The Shadow Child Penalty and Racial Inequality in Labour- and Marriage-Market Risk *

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Abstract

This paper documents novel findings that Black women in the U.S. experience child penalties in ways that fundamentally differ from those faced by White women. The child penalty in employment is one-third as large for Black women (10%) compared to White women (30%). Educated, high-wage, married Black women return to the labor market almost immediately after childbirth. This racial difference in the labor-leisure trade-off is driven by subjective expectations: Black households face higher probabilities of layoff in the labor market, as well as higher probabilities of separation, divorce, and not remarrying. Using a structural life-cycle model, I show that high-ability Black women use labor market attachment for self-insurance while sacrificing their own leisure to maintain high levels of parenting time. This generates lower observed penalties in wages and labor force participation, but larger unobserved penalties through sacrificed leisure. Counterfactual simulations reveal that equalizing marriage probabilities and layoff shocks can close up to 75% of the racial gap in child penalties in employment. Welfare improves primarily through increased leisure for Black women. These results highlight the importance of uncertainty and dynamic household choices in explaining persistent racial gaps in female labor supply and child penalties.

JEL Codes: J12, J13, J16, J22, J31, J71
Keywords: child penalty, racial gap, labor supply, marriage, uncertainty, parenting

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1 Introduction

"The birth date is scheduled for May 22. I'll be back at my desk on May 25, having missed only three work days, none of which are in court . . . I can and will continue my full workload with no interruptions."

— Lucca Quinn[1], *The Good Fight*, Season 2, Episode 6

Households face a range of risks—job loss, income shocks, divorce—that shape household choices (Attanasio et al., 2005; Bertola et al., 2005; Blundell et al., 2008, 2016b; Daminato and Pistaferri, 2020; Fernández and Wong, 2014, 2017; Jappelli and Pistaferri, 2017; Low et al., 2010; Meghir and Pistaferri, 2004, 2011; Pistaferri, 2003). Exposure to these shocks is far from uniform: disadvantaged groups bear a disproportionate share. These shocks not only impose direct welfare costs when they occur; they may trigger behavioral responses that carry hidden welfare costs, as households adjust their allocation of time to self-insure in an environment of incomplete insurance. Focusing solely on observed employment outcomes therefore understates the true inequality, because it overlooks the leisure forgone and other welfare losses embedded in these second-best responses. Consequently, any assessment of inequality must account for both differential risk exposure and the welfare loss embedded in these behavioral adjustments.

This paper is motivated by a longstanding empirical puzzle: Black women supply more labor than White women despite facing greater disadvantages in opportunities, characteristics, and discrimination (Fisher and Houseworth, 2012).[2] Classic work by Goldin (1977) and Boustan and Collins (2014) shows that this participation gap cannot be explained by contemporaneous observables alone. Likewise, studies of the motherhood wage penalty find little or no penalty for African-American women (Glauber, 2007; Hill, 1979; Waldfogel, 1997).

Using Panel Study of Income Dynamics data and an event-study decomposition, this paper establishes three main empirical findings about the racial gap in the child penalty in employment in the U.S. First, Black mothers experience only 10% declines in employment and earnings after childbirth, whereas White mothers face 30% reductions, relative to their

[1]Lucca Quinn is portrayed as a Black lawyer navigating a predominantly white legal world. Cush Jumbo, the actress who plays her, was also pregnant while filming this episode.

[2]Bertrand and Mullainathan (2004) find that African American applicants receive 50% fewer callbacks than White applicants with identical resumes (8.39% vs. 3.48%). While additional credentials increase callback rates for White applicants, they have no effect for African Americans, causing the gap to widen with more experience. This racial gap in callbacks is consistent across occupations and industries, including among "Equal Opportunity Employers." Kline et al. (2023) find that among 108 of the largest U.S. employers, distinctively Black names reduce callback rates by 2.1 percentage points, with substantial variation across firms (1.9% standard deviation). Discrimination is highly concentrated: twenty-three firms are statistically identified as discriminatory, and racial callback gaps are persistent across time and geography.

partners. Similar patterns are observed in annual labor income, annual hours worked, and hourly wage.

Second, the racial gap is most pronounced among married women with high wages prior to childbirth. I show that the racial gap is not driven by compositional differences in single parenthood, cohabitation, or low-wage work out of necessity. Instead, the racial gap is driven by highly educated, high-wage women making opposite choices after childbirth: highly educated, married Black mothers return to work almost immediately after childbirth, whereas similarly situated White women experience the largest declines in employment after childbirth.

However, there may still be racial differences in observable characteristics even among highly educated, high-wage women. The third finding is that the racial gap in the child penalty remains, even after I reweight so that the two groups share the same distributions across a wide range of relevant observables around the time of childbirth. The differential response in female labor supply after childbirth could be influenced by factors such as budget constraints, informal help from family members, gender attitudes toward women working, job characteristics requiring a quick return to work—such as "greedy jobs"[3]—or lower expectations of children's future earnings. To test these hypotheses, I construct inverse probability weights to ensure that the Black population in the sample has an identical distribution to the White population across these variables.

What distinguishes highly educated and high-wage women by race? This paper explores two key components: uncertainty in the labor market and the marriage market. First, in the labor market, Black individuals face higher risks of job loss (Derenoncourt et al., 2023). These shocks not only create greater uncertainty but also lead to lower labor income growth over the life cycle, as on-the-job human capital accumulation is more frequently disrupted (Rauh and Valladares-Esteban, 2023). In contrast, spouse mortality and incarceration shocks are unlikely to be the main drivers, as they are concentrated among high school dropouts, so it is difficult for them to explain why highly educated Black women return to the labor market immediately.[4]

Before I introduce the life-cycle model of time allocation choice in the presence of uncertainty, I first document three sets of key stylized facts about racial inequality in risks in

[3]Greedy jobs are defined as jobs in which temporal flexibility is costly to organize and in which there are rewards for long hours and constant availability to employers.

[4]The racial gap in spousal-death shocks is driven largely by high-school dropouts as shown in A.13b. Among Black women with high school diplomas or above, only 7.74% of them married high school dropouts, as shown in **??**. Similarly, spouse incarceration is unlikely to matter as much for highly educated Black women. Regarding incarceration, the PSID sample has a very low incarceration rate. Less than 1% of the sample was ever incarcerated, making it unlikely that immediate labor force return among high-wage Black women is driven by such rare events. Quantitatively, the results remain unchanged even if the incarceration rate is set at 0.3% for Black men and 0.1% for White men.

the labor market, marriage market, and time allocation at home that the model will integrate with the aim of explaining the racial gap in child penalties and assessing the welfare implications of the unobserved penalty.

The first set of stylized facts concerns higher labor market risks faced by Black households. Black individuals experience greater employment volatility, with higher rates of job loss and lower rates of reemployment compared to their White counterparts. This pattern of elevated labor market risk is also reflected in subjective expectations: among employed individuals, Black women and men report perceived probabilities of layoff in the next 12 months that are, on average, 7 percentage points higher than those of White individuals across all education levels, even after controlling for occupation at the three-digit level. This convergence between objective labor market patterns and subjective expectations signals consistently higher job insecurity among Black respondents.

The second set of stylized facts I document is that the marriage market is particularly challenging for Black women, extending beyond the probability of entering a first marriage.[5] Black women face higher probabilities of divorce from a first marriage and significantly lower probabilities of entering a second marriage compared to White women. Additionally, Black women are more likely to marry less educated men, experience shorter durations of marriage, and have partners with lower education in second marriages. Subjective expectations further reflect this disadvantage: educated Black individuals report predicted probabilities of divorce that are, on average, 4 percentage points higher than those of their White counterparts.

The third set of stylized facts shows that full-time employed mothers still provide a substantial amount of parenting time (6 hours) compared to non-employed mothers (8 hours), as evidenced by time diary data. Parenting time from fathers is less than 1 hour on average. Maternal parenting time does not differ significantly by race, regardless of employment status. Working mothers primarily sacrifice their own leisure time to balance parenting and labor supply needs.[6] This trade-off leads to a "shadow penalty" for Black women: a high child penalty in leisure.[7]

In addition, I use quasi-experimental evidence to empirically test the hypothesis that Black women return to the labor market faster due to perceived risks. I exploit the timing of childbirth and the timing of the introduction of unilateral divorce reforms across states

[5] Ciscato (2024) shows that entry barriers are very high for Black women in the racially segregated marriage market in the U.S.

[6] This may help explain why studies on the effect of maternal labor supply during childhood generally find very small or mixed effects on child development (Agostinelli and Sorrenti, 2021; Baum, 2003; Bernal, 2008; Bernal and Keane, 2011; Caetano et al., 2021; Carneiro and Rodrigues, 2009; Carneiro et al., 2015; Del Bono et al., 2016; Løken et al., 2018; Ruhm, 2004).

[7] One hypothesis is that Black men may spend more time in the household doing childcare or housework, thereby facilitating Black women's return to work. However, using PSID data, I show that there is no racial difference in the amount of time men spend at home doing childcare or household chores.

that allow one spouse to initiate divorce without mutual consent. States also differ in how assets are divided upon divorce. Using a triple difference-in-differences approach, I show that Black women who gave birth shortly after the reform experience significantly smaller child penalties in employment compared to those who gave birth before the reform, particularly in title-based states, where assets are divided strictly according to the recorded owner and are therefore least favorable to women. A falsification test on single women, who are not exposed to marital dissolution risks, finds no significant effects, reinforcing the interpretation that the observed changes are driven by marital institutions rather than broader economic trends.

I develop and estimate a structural model of female labor supply, parenting, leisure, and housework in the presence of risk in employment and marriage. The aim of the structural model is to integrate these stylized facts to quantify how much the racial gap in expectations regarding risks in the labor market and marriage market contributes to the racial gap in child penalties, and to evaluate the welfare implications of the shadow penalty. Women make decisions about consumption, saving, labor supply, parenting, leisure, marriage, and divorce under high-dimensional uncertainty. This framework captures how expectations about future marriage stability, spousal job layoffs, and her employment layoffs influence female labor supply choices across racial groups. Women can use savings and human capital accumulation in the labor market to self-insure against idiosyncratic shocks, smoothing consumption across different states of labor income and marital status. The model enables me to assess how differences in expectations and constraints drive persistent racial gaps in female labor supply and earnings.

The life-cycle model of consumption, savings, and employment choices closely follows Blundell et al. (2016a), Attanasio et al. (2008), and Adda et al. (2017), but introduces important extensions, as the model explicitly incorporates parenting, hours of work, and leisure choices. It naturally makes the marginal utility of consumption not separable from marriage, childbirth, and labor supply through time allocation decisions.

