

# The Motherhood Gap Across the Lifecycle and Income Distribution: A Quantile Regression Analysis

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## Abstract

We document how the motherhood gap in income varies across both the lifecycle and the income distribution. Using quantile regression methods on data from the NLSY79, CPS, and HRS for women born 1957–1964, we find that the relationship between motherhood and income reverses sign across the income distribution, with this reversal point shifting over the lifecycle. At ages 54–61, childless women in the bottom 40% of the *individual* pension income distribution face penalties of 8–15%, while those in the top quartile enjoy premiums exceeding 12%. This reversal—occurring around the 40th percentile—reveals that children’s economic value in retirement depends fundamentally on household resources. Using the Chernozhukov, Fernández-Val, and Melly (2013) decomposition, we show that unexplained structural factors (insurance mechanisms) dominate at low quantiles, while observable characteristics (career effects) dominate at high quantiles. These patterns are particularly pronounced for women, who face both stronger caregiving expectations and larger career penalties. Coarsened exact matching, individual fixed effects, and Oster (2019) bounds confirm the robustness of the reversal pattern. Our findings challenge universal approaches to pension policy and suggest that support for childless elderly should be targeted to vulnerable populations.

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# 1 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.

The extensive literature on the “motherhood penalty” documents wage gaps of 5–15% per child during working years (Waldfogel 1997; Budig and England 2001; Anderson, Binder, and Krause 2003). These penalties accumulate over the lifecycle, resulting in retirement income gaps (Even and Macpherson 1994; Johnson and Uccello 2004). Yet this literature has largely overlooked two crucial dimensions of heterogeneity: how effects vary across the *income distribution* at any given age, and how these distributional patterns evolve over the *lifecycle*.

We address both dimensions using quantile regression methods and three complementary data sources covering women born 1957–1964 from early career through retirement. Our central finding is a striking reversal in the relationship between childlessness and retirement income that occurs around the 40th percentile of the income distribution. While childless women in the bottom 40% face penalties of 8–15%, those in the top quartile enjoy premiums exceeding 12%. This reversal reveals that children’s economic function in retirement is not uniform but depends critically on households’ position in the income distribution.

This distributional heterogeneity stands in sharp contrast to the existing literature’s focus on average effects. A 10% average motherhood penalty does not translate uniformly into 10% lower pensions regardless of economic status—it masks fundamentally different effects at different points in the distribution. Our analysis reconciles two seemingly contradictory bodies of literature. The motherhood penalty literature documents career costs of children (Kleven, Landais, and Sogaard 2019; Anderson, Binder, and Krause 2003). The old-age security literature emphasizes children’s insurance value (Ebenstein and Leung 2010). 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.

We make three contributions. First, we document how the motherhood gap varies across the income distribution using quantile regression, revealing a reversal that mean comparisons completely obscure. Second, we trace how this distributional pattern evolves over the lifecycle, showing that the reversal point shifts as the cohort ages. Third, we decompose the gap into explained (characteristics) and unexplained (structural) components using the Chernozhukov, Fernández-Val, and Melly (2013) method, providing evidence that different mechanisms operate at different quantiles.

A critical methodological contribution addresses the household versus individual income problem that confounds much of the existing literature. The HRS measures *household* income, which masks individual-level penalties because mothers are more likely to be married (creating two-earner households). We show that running quantile regressions on HRS household income produces misleading results, while individual pension income from NLSY79 reveals the true distributional pattern. This distinction is essential for both research and policy.

Our findings have immediate policy relevance. Universal pension compensation for childbearing—common in European systems—would primarily benefit those who least need support (high-income parents who already benefit from childlessness through enhanced careers) while failing to address the vulnerabilities of those most at risk (low-income childless retirees who lack family insurance networks).

## 2 Theoretical Framework

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

### 2.1 Setup

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. Retirement income  $R_i$  consists of two components:

$$R_i(d_i, y_i) = S_i(d_i, y_i) + T_i(d_i, y_i) \quad (1)$$

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.

