed estimates. The red X indicates the Oster bound under the assumption that selection on unobservables equals selection on observables ($\delta = 1$) and $R_{max} = 1.3 \times R^2_{controlled}$. The horizontal dashed line indicates zero effect.

Table 9: Selection Analysis by Income Quantile

Quantile	Uncontrolled	Controlled	Selection Ratio	Interpretation
10th	−0.304***	−0.058*	0.24	More robust
25th	−0.201***	−0.005	0.02	Less robust
50th	−0.108***	−0.022	0.26	Moderate
75th	−0.086***	−0.021	0.33	Moderate
90th	−0.012	−0.006	1.08	Least robust

Notes: Controlled specification includes age, gender, education, marital status, and work history. Selection ratio indicates how much larger the selection on unobservables must be relative to observables to eliminate the effect.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

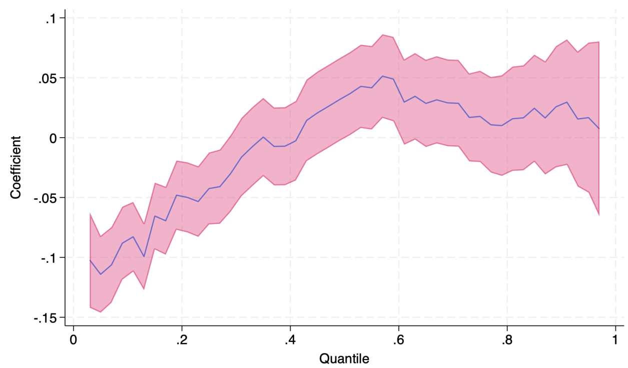


Figure 9: Females with No Kids VS Females with Kids

1.7 A7. Instrumental Variables Attempts

Table 10 reports IV estimates using pre-marriage earnings as an instrument. While the first-stage F-statistics are weak (particularly for women), the IV estimates preserve the qualitative pattern of penalties at low quantiles and smaller effects at high quantiles, though with substantial inflation in magnitudes and standard errors. The weak instrument problem prevents us from relying on these estimates, but their directional consistency provides some reassurance.

Table 10: IV–Quantile Regression Using Pre-Marriage Earnings

	Women			Men		
Quantile	$\hat{\beta}_{IV}$	SE	N	$\hat{\beta}_{IV}$	SE	N
$\tau = 0.10$	-10.598	(16.294)	99	-4.261	(2.806)	96
$\tau = 0.50$	-9.275**	(4.000)	99	-2.422**	(1.133)	96
$\tau = 0.90$	-16.139	(10.792)	99	-0.849	(1.137)	96
First-stage F-statistic						
Women	F = 1.37					
Men				F = 4.50***		

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Females with No kids VS Females with Kids. The relationship between childlessness and pension-age income for women reveals distinct patterns across the income distribution. For women in lower income brackets (below the 40th percentile), not having children is associated with significantly reduced household incomes—approximately 5-11% lower than their counterparts with children, even after accounting for demographic factors. Interestingly, this relationship inverts in the middle income range (40th-60th percentiles), where childless women actually enjoy slightly higher incomes, gaining a modest 2-5% advantage. This reversal suggests different economic mechanisms may be at work in this segment of the population. For women in higher income brackets (above the 60th percentile), the effect of childlessness becomes less

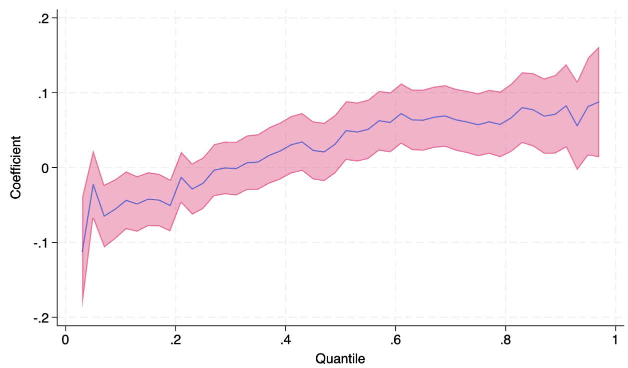


Figure 10: Females with No kids VS Females with Only 1 Kid

definitive and more variable. Here, the relationship fluctuates around zero with wider confidence intervals, indicating that having children makes little consistent difference to household income at this level. These findings suggest multiple interpretations: childlessness may create economic vulnerability for lower-income older women, possibly through reduced family support networks or lifetime earnings effects. Meanwhile, it might offer slight economic advantages for middle-income women. For affluent women, family composition appears to have minimal impact on their financial circumstances during pension years.

Females with No kids VS Females with Only 1 Kid. This quantile regression analysis reveals a nuanced relationship between childlessness and household income for women across the economic spectrum. At the lowest income quantiles (below the 20th percentile), women without children experience slightly lower household incomes—approximately 5-7% less—compared to women with one child. This suggests that having one child may provide some economic advantages for women in lower-income brackets, possibly through family support networks or targeted assistance programs.