Female labor supply choices have four impacts in the model. First, they increase consumption. Second, they reduce the time available for leisure and parenting, thereby altering the optimal allocation of time between these activities, which in turn influences the marginal utility of consumption. Third, the law of motion for human capital links current and past labor supply decisions to future wage offers, incorporating human capital accumulation, depreciation, and stochastic shocks.[8] Fourth, future wage offers also influence the probability of marriage and partner selection. Together, these equations formalize the household's intertemporal choices under uncertainty.[9]

[8]The general interpretation of the effect of employment history on future wage offers is called on-the-job learning in the labor literature; however, in this paper, it may differ by race and gender due to discrimination.

[9]This model allows childcare costs and family and government transfers to vary by race and by the age of

The second extension is that I estimate human capital accumulation parameters with weaker assumptions and identification moments. Human capital accumulation parameters are often estimated using the simulated method of moments, which requires solving the life-cycle model to generate simulated data (Adda et al., 2017; Attanasio et al., 2008; Blundell et al., 2016a). However, this approach can be sensitive to model misspecification, particularly regarding parametric assumptions about the type and initial distribution of unobservable heterogeneity. I take a different approach by deriving moment conditions to identify and estimate human capital accumulation parameters using the generalized method of moments (GMM). This method avoids solving the life-cycle model with simulated data, making it more robust to model misspecification. By treating unobservable heterogeneity nonparametrically and differencing it out, this approach is robust to assumptions about the initial distribution of the state space. The only remaining assumption is that unobservable heterogeneity remains constant over time, which is much weaker than requiring a specific parametric form or distribution. As a result, I find that White men experience twice the human capital accumulation from employment compared to Black men, highlighting a significant racial gap in returns to work.

The key insight from the estimated model is that due to higher risks in the labor market and marriage market, high-ability Black women return to work fastest after childbirth and face the lowest child penalty. This is because high uncertainty raises the expected marginal utility of consumption, and high ability increases the return to human capital through greater labor supply, all while maintaining similar parenting time and sacrificing their own leisure. In contrast, White women, who face less uncertainty, have lower expected marginal utility of consumption and thus weaker incentives to return to work quickly. For low-ability Black women, although uncertainty is high, the return to human capital is low, making labor supply less effective as a self-insurance mechanism.

Counterfactual simulations reveal that equalizing divorce risks between Black and White women reduces the racial gap in female labor supply by 38%. Similarly, equalizing labor market layoff risk closes the gap by 40%. Combining both channels results in a welfare improvement for Black women, equivalent to 13.7% of lifetime consumption. In other words, the counterfactual shows how close we could get to first-best if society could supply the missing insurance directly. But until such policies fully offset the extra risk, Black mothers' quick labor-force return remains a second-best response, not a "failure" to reach first-best ideals. With one unavoidable distortion (risk + incomplete insurance) already present, forcing

the child, as estimated from PSID data. The data show that full-time employed Black women spend less on childcare than full-time employed White women, which may reflect greater informal help from family members. The quantitative model incorporates this by allowing childcare costs to vary by race and by the age of the child. The model also accounts for unobservable ability, which influences the return to human capital in the labor market.

"first-best" conditions elsewhere (e.g., encouraging long parental leave or taxing all distortions away) may reduce welfare. The optimal—or second-best—allocation instead balances earnings, human-capital depreciation, precautionary savings, and parenting time given those risks.

The key insight from the welfare analysis is that job loss in the labor market faced by husbands leads to welfare losses for Black women, particularly in terms of leisure, which I refer to as the shadow penalty. More specifically, the welfare analysis shows that equalizing marriage and husband wage transitions for Black women results in a total welfare gain equivalent to 13.7% of lifetime consumption. Most of this gain comes from increased leisure (7.8%), with additional benefits from higher consumption (4.2%) and parenting time (1.7%). This decomposition highlights that improved economic stability translates into broad improvements in well-being, extending beyond material resources.

This paper contributes to several strands of literature. First, it documents and systematically quantifies the racial gap in the child penalty—particularly in employment—and provides an explanation for persistent differences in female labor supply by race. Prior research has established large child penalties in labor supply for women overall (Andresen and Nix, 2022; Cortés and Pan, 2020; Kleven et al., 2019a,b), but several studies have found that the wage penalty is not significant for Black women (Glauber, 2007; Hill, 1979; Waldfogel, 1997). Other work highlights persistent racial gaps in female labor force participation (Boustan and Collins, 2014; Goldin, 1977). By integrating these strands, this study not only quantifies the magnitude of these gaps but also explores the mechanisms driving them using a structural life-cycle model of female employment.

Second, this paper shows that Black women use labor market attachment to self-insure against higher risks of employment and marriage shocks, both to smooth consumption and to remain attractive to highly educated partners in the event of remarriage after divorce. This contributes to the structural labor literature on how uncertainty influences household choices, such as consumption (Bertola et al., 2005; Blundell et al., 2016b) and labor supply (Blundell et al., 2008; Daminato and Pistaferri, 2020; Jappelli and Pistaferri, 2017; Low et al., 2010; Meghir and Pistaferri, 2004, 2011; Pistaferri, 2003). More closely related, female labor supply is shaped by expectations about divorce (Fernández and Wong, 2014, 2017) and can serve as an insurance mechanism against idiosyncratic earnings risk (Attanasio et al., 2005). Building on this work, a growing literature has examined how uncertainty perpetuates racial inequality and affects economic outcomes (Caucutt et al., 2021; Derenoncourt et al., 2023; Rauh and Valladares-Esteban, 2023). This paper contributes by quantifying the impact of various shocks—such as marriage, wage growth, and employment—on the racial gap in the trade-off between female labor supply and parenting.

Third, this paper contributes to the structural labor literature in three key ways (Adda et al., 2017; Attanasio et al., 2008; Blundell et al., 2016a). First, it leverages panel data to provide alternative methods for identifying human capital parameters in the structural life-cycle model, using weaker nonparametric assumptions about unobservable heterogeneity. This approach is more robust to model misspecification, as it does not require solving the life-cycle model with assumptions about the initial distribution of the state space. Second, it extends the model to include parenting and leisure choices, where labor supply affects both time and budget constraints. This extension provides intuition for why the marginal utility of consumption is nonseparable from labor supply (Adda et al., 2017; Attanasio et al., 2008; Blundell et al., 2016a). Third, it incorporates subjective expectations into the structural estimation of the life-cycle model, relaxing and validating the assumption of rational expectations, which often presumes that women perfectly forecast objective statistical probabilities of future life-cycle events.

Finally, this paper contributes to the literature on racial inequality in the labor market. First, the estimated wage increase from last period employment, using identified moment conditions, is twice as high for White men as for Black men. Second, Black individuals have higher subjective probabilities of being laid off within a year. This is true even when controlling for education (18 levels) and occupations at 3 digits. This finding is consistent with the broader literature on racial discrimination in the labor market. The paper highlights that discrimination against Black men may indirectly affect Black women, leading to distorted choices characterized by greater labor market attachment and reduced leisure.

The paper is structured as follows. Section 2 presents the main empirical evidence on racial differences in the child penalty. Section 3 provides additional empirical facts and motivating evidence. Section 4 presents quasi-experimental evidence on the impact of divorce reforms on child penalties. Section 5 describes the life-cycle model. Section 6 explains identification, solution, and estimation. Section 7 discusses the parameter estimates and counterfactual analyses. Section 8 concludes. Additional details and supplementary results are provided in the Appendix.

2 Racial differences in the child penalty

Previous research has shown that the wage penalty, where mothers experience a decline in hourly wage relative to non-mothers, is small and not significant for Black women (Glauber, 2007; Hill, 1979; Waldfogel, 1997). I use event study decomposition with PSID data to examine whether the motherhood wage penalty is mirrored by a lack of labor supply response following childbirth among Black women, compared to White women. I find that Black mothers experience only modest declines in employment (10%) and earnings after childbirth, while White mothers face large and persistent reductions (30%). The next subsection describes the methodology, followed by a description of the data used in this analysis. The results are presented in the subsequent subsection. Then I show that the racial gap is not driven by compositional differences in single parenthood, cohabitation, or low-wage work out of necessity. Instead, the racial gap is driven by highly educated, high-wage women. In the final subsection, I show that even after controlling for the racial differences in the distribution of many observables, the racial gap in the child penalty remains.

2.1 Methodology

I examine whether the child penalty in employment differs by race. I follow the event study decomposition specification widely used in the child penalty literature (Andresen and Nix, 2022; Angelov et al., 2016; Cortés and Pan, 2020; Kleven et al., 2019a).

$$Y_{it} = \alpha' D_{it}^{Event} + \beta' D_{it}^{Age} + \gamma' D_{it}^{Year} + \nu_i \tag{1}$$

where Y_{it} can be annual labor income, annual employment (binary), annual hours worked, or hourly wage of individual i at event time t. The first term, D_{it}^{Event}, includes event time dummies, with $t = 0$ denoting the year of the arrival of the first child; the dummy for $t = -1$ is omitted. Each α' measures the impact of children relative to the year before the child's arrival. The second and third terms, D_{it}^{Age} and D_{it}^{Year}, include a full set of age and year dummies to control nonparametrically for life cycle and time trends. Standard errors are clustered at the individual level. All monetary variables are deflated by the Consumer Price Index (CPI) to 1960 prices and transformed using the inverse hyperbolic sine transformation.[10] The last term, ν_i, is an individual fixed effect that captures unobserved heterogeneity in labor supply choices.

Similar to Kleven et al. (2019b) and Kleven (2023), the estimated effects are converted into percentage effects by calculating

$$P_t^{g,r} = \frac{\widehat{\alpha}_t^{g,r}}{\mathbb{E}[\widetilde{Y}_{it}^{g,r}|t]} \tag{2}$$

where g denotes gender (male or female) and r denotes race (Black or White). Here, $\tilde{Y}_{it}^{g,r}$ is the average predicted outcome for group g and r, excluding the contribution of the event time coefficients, as the counterfactual outcome absent children. Finally, the child penalty is constructed as the average effect of having children on women compared to the effect on

[10]The transformation reduces the influence of outliers. The results do not change without the transformation.

men, within each race.

$$\text{child penalty}^r = \mathbb{E}[P_t^{m,r} - P_t^{w,r} \mid t \geqslant 0] - \mathbb{E}[P_t^{m,r} - P_t^{w,r} \mid t < 0] \tag{3}$$

where $P_t^{g,r}$ is the percentage effect for gender g (male or female) and race r (Black or White), as defined in 2. The child penalty is thus calculated separately for each race.

Furthermore, following Kleven et al. (2019a), Kleven et al. (2019b),Kleven (2023), the short-run penalty is defined as the average percentage by which women's labor outcome falls behind men one to five years after the first child's arrival. The long-run penalty is the average penalty from six to ten years after the first child's arrival.

2.2 Data

I use the Panel Study of Income Dynamics (PSID) from 1968 to 2017. The study began in 1968 with a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Sample selection criteria follow Kleven et al. (2019a) and Cortés and Pan (2020), including only individuals whose first child was born between the ages of 20 and 45. Observations include respondents between ages 18 and 65. Labor market questions refer to the previous calendar year (e.g., whether the respondent was employed last year). Therefore, the analysis begins with 1967, which corresponds to the first wave interview conducted in 1968.