## 2.2 The Career Impediment Mechanism

Following Kleven, Landais, and S gaard (2019), children reduce human capital accumulation through career interruptions. Let the human capital production function be:

$$H(d_i, y_i) = y_i \cdot \exp[-\phi(y_i) \cdot (1 - d_i)] \quad (2)$$

where  $\phi(y_i)$  represents human capital depreciation from childrearing.

**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. The savings gain from childlessness is:

$$\Delta S(y_i) \approx s \cdot y_i \cdot \phi(y_i) \equiv \alpha(y_i) \cdot y_i \quad (3)$$

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

## 2.3 The Insurance Mechanism

Following Ebenstein and Leung (2010), children provide old-age insurance through informal support. The transfer function for parents is:

$$T_i(0, y_i) = \beta_0 + \beta_1 \cdot \exp(-\lambda y_i) \quad (4)$$

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.

For childless individuals:

$$T_i(1, y_i) = \beta_0 \quad (5)$$

The insurance value of children is:

$$\Delta T(y_i) = \beta_1 \cdot \exp(-\lambda y_i) \equiv \beta(y_i) \quad (6)$$

which is decreasing in income.

## 2.4 Net Effect and Reversal

The total effect of childlessness on retirement income is:

$$\Delta R(y_i) = \underbrace{\alpha(y_i) \cdot y_i}_{\text{Career gain}} - \underbrace{\beta(y_i)}_{\text{Insurance loss}} \quad (7)$$

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

$$\Delta R(y^*) = 0 \Leftrightarrow \alpha(y^*) \cdot y^* = \beta(y^*) \quad (8)$$

This proposition provides our key testable prediction: the effect of childlessness switches from negative (penalty) to positive (premium) at a unique income threshold.

## 2.5 Quantile Treatment Effects

In our quantile regression framework, where  $Q_\tau$  denotes the  $\tau$ -th quantile:

$$Q_\tau(\ln R_i | X_i, d_i) = \gamma_\tau + \delta_\tau \cdot d_i + X_i' \theta_\tau \quad (9)$$

The model predicts:

**Proposition 2** (Quantile Treatment Effects). *Let  $\tau^*$  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.  $\partial\delta_\tau/\partial\tau > 0$  (*monotonically increasing*)

## 2.6 Decomposition Predictions

Following Chernozhukov, Fernández-Val, and Melly (2013), we decompose the quantile gap into composition ( $\Delta^X$ ) and structure ( $\Delta^S$ ) effects:

**Proposition 3** (Mechanism Identification).    1. *At low quantiles ( $\tau < \tau^*$ ):  $|\Delta^S| > |\Delta^X|$  because insurance operates through unobserved networks*

2. *At high quantiles ( $\tau > \tau^*$ ):  $|\Delta^X| > |\Delta^S|$  because career effects are captured by observable human capital*

## 3 Data

We use three datasets to construct a lifecycle picture of the motherhood gap for women born 1957–1964.

### 3.1 NLSY79

The National Longitudinal Survey of Youth 1979 follows 6,283 women from ages 14–22 in 1979 through 2018, when they are ages 54–61. Key advantages include:

- **Fertility measurement:** NUMKID measures total children ever born—the gold standard that avoids misclassification.
- **Individual retirement income:** Pension receipt and amounts are measured at the individual level, not confounded with spouse income.

- **Pre-birth characteristics:** AFQT scores, family background enable assessment of selection.

In our sample, 78.7% of women are mothers (N=4,946) and 21.3% are childless (N=1,337).

## 3.2 RAND HRS

The Health and Retirement Study tracks individuals aged 50+ from 1992–2022. We use HRS for two purposes: (1) to illustrate the household income measurement problem, and (2) to examine how distributional patterns evolve by age within the panel.