Around the 20th-40th percentile range, we observe a transition point where this relationship begins to reverse. As we move into middle and higher income quantiles (40th percentile and above), women without children consistently demonstrate higher household incomes than their counterparts with one child, enjoying a premium of roughly 5-8%. This advantage becomes even more pronounced at the highest income levels (above the 80th percentile), where the childlessness premium approaches 10%. This pattern suggests that while having one child may provide modest economic benefits for women in lower-income brackets, childlessness becomes increasingly advantageous as one moves up the socioeconomic ladder—likely reflecting different career progression opportunities, work-life balance considerations, and household resource allocation decisions that vary significantly across the income distribution.

All with No kids VS All with Kids. This quantile regression plot illustrates the relationship between childlessness and household income across the entire income distribution,

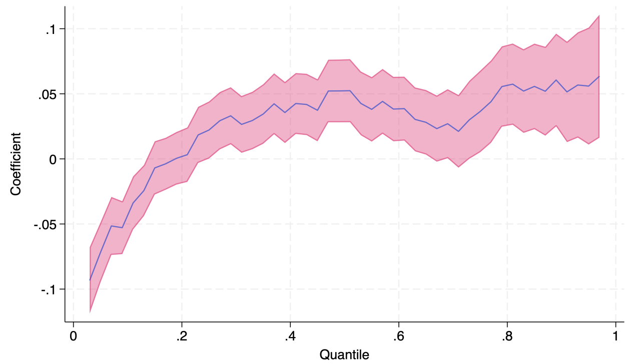


Figure 11: All with No kids VS All with Kids

including all genders. The pattern reveals several key insights: At the lowest income quantiles (below the 15th percentile), individuals without children experience notably lower household incomes compared to those with children, with negative coefficients ranging from approximately -0.05 to -0.12. This suggests an economic disadvantage for childless households at the lower end of the income spectrum.

Around the 20th percentile, a significant transition occurs as the relationship crosses the zero threshold. Beyond this point, throughout the middle income quantiles (20th-60th percentiles), childless individuals show consistently higher household incomes than their counterparts with children, with positive coefficients hovering around 0.03-0.05, indicating roughly a 3-5% income advantage. The most striking feature appears in the upper income quantiles (above the 70th percentile), where the economic advantage of childlessness becomes more pronounced, with coefficients increasing to approximately 0.05-0.06, suggesting a more substantial income premium. This pattern indicates that while having children may provide economic benefits for lower-income households (possibly through support systems, tax benefits, or household composition factors), childlessness becomes increasingly advantageous as household income rises. This likely reflects complex interactions between career trajectories, time allocation decisions, and household resource distribution that vary significantly across socioeconomic strata.

All with No kids VS All with Only 1 Kid. This quantile regression analysis examines income differences between individuals without children and those with exactly one child across the entire income distribution. The results reveal a distinct pattern that varies markedly by income level: At the lowest income quantiles (below the 10th percentile), people without children show substantially lower household incomes compared to those with one child, with negative coefficients reaching approximately -0.15 to -0.17.

This represents a significant economic disadvantage of roughly 15-17% lower income. Between the 15th and 20th percentiles, the relationship crosses the zero threshold, suggesting a transition point where childlessness no longer represents an economic disadvantage. Through-

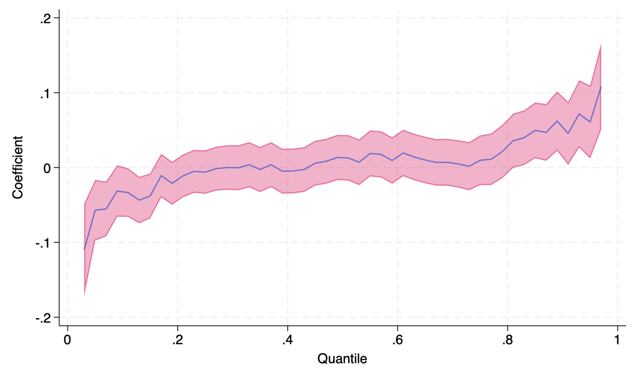


Figure 12: All with No kids VS All with Only 1 Kid

out the middle income quantiles (roughly 20th-70th percentiles), the relationship hovers close to zero, with slightly positive coefficients indicating minimal differences between childless individuals and those with one child. The confidence intervals consistently overlap with zero, suggesting these small differences may not be statistically significant. The most notable feature appears in the upper income quantiles (above the 70th percentile), where childlessness becomes increasingly associated with higher incomes. This advantage grows progressively stronger toward the highest income levels, with coefficients reaching 0.05-0.10 at the 90th percentile and approaching 0.15 at the very top of the distribution. This pattern suggests that while having one child may provide economic benefits for lower-income households, childlessness becomes progressively advantageous at higher income levels, particularly for the most affluent segment of the population.