2.3 Results

I find that Black mothers experience only modest declines in employment child penalty (15%) and earnings after childbirth, while White mothers face large and persistent setbacks (30%), both defined in equation 3. The racial gap is most pronounced among married women. It is driven by highly educated, high-wage Black mothers returning to work almost immediately after childbirth, in contrast to the significant and persistent declines observed for their White counterparts.

This pattern holds after controlling for single parenthood, cohabitation[11], and incarceration. As shown in figure A.19, adding cohabitation does not change the racial gap in marriage rates.

[11]Including cohabitation in the definition of marriage does not substantially change the racial gap in marriage rates in the PSID. At age 25, the share of White women in marriage or cohabitation rises from 50.06% to 52.85%, and for Black women from 37.16% to 40.93%. The gap remains large, indicating that differences in cohabitation rates do not explain the majority of the racial gap in marriage rates.

All women, married women and single women

First, Figure 1 shows the child penalty estimates by race among all women. The results are consistent with the literature finding a substantial racial difference in female labor supply.

Furthermore, I define the sample as single or married based on whether the respondent is single or married (including cohabitation for more than 1 year) at the time of childbirth.

White women are much more likely than Black women to have their first child within marriage. Specifically, 92.07% of White women have their first birth in marriage, compared to 62.30% of Black women, as shown in Table A.2. Conversely, nonmarital first births are substantially more common among Black women (37.70%) than among White women (7.93%). These results highlight substantial racial differences in the sequencing of marriage and childbirth, with nonmarital first births being especially prevalent among Black women in this sample, but also present among White women.

However, Figures 2 and 3 demonstrate that the racial gap in the child penalty is not driven by differences in the composition of single versus married women. The largest penalties are observed among married White women, followed by single women of both races, with married Black women experiencing the smallest penalties. In contrast, among single women, there are no statistically significant differences in child penalties between Black and White women. The substantial racial gap in child penalties among married women—driven by differences in participation, hours worked, and wage rates—highlights that marital status, rather than compositional differences, underlies the observed disparities.

Figure 2 shows the racial differences in the child penalties between Black and White married women. The long-run child penalty in labor earnings is around 44% for White women while around 22% for Black women. The racial gap is driven by all margins, including participation rate, annual hours worked conditional on employment, and wage rate.

In Figure 3, I present the child penalties among single women. There are no statistically significant differences in child penalties between Black and White single women. In terms of marital status, married White women have the largest child penalties, followed by single women regardless of race, then Black married women with the smallest child penalties.

In conclusion, the racial gap in child penalty is only present among married women.

Women with high or low wage prior childbirth

Furthermore, I document that the racial gap in child penalties exists among individuals with high wages prior to childbirth. Specifically, I construct a binary indicator for whether a woman's wage prior to childbirth is ever above the median wage in the sample, which is

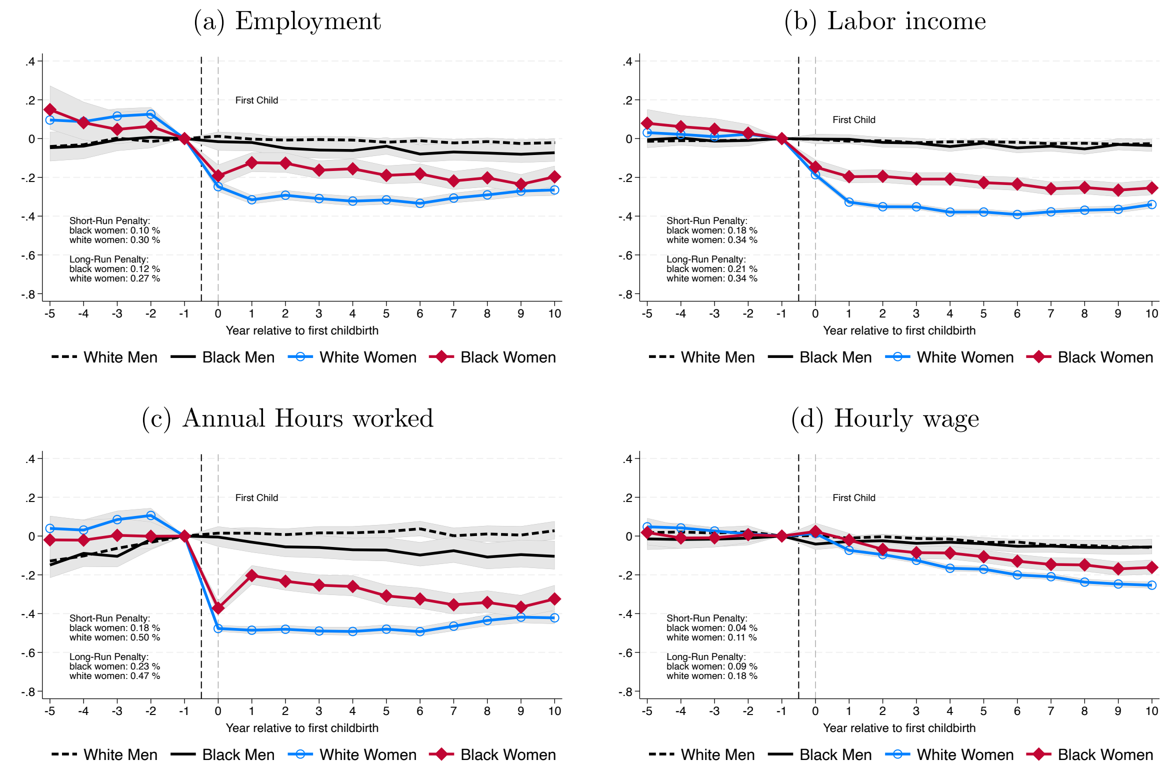

Figure 1: Racial differences in the child penalties (**whole sample**)

Notes: The sample consists of individuals with their first child between 20 and 45. Income and wage adjusted by inflation index (1960 price). Wage and income are transformed by inverse hyperbolic sine. Annual hours worked are conditional on being employed. Source: Panel Study of Income Dynamics, 1967 to 2017.

defined as the median wage among a wage distribution by gender and year.

Table A.3 presents the share of individuals with prior childbirth wages above or below the median, by race and gender. Among women, 54.2% of White women had prior wages always above the median, compared to 36.7% of Black women; conversely, 45.8% of White women and 63.3% of Black women always had prior wages below the median. Among men, 60.1% of White men had prior wages always above the median, compared to 41.5% of Black men, while 39.9% of White men and 58.5% of Black men had prior wages always below the median. These figures indicate that White individuals are more likely to have higher pre-childbirth wages than Black individuals, for both women and men.

Figure 4 shows the racial gap in child penalties is substantially higher among the high wage group, while there is no racial gap among the low wage group (see Appendix Figure A.3).

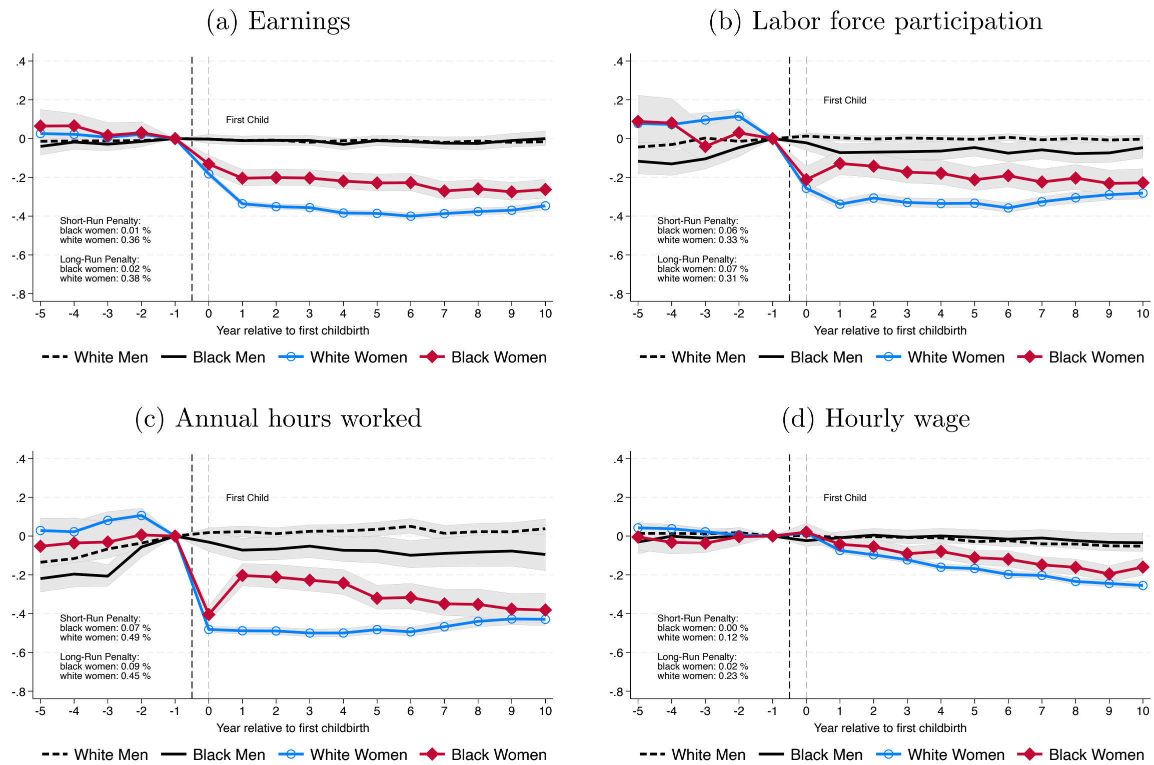

Figure 2: Racial differences in the child penalties (**married at the time of childbirth**)

Notes: The sample consists of individuals whose first child was born between ages 20 and 45, after their first marriage. Income and wages are adjusted to 1960 dollars using the inflation index and transformed by the inverse hyperbolic sine. Annual hours worked are conditional on being employed. Source: Panel Study of Income Dynamics, 1967–2017.

2.4 Testing for alternative explanations

This section systematically tests a range of alternative explanations for the observed racial gap in the child penalty. Using inverse probability weighting (IPW), I examine whether the gap can be explained by differences in observable characteristics, including budget constraints, job characteristics, gender attitudes, informal help from family members, and expectations about children's earnings. For each hypothesis, I report whether controlling for these factors reduces the racial gap in child penalties. For more details, Appendix C explains how the IPW is constructed, presents histograms for each variable before and after IPW reweighting, and provides figures showing the racial penalty event study estimates for Black and White women after controlling for these distributional differences.