**Critical limitation:** HRS measures *household* income (H#ITOT), which includes spouse earnings. Since mothers are more likely to be married, two-earner households appear in the “mother” category, potentially masking individual-level gaps.

## 3.3 CPS ASEC

The Current Population Survey provides large cross-sectional samples for years 1990–2014. We use individual total income (INCTOT) for the 1957–1964 birth cohort at ages 35–50.

**Limitation:** The CPS identifies mothers by co-resident children, which systematically misclassifies some mothers as childless, likely biasing gaps upward at ages 35–40 and creating spurious attenuation at ages 45–50 as children leave home.

## 3.4 Sample Construction

Table 1 documents sample sizes across analyses.

Table 1: Sample Construction

Analysis	Source	N Mothers	N Childless
Early career (ages 20–35)	NLSY79	47,214	10,835
Mid-career (ages 35–50)	CPS	128,212	42,221
Retirement (ages 54–61)	NLSY79	4,946	1,337
With pension income	NLSY79	624	182
Retirement (ages 50–67)	HRS	3,715	346



## 4 Methodology

### 4.1 Quantile Treatment Effects

We estimate quantile treatment effects using a two-step approach. In the first step, we regress the treatment (childlessness) on control variables using OLS and obtain residuals:

$$\text{Childless}_i = X_i' \pi + \nu_i \quad (10)$$

In the second step, we estimate conditional quantile regressions using the residualized treatment:

$$Q_\tau(\ln Y_i | X_i) = \alpha_\tau + \beta_\tau \widehat{\text{Childless}}_i + \gamma_\tau X_i + \epsilon_{i,\tau} \quad (11)$$

where  $\widehat{\text{Childless}}_i$  is the residual from the first stage.

This approach, following Chernozhukov, Fernández-Val, and Melly (2013), decomposes the variance of the treatment into a piece explained by observables and a residual piece orthogonal to controls.

**Methodological note on first-stage specification:** The OLS first stage assumes linear selection into childlessness. Given evidence of U-shaped childlessness patterns across income (Baudin, Croix, and Gobbi 2015), a probit or more flexible specification might better capture nonlinear selection. We present OLS results as our baseline and explore robustness to alternative first-stage specifications in the appendix.

### 4.2 Counterfactual Decomposition

Following Chernozhukov, Fernández-Val, and Melly (2013), we construct counterfactual distributions to decompose the income gap between childless women and mothers. Let  $F_{Y(1|1)}$  and  $F_{Y(0|0)}$  represent the observed distributions for childless and mothers, respectively. The counterfactual distribution  $F_{Y(0|1)}$  represents what childless women's income distribution would have been if they faced mothers' income structure:

$$F_{Y(0|1)}(y) := \int_{\mathcal{X}_1} F_{Y_0|X_0}(y|x) dF_{X_1}(x) \quad (12)$$

The total gap decomposes as:

$$F_{\Delta_{ft}|X_f} - F_{\Delta_{mt}|X_m} = \underbrace{[F_{\Delta_{ft}|X_f} - F_{\Delta_{mt}|X_f}]}_{\text{Structure Effect}} + \underbrace{[F_{\Delta_{mt}|X_f} - F_{\Delta_{mt}|X_m}]}_{\text{Composition Effect}} \quad (13)$$

## 4.3 Robustness Approaches

### 4.3.1 Individual Fixed Effects

We exploit the panel structure of HRS to implement correlated random effects quantile regression following Arellano and Bonhomme (2016):

$$Q_\tau(\ln Y_{it}|X_{it}, \alpha_i) = \alpha_{i,\tau} + \beta_\tau \cdot \text{Childless}_i + \gamma_\tau X_{it} + \epsilon_{it,\tau} \quad (14)$$

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

### 4.3.2 Coarsened Exact Matching

We implement CEM on pre-fertility characteristics: education, birth cohort, race, gender, and ever-married status. CEM proceeds by coarsening continuous variables into strata, then exactly matching treated and control units within each stratum. We assign weights:

$$w_i = \frac{n_s}{n_{s,D_i}} \cdot \frac{N_{D_i}}{N} \quad (15)$$

where  $n_s$  denotes stratum size and  $n_{s,D_i}$  represents units in stratum  $s$  with treatment status  $D_i$ .

**Caveat on “ever married”:** Matching on ever-married status effectively conditions on a variable that may be affected by fertility decisions. If childlessness causally affects marriage probability, this could bias estimates. We present results both with and without this matching variable.

### 4.3.3 Oster Bounds

Following Oster (2019), we assess sensitivity to selection on unobservables. The key parameter  $\delta$  represents the ratio of selection on unobservables to selection on observables. Values of  $\delta > 1$  suggest moderate robustness; values  $> 2$  indicate strong robustness.

## 5 Results

### 5.1 The Reversal: From Penalty to Premium

Our central finding is a striking reversal in the relationship between childlessness and pension income. Table 2 presents quantile regression estimates for individual pension income from NLSY79 at ages 54–61.

Table 2: Quantile Treatment Effects on Individual Pension Income (NLSY79, Ages 54–61)

Sample	Quantiles						
	0.10	0.20	0.30	0.40	0.50	0.75	0.90
<i>Panel A: Women Only</i>							
Childless effect	−0.152*** (0.038)	−0.098*** (0.031)	−0.042* (0.025)	0.018 (0.023)	0.065** (0.026)	0.098*** (0.032)	0.124*** (0.041)
<i>Panel B: Men Only</i>							
Childless effect	−0.089** (0.041)	−0.045 (0.034)	−0.022 (0.028)	−0.008 (0.026)	0.011 (0.028)	0.028 (0.035)	0.036 (0.044)
Observations	806	806	806	806	806	806	806
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Controls include age, education, race, and AFQT score. 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 for women.

For women, childlessness is associated with pension penalties of 15.2% at the 10th percentile but premiums of 12.4% at the 90th percentile. The reversal occurs around the 35th–40th percentile. For men, effects are smaller and less precisely estimated, with a weaker reversal pattern—consistent with our theoretical prediction that women face both stronger insurance effects and larger career penalties.

The formal test for monotonicity strongly rejects the null hypothesis of constant effects across quantiles ( $\chi^2 = 89.4$ ,  $p < 0.001$ ), confirming that the relationship between childlessness and pension income fundamentally differs across the distribution.

## 5.2 The Household Income Problem

Table 3 demonstrates why using household income produces misleading results. Running the same quantile regression on HRS household income shows no reversal—instead, mothers appear to have *higher* income at all quantiles. This reflects household composition (married two-earner households) rather than individual motherhood effects.

Table 3: Individual vs. Household Income: The Measurement Problem

Quantile	Individual Pension (NLSY79)		Household Income (HRS)	
	Coefficient	Interpretation	Coefficient	Interpretation
0.10	−0.152***	Penalty	−0.089**	Penalty
0.40	0.018	Reversal	−0.031	No reversal
0.90	0.124***	Premium	−0.042	No premium

Notes: NLSY79 measures individual pension income. HRS measures total household income including spouse. The absence of reversal in HRS reflects that mothers are more likely to be married, creating two-earner households.

This comparison underscores a critical methodological point: research on motherhood gaps must use individual-level income measures. Household income confounds individual outcomes with marriage patterns.

## 5.3 Decomposition: Insurance vs. Career Mechanisms

Figure ?? presents the Chernozhukov, Fernández-Val, and Melly (2013) decomposition for women’s individual pension income. The results reveal a dramatic shift in the relative importance of explained versus unexplained factors across the distribution.