Budget Constraints To test whether racial differences in budget constraints drive the gap in female labor supply after childbirth, I control for several measures of household

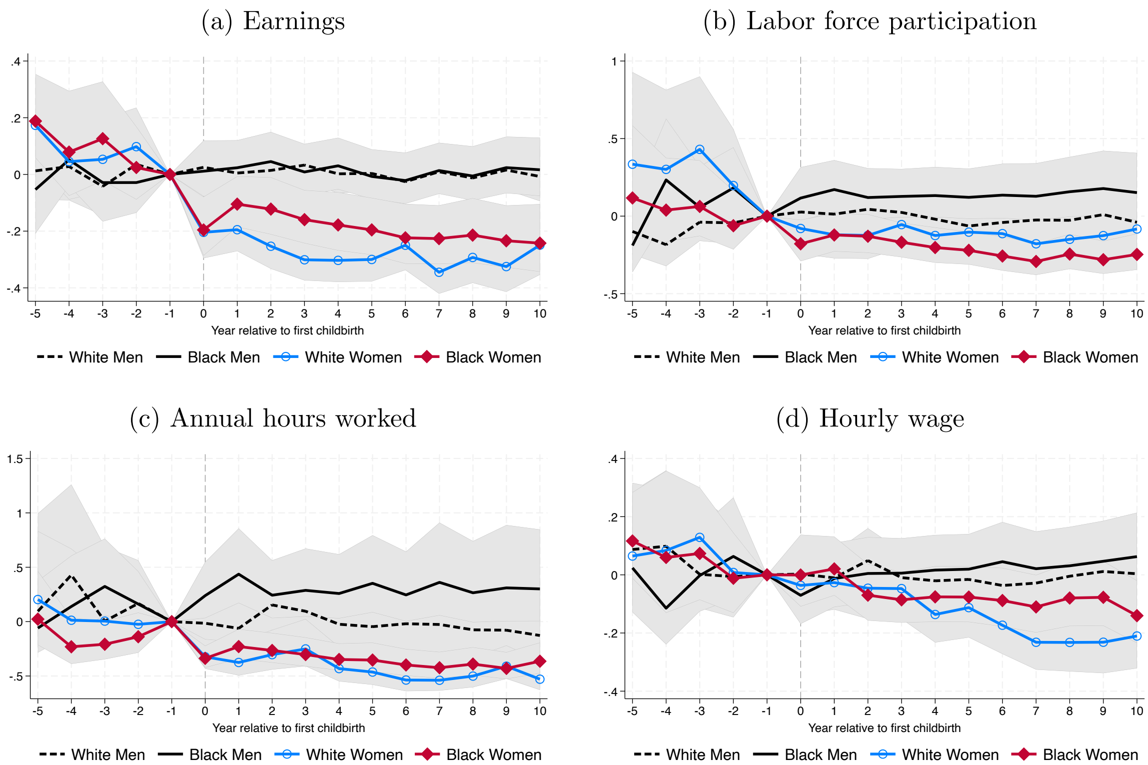

Figure 3: Racial differences in the child penalties (**single women**)

Notes: The sample consists of individuals whose first child was born between ages 20 and 45, before or without first marriage. Income and wages are adjusted to 1960 dollars using the inflation index and transformed by the inverse hyperbolic sine. Annual hours worked are conditional on being employed. Source: Panel Study of Income Dynamics, 1967–2017.

financial resources and obligations. These measures of financial constraints include lifetime average annual mortgage payments, husband's hourly wage, husband's annual labor income, non-labor income, and annual debt. These variables capture both the income available to the household and the fixed financial commitments that may influence a woman's need or ability to work after childbirth.

Job Characteristics Job characteristics may affect the flexibility and incentives for women to return to work after childbirth. This tests whether racial differences in child penalties are driven by Black and White women having different distributions of years of schooling, occupation, or industry. I include years of schooling (as a proxy for skill and job type), occupation, industry, and whether the wife's job provides insurance. These variables help account for differences in job quality, security, and benefits that could influence labor supply decisions.

Gender Attitudes Cultural and household attitudes toward wife work may shape labor

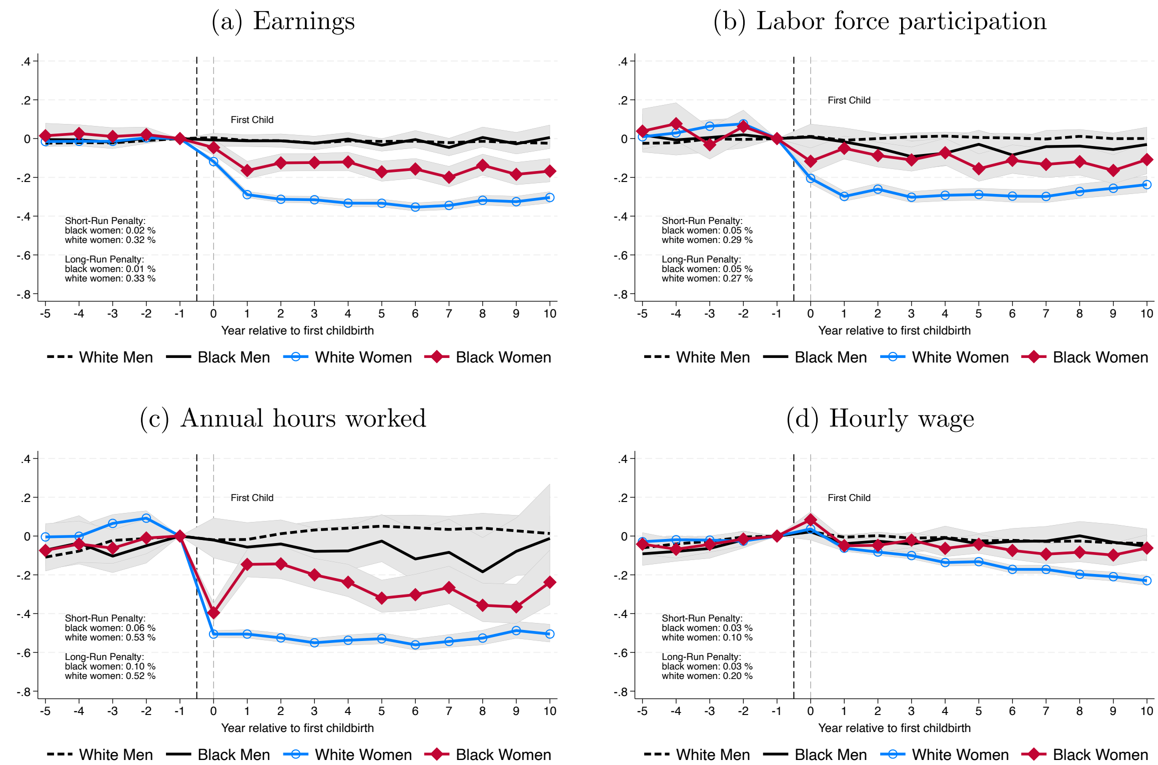

Figure 4: Racial differences in the child penalties (**with prior childbirth wage above the median**)

Notes: The sample consists of individuals with prior childbirth wage above the median (wage distribution by gender and year), with their first child between ages 20 and 45. Income and wage are adjusted by the inflation index (1960 price). Wage and income are transformed by inverse hyperbolic sine. Annual hours worked are conditional on being employed. Source: Panel Study of Income Dynamics, 1967 to 2017.

supply responses. I use survey measures of both the husband's and wife's attitudes about the wife working to proxy for gender norms within the household. These variables capture the extent to which traditional or egalitarian views may affect the decision to return to work.

Informal Help from Family Members Access to informal childcare or support from extended family can reduce the need for paid childcare and facilitate maternal employment. I proxy informal help using the number of relatives living nearby, the number of sisters, and the number of children of the maternal grandmother. These measures reflect the potential for family-based support networks.

Expectations of Children's Earnings Parental expectations about their children's future earnings may influence maternal labor supply, especially if parents believe their children will face discrimination or limited opportunities. I include subjective expectations of children's earnings to capture this channel.

Table 1 summarizes the estimated child penalties with and without controlling for the distributional differences in these variables. Column 1 presents the estimated short-run child penalties in annual labor income for White women, while Column 2 shows the corresponding estimates for Black women. Column 3 reports the child penalties for Black women after applying inverse probability weighting (IPW) so that they have an identical distribution of covariates as White women. Column 4 shows the racial difference in child penalties without IPW reweighting, and Column 5 shows the racial difference after IPW reweighting. Column 6 reports the change in the racial gap (in percentage points) after applying IPW.

The estimated child penalty for Black women remains virtually unchanged even after applying inverse probability weighting to ensure that Black women have an almost identical distribution of covariates as White women. Fully controlling for the distributional differences in these variables does not reduce the racial gap in child penalties by more than 2 percentage points.

Detailed evidence on racial differences in childcare expenditure and transfers by age of the child is provided in Appendix Figure A.37. The figure shows that childcare expenditure is higher for White mothers than for Black mothers, especially for children aged 1–6. While Black mothers may spend less on formal childcare, they appear to receive more support through transfers, which may help offset childcare costs. However, there is no statistically significant racial difference in the amount of transfer received.

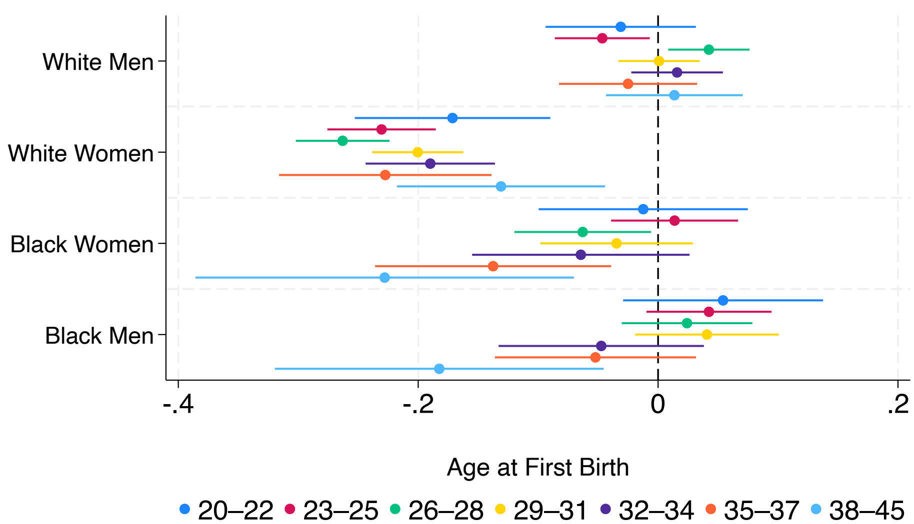

Figure 5: Child penalty by age at first birth

Notes: Each point shows the estimated child penalty by age at first birth and group, with 95% confidence intervals. See text for details.