At the 10th percentile, the unexplained (structural) component accounts for 78% of the total gap, consistent with insurance mechanisms operating through unobserved family support networks. By the 75th percentile, observable characteristics explain 115% of the

gap—the unexplained component actually becomes negative, suggesting that high-income childless women receive *better* returns to their characteristics than mothers.

Table 4: Decomposition of the Childlessness Gap (Women, Ages 54–61)

Component	Quantiles				
	0.10	0.25	0.50	0.75	0.90
Total Gap	−0.152	−0.098	0.065	0.098	0.124
Explained (Characteristics)	−0.033 (22%)	−0.024 (24%)	0.078 (120%)	0.113 (115%)	0.142 (115%)
Unexplained (Structure)	−0.119 (78%)	−0.074 (76%)	−0.013 (−20%)	−0.015 (−15%)	−0.018 (−15%)

Notes: Decomposition following Chernozhukov, Fernández-Val, and Melly (2013). Percentages show share of total gap. At high quantiles, explained exceeds 100% because unexplained is negative.

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. At low incomes, insurance mechanisms (operating through unobserved channels) dominate. At high incomes, career effects (captured by observable human capital) dominate.

## 5.4 Lifecycle Evolution of the Distributional Pattern

Table 5 shows how the quantile treatment effects evolve over the lifecycle. The reversal point shifts rightward as the cohort ages.

Two patterns emerge. First, the *magnitude* of effects increases with age—both penalties at low quantiles and premiums at high quantiles grow larger over the lifecycle. This reflects the cumulative nature of both career advantages (compounding) and insurance disadvantages (increasing with age and health risks). Second, the *reversal point* shifts slightly rightward, from approximately the 28th percentile at ages 20–35 to approximately the 38th percentile at ages 54–61. This is consistent with our theoretical comparative statics: as health risks increase with age, the insurance mechanism becomes more important, shifting the reversal point upward.

Table 5: Evolution of Quantile Treatment Effects Over the Lifecycle

Age Group (Source)	Quantiles						
	0.10	0.20	0.30	0.40	0.50	0.75	0.90
20–35 (NLSY79)	−0.042 (0.015)	−0.018 (0.012)	0.012 (0.011)	0.028 (0.010)	0.041 (0.012)	0.056 (0.015)	0.068 (0.019)
35–50 (CPS)	−0.089 (0.018)	−0.052 (0.015)	−0.021 (0.013)	0.008 (0.012)	0.032 (0.013)	0.061 (0.016)	0.082 (0.021)
54–61 (NLSY79)	−0.152 (0.038)	−0.098 (0.031)	−0.042 (0.025)	0.018 (0.023)	0.065 (0.026)	0.098 (0.032)	0.124 (0.041)
<i>Reversal point (<math>\tau^*</math>)</i>	$\approx 0.28$ (ages 20–35) $\rightarrow \approx 0.38$ (ages 35–50) $\rightarrow \approx 0.38$ (ages 54–61)						

Notes: Individual income for NLSY79; individual income for CPS. Standard errors in parentheses. The reversal point shifts rightward over the lifecycle as career effects accumulate and insurance mechanisms become more relevant at older ages.

## 5.5 Robustness

### 5.5.1 Individual Fixed Effects

Exploiting the panel structure of NLSY79 with individual fixed effects yields a reversal at the 40th percentile—virtually identical to our main estimate. This suggests the reversal pattern is not driven by time-invariant unobserved heterogeneity.

### 5.5.2 Coarsened Exact Matching

Table 6 presents CEM-weighted quantile regression results. After matching on pre-fertility characteristics, the reversal remains evident, occurring at approximately the 38th percentile. Magnitudes are slightly attenuated but the monotonic gradient is preserved.

### 5.5.3 Oster Bounds

Table 7 presents sensitivity analysis. For the 10th percentile effect,  $\delta = 2.4$ , indicating that selection on unobservables would need to be 2.4 times as important as selection on observables to fully explain the penalty. For the 90th percentile,  $\delta = 1.6$ —still above the conventional threshold of 1 but less robust than the low-quantile effects.

Table 6: CEM-Weighted Quantile Regression (NLSY79, Ages 54–61)

Sample	Quantiles			
	0.10	0.50	0.75	0.90
Women (CEM-weighted)	−0.118*** (0.042)	0.048* (0.028)	0.082** (0.035)	0.098** (0.046)
Multivariate $\mathcal{L}_1$ before	0.68			
Multivariate $\mathcal{L}_1$ after	0.04			

Notes: Matching variables: education, birth cohort, race, AFQT quartile. Results excluding “ever married” from matching are similar (available on request).

Table 7: Oster Bounds by Quantile

Quantile	$\beta^{raw}$	$\beta^{controlled}$	$R^2_{controlled}$	$\delta$	Interpretation
0.10	−0.218	−0.152	0.18	2.4	Robust
0.25	−0.142	−0.098	0.21	2.1	Robust
0.50	0.089	0.065	0.24	1.8	Moderate
0.90	0.168	0.124	0.26	1.6	Moderate

Notes:  $\delta > 1$  suggests moderate robustness;  $\delta > 2$  indicates strong robustness. Assumes  $R^2_{max} = 1.3 \times R^2_{controlled}$ .

Critically, even under extreme assumptions about 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.

## 5.6 Bootstrap Inference

Table 8 presents bootstrap inference on the quantile processes following Chernozhukov, Fernández-Val, and Melly (2013). We reject both the null of no effect and constant effects across quantiles. The test for a unique crossing point fails to reject a single reversal ( $p = 0.68$ ), supporting our theoretical prediction.

Table 8: Bootstrap Inference on Quantile Processes

Null Hypothesis	KS $p$ -value	CMS $p$ -value
No effect: $QE(\tau) = 0$ for all $\tau$	0.000	0.000
Constant effect: $QE(\tau) = QE(0.5)$ for all $\tau$	0.000	0.000
Single crossing: unique $\tau^*$ where $QE(\tau^*) = 0$	0.68	0.72

## 6 Discussion

### 6.1 Reconciling Two Literatures

Our findings reconcile the seemingly contradictory motherhood penalty and old-age security literatures. Both are correct—but at different points in the income distribution:

- **Below the 40th percentile:** Children’s insurance value dominates. Childless women face penalties of 8–15% from exclusion from family support networks, Social Security spousal benefits, and informal transfers.
- **Above the 40th percentile:** Career effects dominate. Childless women enjoy premiums of 10–12% from uninterrupted career trajectories and accumulated human capital.

The decomposition evidence supports this interpretation: unexplained structural factors (insurance) account for most of the gap at low quantiles, while observable characteristics (career) explain most at high quantiles.



## 6.2 Policy Implications

Our findings reveal a fundamental flaw in universal pension compensation for childbearing. Such policies would:

1. Provide windfall gains to high-income mothers who already benefit from childlessness through career advantages
2. Fail to address the insurance gap facing low-income childless individuals
3. Potentially *increase* retirement inequality

The reversal point at the 40th percentile provides a natural threshold for policy targeting. Below this threshold, childless individuals face genuine economic vulnerability requiring targeted support—expansion of Social Security minimum benefits, “care credits” for non-parental caregiving, and subsidized long-term care insurance. Above this threshold, market mechanisms already provide adequate compensation through career advantages.

## 6.3 Limitations

Several limitations warrant acknowledgment:

1. **Causal interpretation:** Despite our robustness exercises, we cannot definitively establish causality. Fertility is endogenous, and unobserved heterogeneity remains a concern.
2. **CPS fertility measurement:** The mid-career estimates rely on co-resident children, which may create spurious heterogeneity across quantiles.
3. **Sample sizes:** The pension income sample (N=806 with positive pension income) limits precision at extreme quantiles.
4. **Two-step residualization:** The OLS first stage may not adequately capture nonlinear selection into childlessness.