Table 1: Short-run labor income penalty with and without IPW

IPW covariates	White Women	No IPW Black Women	IPW Black Women	No IPW Racial Gap	IPW Racial Gap	P.P.
Budget Constraints						
Annual mortgage payment	41%	22%	19%	-19%	-22%	-0.02
Husband hourly wage	40%	21%	21%	-20%	-20%	0.00
Husband annual labor income	40%	21%	19%	-19%	-21%	-0.02
Non-labor income	41%	21%	21%	-20%	-20%	0.00
Annual debt	40%	16%	15%	-24%	-24%	-0.01
Job Characteristics						
Years of schooling	42%	19%	21%	-23%	-21%	0.02
Occupation	37%	22%	22%	-15%	-15%	0.00
Industry	42%	24%	25%	-18%	-17%	0.01
Wife's job insurance	42%	24%	23%	-18%	-19%	-0.01
Gender Attitudes						
Husband's attitude	45%	24%	22%	-21%	-24%	-0.02
Wife's attitude	45%	22%	24%	-23%	-21%	0.02
Informal Help from Family						
Relatives nearby	53%	16%	18%	-37%	-35%	0.01
Number of sisters	39%	16%	15%	-23%	-24%	-0.01
Number of children of grandmother	45%	22%	24%	-23%	-21%	0.02
Expectations						
Expectation of children's earnings	42%	24%	25%	-18%	-17%	0.01

Notes: Short-run penalty is the average child penalty between 1–5 years after childbirth. The sample consists of married women in male-headed households, having their first child between ages 20 and 45. Income and wage are adjusted by the inflation index (1960 price) and transformed by inverse hyperbolic sine. Source: Panel Study of Income Dynamics, 1967 to 2017.

To examine how the child penalty varies by birth cohort, I estimate separate regressions for each cohort bin. Specifically, for each bin, I restrict the sample to individuals whose birth year falls within that bin and estimate a fixed effects regression of labor income on indicators for the post-childbirth period and group (White female, Black female, Black male), controlling for age and year fixed effects. The variable `postchild` equals 1 for observations 0 to five years after childbirth and 0 for observations from five years before up to the year of childbirth. The resulting coefficients capture the short-run child penalty for each group and cohort. To estimate the child penalty by cohort, I run the following fixed effects regression for each cohort bin:

$$X_{it} = \sum_{g} \beta_g \, \text{postchild}_{it}^{g} + \sum_{j} \gamma_j \, \text{age}_{ijt} + \sum_{k} \delta_k \, \text{year}_{ikt} + \alpha_i + \varepsilon_{it} \tag{4}$$

where X_{it} is labor income for individual i at time t, and $\text{postchild}_{it}^{g}$ is an indicator for years after childbirth for group g (White male, female, Black female, Black male). The model includes age and year fixed effects and individual fixed effects.

Over the decades, the child penalty for White women has been gradually reducing, while the child penalty for Black women remains smaller and stable across decades, as shown in Appendix Figure A.16. Similarly, as shown in Figure 5, the racial gap in child penalties is very similar across age at first birth among White women. For the Black population, the penalty is smaller when the first birth is at a younger age.

3 Stylized facts: racial differences in labor market and marriage market

This section presents key empirical facts on racial differences in the labor market and marriage market to highlight the distinct economic and family environments faced by Black and White women. It provides empirical foundations for the mechanisms explored in the life-cycle model that female labor supply shapes consumption, time for leisure and parenting, future wage offers through human capital accumulation, and remarriage prospects.[12] By documenting these differences, I motivate the model's focus on uncertainty, marriage dynamics, and labor supply as central drivers of the racial gap in child penalties. These are moments that the structural model will need to match.

Other facts such as racial differences in childcare expenditure, transfers from family and government, are presented in Appendix A.9.

[12] The effect of employment history on future wages—on-the-job learning—may differ by race and gender due to discrimination.

3.1 Stylized fact 1: labor market

Figure A.1 shows that there is a substantial racial gap in wage growth over the life cycle Rauh and Valladares-Esteban (2023). White men have higher wage growth than Black men, and this is true both within education groups and across education groups.

Figure A.2 illustrates key labor market dynamics for men by age and race. The first panel shows the employment rate, highlighting that White men maintain consistently higher employment rates across the life cycle compared to Black men. The second and third panels present the probabilities of transitioning into and out of employment, respectively. Black men experience lower rates of entering employment but higher rates of exiting employment, indicating greater labor market volatility and instability relative to their White counterparts. These patterns underscore the heightened employment uncertainty faced by Black men, which may have important implications for household economic security and the labor supply decisions of their partners. The observed racial disparities in employment stability are consistent with the broader literature on labor market discrimination and structural barriers affecting Black workers.

These patterns in observed labor market transitions are mirrored in subjective expectations about job security.

In 1994, the PSID asked employed individuals to estimate the probability that they would be laid off in the next 12 months, with responses ranging from 0 to 100 percent. Respondents were also asked, "Suppose you were to lose your job this month, what do you think the chances are that you could find an equally good job in the same line of work within the next few months?" This subjective measure provides insight into perceived job security and labor market uncertainty. Table A.4 summarizes the reported probabilities of being laid off in the next 12 months by race, gender, and education group.

As shown in Table A.4, Black respondents report significantly higher subjective probabilities of being laid off in the next 12 months compared to their White counterparts, across gender and education groups. This subjective measure of job insecurity echoes the objective data on employment transitions, reinforcing the finding that Black individuals face greater perceived and actual uncertainty in the labor market. These heightened expectations of job loss likely contribute to stronger precautionary motives and influence household labor supply decisions.

3.2 Stylized fact 2: marriage market

This section presents empirical facts on racial differences in the marriage market.

Figure A.4 documents substantial racial differences in marriage patterns. Black women have a significantly higher rate of never being married compared to White women, as well as a lower probability of entering a first marriage. Among those who do marry, Black women are also less likely than White women to enter a second marriage following divorce or separation. These patterns highlight persistent racial disparities in both the likelihood of ever marrying and the chances of remarriage, which are important for understanding differences in family structure and economic security across groups.

Figure A.5 shows total marriage rates by race and education group. The results indicate that Black women face a substantial disadvantage in the marriage market compared to White women, and this disadvantage persists across all education levels. Whether women are high school dropouts, high school graduates, or have a college degree, Black women consistently have lower marriage rates than their White counterparts. This suggests that the racial gap in marriage market outcomes is not explained by differences in educational attainment.

The marriage market is also highly assortative with respect to education, meaning individuals tend to marry partners with similar educational attainment. However, as shown in Table A.5, Black women are less likely than White women to marry men with similar education levels, both in first and second marriages. The cell percentages in these tables indicate that educational homogamy is stronger among White couples, while Black women are more likely to experience educational mismatch in their marriages. As shown in Panel A of Table A.5, 54.25% of married White women have at least a college-level education, and 39.59% of them are married to men with at least a college-level education. Conditional on marriage, the probability of first marriage to a highly educated man among highly educated White women is 72%. In contrast, among Black married women, only 25.69% out of 46.77% with at least a college-level education are married to similarly educated men. The probability of first marriage to a highly educated man for highly educated married Black women is 55%. This reflects the fact that in the marriage market most married White men are college educated (51.78%), while most married Black men are high school graduates (41.42%). Similar patterns are observed in second marriages, as shown in Table A.6.

This pattern of lower educational matching among Black women may reflect broader structural barriers in the marriage market and has important implications for household economic outcomes and stability.

Furthermore, Black women are disadvantaged in the marriage market in terms of marriage exit rates. Figure A.6 shows that first marriages for Black women are more likely to end in divorce or separation compared to White women. This is true for all education groups.

These patterns in marriage market outcomes are also reflected in subjective expectations about relationship stability. Table A.7 presents the subjective probability of divorce by gender and education. The results show that educated Black women report higher perceived probabilities of divorce than their White counterparts among those who predict positive probabilities of getting married.

The disadvantage in the marriage market for Black women is not PSID-specific. Using CPS data, I verify very similar patterns: Black women have lower marriage rates and higher divorce rates. Similar patterns hold across education groups. Figure A.7 shows the age trends in marital status by education. Panel (a) shows that divorce rates are significantly higher for Black women compared to White women; this is true across all education groups. Panel (b) shows that marriage rates are significantly lower for Black women compared to White women.

3.3 Stylized fact 3: Parenting Time by Age of the Child, Race and Gender of Parent, and Employment Status

Figure A.8 shows that parenting time differs primarily by gender rather than by race. Mothers spend more time on parenting than fathers, and even among full-time employed parents, mothers devote a considerable amount of time to parenting. Fathers spend significantly less time on parenting, and the gender gap in parenting time is very similar across races. Thus, the hypothesis that Black fathers spend more time on parenting—allowing Black women more time to work—is not supported by the data.

4 Quasi-experimental evidence

This section presents quasi-experimental evidence on the impact of divorce regimes on employment outcomes. The analysis leverages policy reforms that changed divorce laws, particularly the introduction of unilateral divorce, which allows one spouse to initiate divorce without mutual consent. This reform is expected to affect expected risks and therefore influence labor supply decisions, especially after childbirth. Following the same logic, the hypothesis is that unilateral divorce laws will increase Black women's employment and reduce the magnitude of child penalties, such that they return to the labor market faster due to the increased expected risk of divorce.

The exogenous variation exploits the timing of childbirth and the timing of unilateral divorce reform within states across time in the U.S.

To examine how divorce law influences women's employment decisions after childbirth, I exploit variation in the timing of unilateral divorce reforms across U.S. states and link this to the timing of first childbirth. The identifying variation comes from comparing women who gave birth shortly before and shortly after the introduction of unilateral divorce in their state. This approach assumes that, conditional on controls, the timing of childbirth around the policy change is quasi-random.

Importantly, I further exploit institutional variation in states' property division regimes at the time of divorce — distinguishing among title-based, community property, and equitable distribution systems. These regimes determine the financial consequences of marital dissolution and, therefore, influence the bargaining environment within marriage. My hypothesis is that the effect of unilateral divorce reform on women's labor supply should be stronger in title-based states, where women have weaker claims to household assets upon divorce. In such states, unilateral divorce may reduce the expected cost of separation for husbands without improving financial protections for wives, shifting the intra-household bargaining position and thereby affecting women's post-childbirth employment choices.

This empirical setup constitutes a difference-in-differences-in-differences (DDD) design. The first difference compares women who give birth before vs. after the implementation of unilateral divorce. The second difference contrasts outcomes across states that implement the reform and those that do not (at a given point in time). The third difference leverages variation in asset division regimes, which determine the expected financial exposure upon divorce. This triple-difference approach allows me to isolate the effect of unilateral divorce reform on employment outcomes by controlling for common time trends, state-specific shocks, and differences across legal regimes.

As shown in column 1 of table 2, I find that Black women who give birth shortly after the introduction of unilateral divorce face a significantly smaller child penalty in employment compared to women who give birth shortly before the reform. This effect is concentrated in title-based states, where the financial risk upon divorce is highest for women. These results suggest that changes in divorce law can shape women's labor supply changes after childbirth through forward-looking responses to anticipated shifts in post-divorce security.