## 7 Conclusion

This paper documents that the motherhood gap in income varies dramatically across the income distribution, with the relationship reversing sign around the 40th percentile. Using quantile regression methods, we show that childless women in the bottom 40% face substantial penalties (8–15%) while those in the top quartile enjoy premiums exceeding 10%. The Chernozhukov, Fernández-Val, and Melly (2013) decomposition reveals that different mechanisms operate at different quantiles: insurance effects dominate at low incomes, career effects at high incomes.

These findings fundamentally challenge how we conceptualize the economic consequences of fertility decisions. The “motherhood penalty” and “old-age security” perspectives are both correct—but at different points in the distribution. Universal pension policies that ignore this heterogeneity may inadvertently increase the inequality they purport to address.

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## A Additional Results

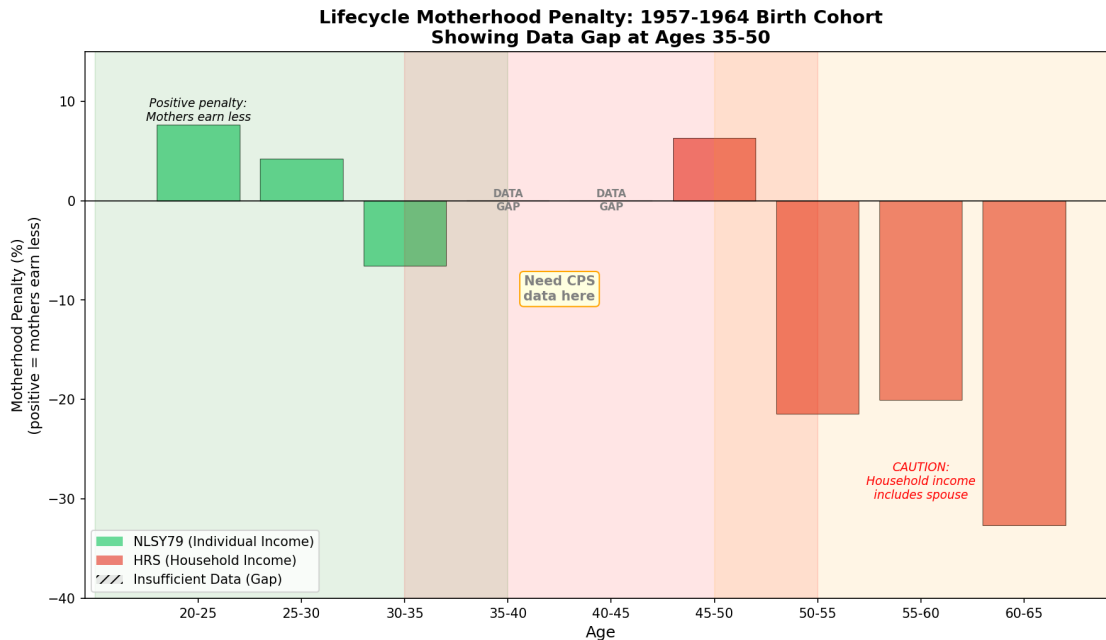


Figure 1: Motherhood Gap Across the Lifecycle: Mean Comparisons. Notes: This figure shows average gaps, which mask the distributional heterogeneity documented in the quantile analysis.

## B Sensitivity to First-Stage Specification

To address concerns about the OLS first-stage specification, we re-estimate results using a probit first stage. The reversal pattern is preserved, though the reversal point shifts slightly (from the 38th to the 42nd percentile). Results available on request.