As a falsification test, I replicate the same empirical specification on a sample of single women, who by definition are not directly exposed to marital dissolution risk at the time of childbirth. If the main results were driven by confounding time-varying shocks to the labor market or fertility trends, I would expect to observe similar effects in this group. As shown in Column 2 of Table 2, the results show no significant effect of unilateral divorce law changes on the employment outcomes of single women, providing strong support for the interpretation that the observed effects among married women are indeed driven by changes in marital institutions rather than general economic conditions.

Table 2: Effect of Divorce Regime on child penalties in employment for Black women

	(1) Married	(2) Single
After childbirth	-0.15***	-0.13*
	(0.03)	(0.07)
After childbirth x Unilateral x Community Property	-0.02	0.08
	(0.04)	(0.16)
After childbirth x Unilateral x Title based	0.18***	0.20
	(0.03)	(0.13)
After childbirth x Unilateral x Equitable distribution	-0.07	-0.01
	(0.05)	(0.12)
Unilateral x Title based	0.21***	-0.06
	(0.04)	(0.11)
Unilateral x Equitable distribution	0.31***	0.04
	(0.04)	(0.11)
Age FE	Yes	Yes
Year	Yes	Yes
State	Yes	Yes
N	4138	1921

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: After childbirth variable is valued 1 for observations 0 to 5 years after childbirth and 0 if -1 to -5 years before childbirth. Standard error clustered at state level. Standard errors are in parentheses. Unilateral law reform in states with community property took place before 1980 which is the first year individual data of employment variable is available at PSID. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

5 Life cycle model

The aim of this paper is to use the structural model to show that the racial gap in child penalties can be obtained solely by racial differences in marriage uncertainty, income risks and expectations in wage growth without imposing racial differences in unobservable parameters, including preferences parameters or childcare costs [13].

5.1 Outline of the model

The model structure is similar to Attanasio et al. (2008); Blundell et al. (2016a). The unit of analysis a woman. I assume that in the inital period, age 20 and time increments in years. Each year, the woman make choices of employment, consumption, saving, marriage and fertility. The initial period is endowed with asset, human capital, unobserable type of ability in wage.

Female labor supply The female is equipped with an initial level of human capital $h_{f,1}$. As current model assume that man always work, therefore we simplify notation to use l_j as discrete choice of female labor force participation. At each age she decides whether to participate in the labor market ($l_j = 1$) or stay at home ($l_j = 0$). Participation in the labor market generates positive spillovers to future periods in the form of experience effects. Specifically, following Attanasio et al. (2008), I assume that the human capital of the woman evolves over time according to

$$\ln h^f_{i,t+1} = \ln h^f_{i,t} + (\xi + \tau t) l^f_{i,t} + \delta(1 - l^f_{i,t}) \tag{5}$$

Therefore, employment l^f_j generates an experience effect of one year of work on human capital accumulation by ξ and a depreciation of human capital at rate δ otherwise. In addition, female labor income in the labor market depends on the household-specific permanent productivity

[13] Keane and Wolpin (2010) uses racial-specific utility parameters for marriage, fertility, and leisure to rationalize different choices in employment, work, marriage, and fertility of Black, Hispanic, and white women. However, measurement error and model misspecification can imply an unwarranted inter-personal comparison of preference. Revealed preference may not suited for making interpersonal comparison. For example, (Okun, 1960) criticise Becker (1960) for not recognizing model misspecification to make inter-personal comparison of parental utility. "One cannot conclude that the family which purchases less for their child derives less utility from him in comparison with the family which purchases more. Such a conclusion implies an unwarranted inter-personal comparison of utility". The same reasoning applies here. For example, Black women may have a higher labor supply due to more informal help in childcare from family networks which is not in the model. Relying on leisure parameters to fit the racial gap in labor supply would lead to unwarranted estimates implying that they have lower utility in time spent with children or higher utility in consumption. The list of model misspecification and measurement errors is endless. Furthermore, reliance on interpersonal differences in preference is an easy but unrefutable way to explain differential choices (Borjas and Van Ours, 2010). Instead, models stress the impact of variables (observed and measured) are testable and refutable (Borjas and Van Ours, 2010). Therefore, this paper does not use racial-specific unobservable preferences to explain the racial differences in choices but the time series of marital status across the life cycle.

component θ, an individual-specific autoregressive shock $\eta_{f,j}$, as well as the wage rate of women w_f per unit of effective labor. In total, female labor income is

$$y_t^f = w^f \exp{(h_t^f + \theta + \eta_{f,j})} l_t^f \tag{6}$$

Male labor supply If married, husband may work or get unemployed in certain period. The human capital process is similar to female human capital process. The husband is endowed with an initial level of human capital $h_{m,1}$. The husband work status are ($l_j = 1$) or not ($l_j = 0$). The difference is that it is exogenous set and stochasitc. The husband's human capital evolves over time according to

$$h_{m,j} = b_j \dot{\exp}[\theta + \eta_{m,j}] \tag{7}$$

which is due to the exogenous age-productivity profile b_j at age j, a household-specific permanent productivity component θ which does not change over the life cycle (unobservable heterogeneity) and an individual-specific autoregressive component $\eta_{m,j}$. Supplying $h_{m,j}$ units of productive labour to the market, the husband generates a labor income $y_m, j = w_m h_{m,j}$ where w_m denotes the wage rate of men per unit of effective labor. Labor productivity drops to zero at the exogenous retirement age 60. The employment is also stochastic using PSID transition employment probability by age.

Choices Each year, she decides how much to consume c_j, how much assets to hold to save for the next period a_{j+1}, and whether to participate in the labor market l_j, parenting and leisure time. She has preferences over consumption, leisure, and parenting, which can be represented by a time-separable expected utility function of the form in which discounting factor is β, n_j adult equivalence consumption scale same as Blundell et al. (2016a) and Adda et al. (2017) that $n_j = 1$ for singles, 1.6 for couples, 1.4 for mothers with child, and 2 for couples with children. Next,conditional on meeting a partner, she decides whether to marry or not. If married, she decides whether to divorce. Then conditional on whether fertile, she also decides whether to have a child or not.

Utility: Lifetime utility is given by

$$\mathbb{E}\left[\sum_{t=1}^{T} \beta^{t-1} u(c_t, p_t, l_t)\right] \tag{8}$$

where instantaneous utility is derived from consumption c_t, parenting time p_t, and leisure time $1 - \zeta l_t^f - k_t p_t^f$. The utility function is Cobb-Douglas in consumption, parenting, and leisure:

$$u(c_t, p_t, l_t) = \frac{1}{1-\frac{1}{\gamma}} \left[\left(\frac{c_t}{n_t} \right)^{\nu} p_t^{k_t\alpha} (1 - \zeta l_t^f - k_t p_t^f)^{1-\nu-k_t\alpha} \right]^{1-\frac{1}{\gamma}} \tag{9}$$

where k_t is an indicator for the presence of a child. Without a child ($k_t = 0$), the problem reduces to the classic consumption, labor, and leisure choice.

The dynamic budget constraint is

$$a_{t+1} + c_t = (1+r)a_t + m_t y_t^m l_t^m + y_t^f l_t^f + \tau_j \, k_t \, \mathbb{I}(k_j = j) - \pi_j \, k_t \, \mathbb{I}(k_j = j) \, l_t^f \tag{10}$$

where r is the interest rate, m_t indicates marital status (1 if married, 0 otherwise), y_t^m is the husband's income, l_t^m is the husband's labor supply, y_t^f is the female's income, l_t^f is the female's labor supply, τ_j is the sum of family and government transfers when the child is age j (estimated from PSID), π_j is the price of childcare for a child of age j, k_t indicates the presence of a child (1 if there is a child, 0 otherwise), and $\mathbb{I}(k_j = j)$ is an indicator for having a child of age j.

To ease computational burden, marriage dynamics are set exogenous in this paper. Ciscato (2024) documents that the racial gap in marriage is largely explained by racial segregation in the marriage market, higher search friction experienced by black women and also a unfarvourable gender ratio instead of preference differences or marital gains. By estimating a dynamic matching model with endogenous separation and remarriage, Ciscato (2024) find that when racial segmentation is removed, the gap is reduced by 43.1% in the odds of having a partner between White and Black women. The remaining gap is largely explained by the higher search friction.

Descrptive evidence in PSID data is inalign with findings from Ciscato (2024). The racial gap in marriage is primarily driven by inflow into marriage (which identify search friction) but not by flow out of marriage (martial gains and preference) [14] Therefore, I assume that marriage is a stochastic process with transition probabilities estimated from PSID data.

5.2 The dynamic programming problem

The household's state vector can be written as

$$z = (t, a, h^f, \theta, \eta^m, \eta^f, k_t, k_j) \tag{11}$$

To simplify notation, I use z^+ to denote the state vector in the next period.

[14] With only matching outcome such as marriage rate, matching quality and search friction are not separately identified unless relationship duration data assist identify marital quality, see details in Bruze et al. (2015); Goussé et al. (2017).

The dynamic programming problem is

$$
\begin{aligned}
\max_{c,\,p,\,l,\,a^+} \quad & \frac{1}{1-\frac{1}{\gamma}} \left[\left(\frac{c_t}{n_t}\right)^{\nu} p_t^{k_t\alpha} (1-\zeta l_t^f - k_t p_t^f)^{1-\nu-k_t\alpha} \right]^{1-\frac{1}{\gamma}} \\
& + \beta\, \mathbb{E}\left[V(z^+) \mid \eta^f, \eta^m \right] \\
\text{s.t.} \quad & a^+ + c = (1+r)a + m_t y_t^m l_t^m + y_t^f l_t^f + \tau_j\, k_t\, \mathbb{I}(k_j = j) - \pi_j\, k_t\, \mathbb{I}(k_j = j)\, l_t^f, \\
& a^+ \geq 0, \\
& 1 \geq 1 - \zeta l_t^f - k_t p_t^f \geq 0, \\
& h_{t+1}^f = h_t^f + (\xi + \tau t) l_t^f + \delta(1 - l_t^f), \\
& \eta^{+m} = \rho \eta^m + \epsilon^{+m}, \quad \epsilon^{+m} \sim \mathcal{N}(0, \sigma_{\epsilon^m}^2), \\
& \eta^{+f} = \rho \eta^f + \epsilon^{+f}, \quad \epsilon^{+f} \sim \mathcal{N}(0, \sigma_{\epsilon^f}^2)
\end{aligned}
\tag{12}
$$

where ϵ^{+m} and ϵ^{+f} both follow a normal distribution $\mathcal{N}(0,\, \sigma_\epsilon^2)$. $z^+ = (t{+}1, a^+, h_f^+, \theta, \eta^{+m}, \eta^{+f}, k_{t+1}, k_{j+1})$. For simplicity, stochastic processes η^m and η^f are assumed independent, although they have identical autocorrelations and variances.