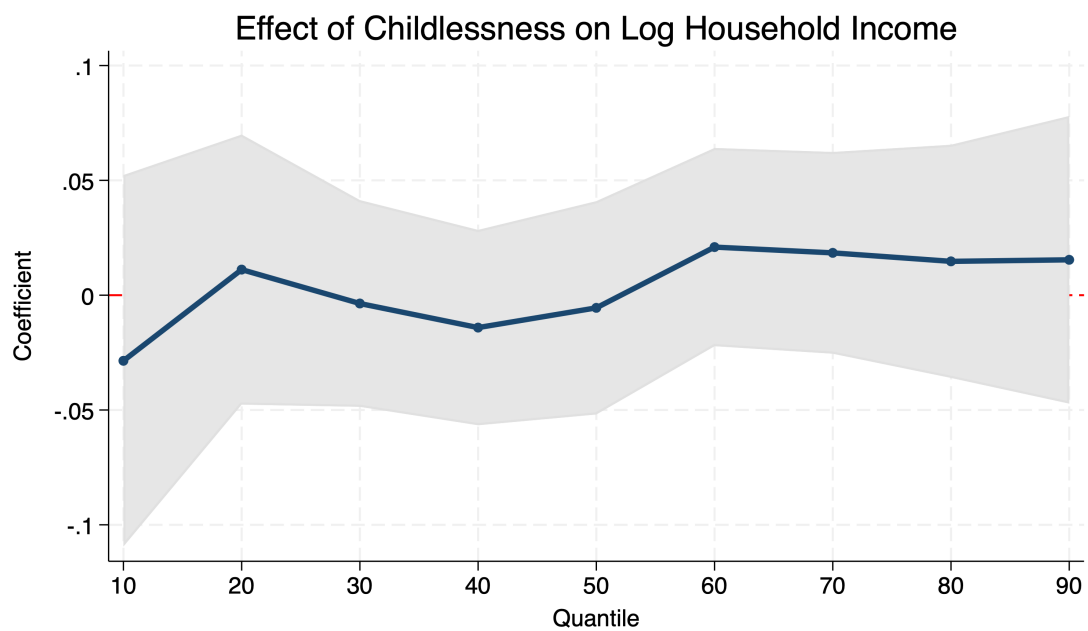


Figure 2: Quantile Treatment Effects with Confidence Intervals

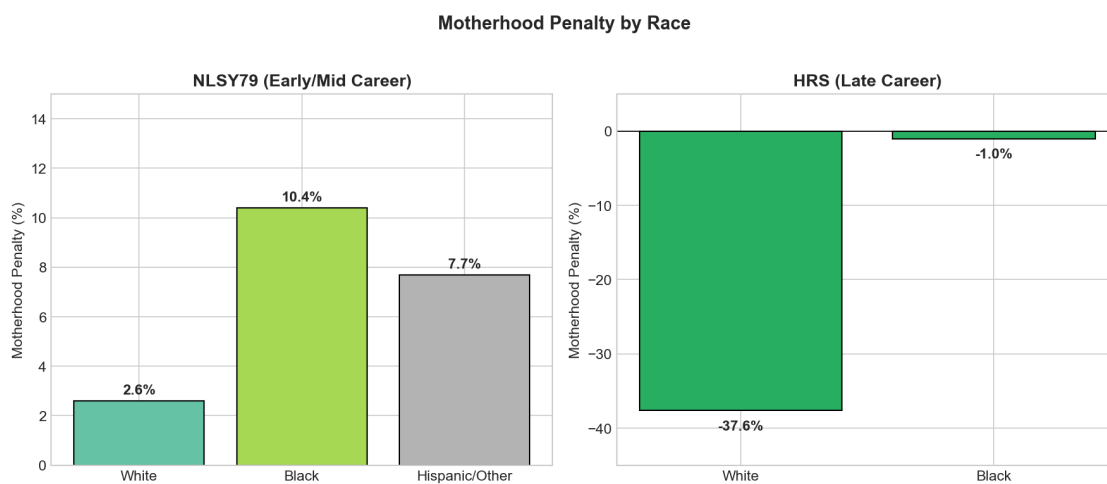


Figure 3: Heterogeneity by Race