As labor supply is a discrete choice, the solution involves three steps. First, I solve the optimization problem for parenting and leisure choice given each possible labor supply choice l_j. Second, after obtaining optimal parenting and leisure choice, solve the optimization saving and consumption choice given labor supply choice. Finally, I choose the labor supply that maximizes the value function $\hat{V}(z, l)$.

1. Parenting and leisure choice Given the labor supply choice l_j, the optimization problem for parenting and leisure choice is

$$
\max_{p_t} \quad p_t^{k_t\alpha} (1 - \zeta l_t - p_t^f)^{1-\nu-k_t\alpha} \tag{13}
$$

The intuition is that conditional on labor supply, leisure and parenting do not have a price as they do not enter budget constraint. so it is a trade off within time constraint which is aready substituted inside utility function. However, labor supply choice l_j will impact the time constraint which eventually influence marginal utility of consumption. Time endowment is 1 if not working and become $1 - \xi$ if working. intuitively, it means if choose not to work, you have 24 hours to spend on leisure and parenting. If you choose to work (8 hours), then you have a smaller time budget (16 hours) to spend on leisure and parenting. The first-order condition for parenting and leisure choice is

$$
\frac{k_t\alpha}{p_t} = \frac{1 - \nu - k_t\alpha}{1 - \xi l - p_t} \tag{14}
$$

Optimal choice for parenting (p_t) and leisure ($1 - \xi l_t - p_t$) is given by

$$p_t^* = \frac{\alpha k_t}{1-\nu}(1-\xi l) \tag{15}$$

Both labor supply and having a child or not is binary. Therefore, the optimal parenting choice can be summarized as

$$p_t^*(k_t, l_t) = \begin{cases} 0 & \text{if } k_t = 0 \text{ and } l_t = 1, \\ 0 & \text{if } k_t = 0 \text{ and } l_t = 0, \\ \frac{\alpha}{1-\nu}(1-\xi) & \text{if } k_t = 1 \text{ and } l_t = 1, \\ \frac{\alpha}{1-\nu} & \text{if } k_t = 1 \text{ and } l_t = 0. \end{cases} \tag{16}$$

2. Consumption-saving choice Conditional on the woman participating in the labor market, savings and consumption can be determined by solving the conditional optimization problem

$$\begin{aligned} \tilde{V}(z,l) = \max_{c,a^+} \quad & \frac{1}{1-\frac{1}{\gamma}} \left[\left(\frac{c_t}{n_t} \right)^{\nu} (p_t^*)^{k_t \alpha} (1 - \zeta l_t - k_t p_t^*)^{1-\nu-k_t\alpha} \right]^{1-\frac{1}{\gamma}} \\ & + \beta \mathbb{E} \left[V(z^+) \mid \eta_f, \eta_m \right] \\ \text{s.t.} \quad & a^+ + c = (1+r)a + m_t y_t^m l_t^m + y_t^f l_t^f + \tau_j \, k_t \, \mathbb{I}(k_j = j) - \pi_j \, k_t \, \mathbb{I}(k_j = j) \, l_t^f, \\ & a^+ \geq 0, \\ & 1 \geq 1 - \zeta l_t - k_t p_t^* \geq 0, \\ & h_{t+1}^f = h_t^f + (\xi + \tau t) l_t^f + \delta(1 - l_t^f), \\ & \eta^{+m} = \rho \eta^m + \epsilon^{+m}, \quad \epsilon^{+m} \sim \mathcal{N}(0, \sigma_{\epsilon^m}^2), \\ & \eta^{+f} = \rho \eta^f + \epsilon^{+f}, \quad \epsilon^{+f} \sim \mathcal{N}(0, \sigma_{\epsilon^f}^2) \end{aligned} \tag{17}$$

Solve for first-order condition with envelope theorom leads to intertemporal condition.

$$\begin{gathered} \frac{\nu}{c} \left[\left(\frac{c}{n} \right)^{\nu} (p^*)^{k\alpha} \left(1 - \zeta - p^*\right)^{1-\nu-k\alpha} \right]^{1-\frac{1}{\gamma}} = \beta(1+r) \cdot \\ \mathbb{E} \left[\frac{\nu}{c(z^+)} \left[\left(\frac{c(z^+)}{n_{j+1}} \right)^{\nu} (p^*)^{k\alpha} \left(1 - \zeta - p^*\right)^{1-\nu-k\alpha} \right]^{1-\frac{1}{\gamma}} \mid \eta_f, \eta_m, k, m \right] \end{gathered} \tag{18}$$

This equation represents the intertemporal first-order condition for optimal consumption, balancing the trade-off between current and future utility. On the left-hand side is the marginal utility of consumption at time t. On the right-hand side is the marginal utility of resources transfered to period $t+1$, taking into accout the discount factor β and the interest rate $(1+r)$. The expectation operator $\mathbb{E}$ accounts for uncertainty in future states, conditional on current shocks (η_f, η_m), marital status (m_t), and fertility status (k_t). This ensures that the household optimally allocates resources across periods, considering the trade-offs between consumption, parenting, and leisure today versus the expected benefits of saving for future consumption (conditional on current labor supply choice is already made).

3. Labor force participation decision Now knowing the utility $\hat{V}(z,l)$ with each choice of labor supply, the utlity maximizing rule is to choose l that maximizes $\hat{V}(z,l)$. The optimal labor supply decision is

$$l(z) = \begin{cases} 1 & \text{if } V(\hat{z,1}) \geq V(\hat{z,0}) \\ 0 & \text{Otherwise.} \end{cases} \tag{19}$$

Building on the work of Blundell et al. (2016, 2018), Attanasio (2008), and Heckman (1974), which model nonseparability between consumption and female employment by multiplying consumption in utility with binary indicators for the presence of children and female employment status, this model adopts a different approach. It incorporates nonseparability directly through utility maximization, where marginal utility from consumption is endogenously influenced by labor supply and the presence of children. This influence arises through changes in the time constraint and the optimal allocation of time between leisure and parenting. Therefore, this framework provides a structural interpretation for these taste shifters. While the quantitative outcomes may align—since taste shifters effectively summarize various forces as sufficient statistics—this structural approach offers additional insights into how marginal utility from consumption is shaped by labor market participation and the presence of children. Furthermore, the model captures parenting hours even when women are employed, reflecting the empirical observation that parents continue to allocate time to their children despite full-time employment. Finall, we determine the solution to the household problem across all state space by backard interation with terminal condition that utility is 0 after the end of life.

$$V(T+1) = 0 \tag{20}$$

6 Identification, Solution, and Estimation

The purpose of this section is to identify the moments from the available data that can be used to estimate key parameters of the model. It begins by demonstrating how human capital parameters can be identified from observable data, thereby guiding the selection of moments to include in the Simulated Method of Moments (SMM) estimation using data from the Panel Study of Income Dynamics (PSID) for life-cycle measurements.

The magnitude of human capital parameter matters. Similar as interest rate for assets to smooth consumption in the presence of uncertainty, the level of accumulation of human capital by working determines the extent to which women can use labor market attachment to self insure against future uncertainty they are worried about. Therefore, the magnitude of accumulation and depreciation determines the ability to remove resources into future to self insure across periods.

A brief summary of the identification analysis is as follows. The human capital accumulation ξ and τ and depreciation parameters δ are point-identified from longitudinal data on wages. Longitudinal data on the variace of wage growth pin down the autocorrelation parameter and the variance of idiosyncratic shocks. However, without differencing, observable wage moments have selection bias as unobservable heterogeneity parameter θ influence whose wage can be observed through its influecing the policy function for labor supply choice, which is solved numerically via backward iteration. Therefore, θ remains the key parameter without analytical solution that requires estimation through the simulated method of moments.

6.1 Identification of human capital parameters with panel data

The estimation of human capital parameters in this paper is robust to the initial condition parameteric assumption, as it directly use identification moments with generalised method of moments (GMM). The goal of this section is to find the moments that can identify the human capital parameter process without parameteric assumption on the initial state distribution and the functional form of unobservable heterogeneity θ_i, compared to Adda et al. (2017); Attanasio et al. (2008); Blundell et al. (2016a)

To identify the paramters of human capital accumulation and depreciation, we must observe the difference in how wages evolve between those who were not in employment and those who were, while also taking into account individual heterogeneity using longitudinal data. Now I formally show how moments from 3 periods of wage and employment panel data can identify human capital function. Recall, the law of motion of human capital for individual i at time t is

$$h_{i,t+1} = h_{i,t} + (\xi + \tau t)l_{i,t} + \delta(1 - l_{i,t}) \tag{21}$$

where $l_{i,t}$ is valued 1 if individual i is employed at time t and 0 otherwise. The perfect collinearity of l_t and $1 - l_t$ already causes the problem of identification of ξ and δ if we only have two periods of wage data. Recall, the idiosyncratic shock $\eta_{i,t}$ in the model is assumed to follow an AR(1) process that $\epsilon_{i,t} \sim \mathcal{N}(0, \sigma_\epsilon^2)$

$$\eta_{i,t+1} = \rho\eta_{i,t} + \epsilon_{i,t+1} \tag{22}$$

Wage in the first period (t) consists of the human capital $h_{i,t}$, the unobservable heterogeneity θ_i and the idiosyncratic shock $\eta_{i,t}$ and base wage $\bar{w}$ (population wage level for the least skilled worker) with human capital normalised to 0.

$$w_{i,t} = \bar{w}\exp(h_{i,t} + \theta_i + \eta_{i,t}) \tag{23}$$

By definition of wage, these people are employed ($l_{i,t} = 1$) otherwise we won't observe their wages. Therefore, human capital for the next period accumulates by $\xi + \tau t$.

$$h_{i,t+1} = h_{i,t} + \xi + \tau t \tag{24}$$

For the next period ($t+1$), if individual i is employed $l_{i,t+1} = 1$, we will observe the wage

$$w_{i,t+1} = \bar{w}\exp(h_{i,t} + \xi + \tau_t + \theta_i + \rho\eta_{i,t} + \epsilon_{i,t+1}) \tag{25}$$

The human capital accumulates by $\xi + \tau(t+1)$.

$$h_{i,t+2} = h_{i,t+1} + \xi + \tau(t+1) = h_{i,t} + 2\xi + 2\tau t + \tau \tag{26}$$

Instead, if individual i is not employed, the wage is missing. The human capital depreciates.

$$h_{i,t+2} = h_{i,t+1} + \delta = h_{i,t} + \xi + \tau t + \delta \tag{27}$$

For the period ($t+2$), if individual i is employed, the wage is

$$w_{i,t+2} = \bar{w}\exp(h_{i,t+2} + \theta_i + \rho^2\eta_{i,t} + \rho\epsilon_{i,t+1} + \epsilon_{i,t+2}) \tag{28}$$

Human capital for the period $t+2$ will depends on if she was working in period $t+1$. First of all, we use first difference of wages to remove both observable heterogeneity θ_i and $h_{i,t}$. Expected wage difference between period $t+2$ and t conditional on not working in period $t+1$ in expectation is

$$\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t} | l_{i,t+1} = 0) = \xi + \tau t + \delta \tag{29}$$

The expected wage difference between period $t+1$ and t is

$$\mathbb{E}(\ln w_{i,t+1} - \ln w_{i,t}) = \xi + \tau t \tag{30}$$

The expected wage difference between period $t+2$ and $t+1$ is

$$\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1}) = \xi + \tau(t+1) \tag{31}$$

In expectation, wage difference between period $t+2$ and period t conditional on working in period $t+1$ [15] is

$$\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t} | l_{i,t+1} = 1) = 2\xi + 2\tau t + \tau + (\rho^2 - 1)(\rho^t)\mathbb{E}(\eta_{i,0}) = 2\xi + 2\tau t + \tau \tag{32}$$

The first parameter identified is the linear age-specific accumulation parameter τ.

$$\tau = \mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1}) - \mathbb{E}(\ln w_{i,t+1} - \ln w_{i,t}) \tag{33}$$

which is difference between wage growth in period $t+2$ and period $t+1$. This parameter is overidentifed as we can also use the other moment

Here, the intuition is that we can also use second-period growth to predict what wage in period $t+2$ would be if both period grow in the same rate, then we back out the age-specific accumulation from the discrepency between prediction and actual two-period wage growth. Once τ is identified, we identify ξ

$$\begin{aligned} \xi =& \mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1}) - \tau(t+1) \\ &= \mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1}) - (t+1)\left[\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1}) - \mathbb{E}(\ln w_{i,t+1} - \ln w_{i,t})\right] \end{aligned} \tag{34}$$

After ξ and τ are both point identified, we can identify the depreciation parameter δ by comparing two period wage differences between those working in period $t+1$ and those not working in period $t+1$.

$$2\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1} | l_{i,t+1} = 0) - \mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1} | l_{i,t+1} = 1) = 2\delta - \tau \tag{35}$$

Finally, we identify the depreciation parameter δ

$$\begin{aligned} \delta =& \mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1} | l_{i,t+1} = 0) - \frac{1}{2}\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1} | l_{i,t+1} = 1) + \tau \\ &= \mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1} | l_{i,t+1} = 0) - \frac{1}{2}\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1} | l_{i,t+1} = 1) \\ &+ \frac{1}{2}\mathbb{E}(\ln w_{i,t+2} - \ln w_{i,t+1}) - \frac{1}{2}\mathbb{E}(\ln w_{i,t+1} - \ln w_{i,t}) \end{aligned} \tag{36}$$

We estimate τ and ξ using moment condition from equation (37), (38) and (39) using generalised method of moments (GMM) estimator. The benefit of using GMM to estimate the

[15] Due to the autoregressive nature of idiosyncratic shocks, $\eta_{i,t} = \rho^t \eta_{i,0} + \sum_{k=1}^{t} \rho^{t-k} \epsilon_{i,k}$

Table 3: Accumulation parameters

	Men		Women	
	White	Black	White	Black
	(1)	(2)	(3)	(4)
Accumulation × Age				
τ	-0.014***	-0.007*	-0.006	-0.004
	(0.005)	(0.004)	(0.005)	(0.005)
Accumulation				
ξ	0.251***	0.132*	0.109	0.070
	(0.083)	(0.076)	(0.083)	(0.082)
Observations	171523	151636	84486	80680

Notes: We estimate τ and ξ using moment conditions from equations (37) and (38) with the a two-step generalized method of moments (GMM) estimator. In the first step, an initial weighting matrix is used to estimate the parameters. In the second step, the weighting matrix is updated based on the residuals to improve efficiency. The initial weighting matrix is the identity matrix. Standard errors in parentheses. Standard errors are robust to heteroskedasticity, meaning they remain valid even if the variability of the errors changes across observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

parameter outside the simulated method of moments is that it allows a very flexible structure of estimate. We can obtain estimates by race, age, and gender. Moment condition of δ invovles labor supply choices in the conditional moments which needs to be solved by policy function iteration. Therefore , we need to use the simulated method of moments to estimate δ.

6.2 Estimation of human capital accumulation parameters

Here, we estimate ξ and τ using GMM estimator using moment conditions of equation (37) and (38). Further, can some of the accumulation parameters may be due to location, occupation or industry? Therefore, I estimate individual level ξ and τ to examine if some racial and gender differences in accumulation parameters are due to location, occupation or industry choices which is out of the scope of the paper.

6.3 Unobservable heterogeneity and autocorrelation

Because wages are not observed when individuals are not employed, variance of wages is influenced by the labor supply choices. The policy function of labor supply is only clear after it is solved numerically backward iteratively within a life cycle framework. Therefore, θ does not have an analytical solution to be point identified. Instead, the simulated Method of Moments (SMM) is used to estimate θ.

First, I document what moments I choose for SMM to estimate the persistence parameter ρ, the unobserved heterogeneity θ, and the variance of idiosyncratic shocks σ_ϵ^2 and explain why these moments are informative.

6.3.1 Moment for ρ

Even though the wage process involves unobserved components and lacks a closed-form solution for the conditional distribution of wages, it is still possible to identify the persistence parameter ρ by constructing moment conditions that eliminate other parameters. Such moment that is only influenced by ρ is the ratio between variance of ln wage growth over two periods and the variance of ln wage growth over one period. Recall that the AR(1) process for shocks is given by:

$$\eta_{i,t+1} = \rho\eta_{i,t} + \epsilon_{i,t+1}, \quad \epsilon_{i,t+1} \sim \mathcal{N}(0, \sigma_\epsilon^2). \tag{37}$$

Using this structure, we derive the variance of one-period and two-period log wage growth.[16] First, for one-period wage growth:

$$\ln w_{i,1} - \ln w_{i,0} = (\rho - 1)\eta_{i,0} + \epsilon_{i,1}, \tag{38}$$

which implies:

$$\text{Var}(\ln w_{i,1} - \ln w_{i,0}) = \left((\rho - 1)^2 + 1\right) \sigma_\epsilon^2. \tag{39}$$

Next, for two-period wage growth:

$$\ln w_{i,2} - \ln w_{i,0} = (\rho^2 - 1)\eta_{i,0} + \rho\epsilon_{i,1} + \epsilon_{i,2}, \tag{40}$$

which leads to:

$$\text{Var}(\ln w_{i,2} - \ln w_{i,0}) = \left((\rho^2 - 1)^2 + \rho^2 + 1\right) \sigma_\epsilon^2. \tag{41}$$

Take the ratio of these two variances eliminates σ_ϵ^2 involving only ρ:

$$R(\rho) \equiv \frac{\text{Var}(\ln w_{i,2} - \ln w_{i,0})}{\text{Var}(\ln w_{i,1} - \ln w_{i,0})} = \frac{\rho^4 - \rho^2 + 2}{\rho^2 - 2\rho + 2}. \tag{42}$$

As a moment contains information that is uniquely relevant to ρ, this ratio moment is a key input for estimating ρ using data on observed wage growth variances. Because the ratio

[16] The fixed effect θ_i is differenced out. For every one observed wage in period 0 and period 1, by definition they were employed in both periods. Given the assumption that initial human capital is zero, human capital in period 1 is ξ for everyone. Therefore, there is no heterogeneity in human capital either. The only remaining component driving wage variance is the persistent shock process $\eta_{i,t}$.

depends solely on ρ, it avoids complications associated with unobserved heterogeneity θ and the shock variance parameter σ. As such, it plays an important role in aiding convergence in the simulated method of moments by helping to isolate the dynamic persistence of wage shocks from other sources of variation.

6.3.2 Moment for σ_ϵ^2

Once we use the variance ratio moment to pin down ρ, the level of one-period wage growth variance becomes highly informative about σ_ϵ^2.

$$\mathrm{Var}(\ln w_{i,1} - \ln w_{i,0}) = ((\rho - 1)^2 + 1)\sigma_\epsilon^2 \tag{43}$$

Conditional on a known value of ρ, the one-period wage growth variance depends on σ_ϵ^2. Notice this is not influenced by individual heterogeneity θ_i. Therefore, this moment is useful to back out the scale of transitory wage shocks after $R(\rho)$ targets ρ.

6.3.3 Moment for θ

The cross-sectional variance of observed wages in the initial period, $\mathrm{Var}(\ln w_{i,0})$, is the key moment used to estimate the distribution of unobserved heterogeneity, θ_i, in combination with a numerically solved labor supply policy function that captures selection into employment.

This moment embeds information about multiple structural parameters: the persistence of wage shocks (ρ), idiosyncratic variance (σ_ϵ^2), and heterogeneity across individuals (θ_i). However, since wages are only observed for those who choose to work, the empirical variance is shaped by endogenous selection—determined by the labor supply policy function, which depends on state variables including θ_i.

Because this decision rule results from forward-looking utility maximization, it has no closed-form expression and must be solved numerically via backward induction. This numerical solution accounts for the dynamic, stochastic environment individuals face and is essential for recovering the distribution of θ_i.

To estimate parameters under selection, we use the Simulated Method of Moments (SMM), matching simulated and empirical moments shaped jointly by wages and labor supply. While $\mathrm{Var}(\ln w_{i,0})$ helps identify θ_i, we rely on two additional moments—wage autocorrelation $R(\rho)$ and the variance of wage changes, $\mathrm{Var}(\ln w_{i,1} - \ln w_{i,0})$—to separately identify ρ and σ_ϵ^2 and disentangle them from θ_i.

6.4 Solution method

With the terminal condition that all resources are consumed in the last period, the solution is solved by backward iteration. This terminal condition simplifies the problem by providing a known policy function and value function in the final period, which serve as the starting point for iterating backward over ages. The model is solved by backward induction, starting from a terminal condition where all resources are consumed in the final period. To efficiently handle the high-dimensional state space and continuous savings choice, I use the Endogenous Grid Method (EGM) (Carroll, 2006), which offers significant computational advantages over traditional value function iteration. For each discrete labor supply option, policy functions for savings and consumption are computed using EGM, and the optimal labor supply is determined by comparing value functions across choices

The model is solved by backward induction, setting the terminal value function to zero. I use the endogenous grid method for iteration, which is more efficient than standard value or policy function iteration, and estimate parameters using the Simulated Method of Moments (SMM) by matching simulated moments to empirical data.

Table 4 lists the key parameters calibrated from the literature, including the risk aversion parameter (γ), discount factor (β), and interest rate (r). These values are chosen to match established estimates in prior work and ensure comparability with related studies.

Table 4: Parameters calibration from literature

Parameter	Value	Source
γ	0.64	Blundell et al. (1994, 2016); Attanasio and Weber (1995)
β	0.98	Blundell et al. (2016); Attanasio et al. (2008)
r	0.015	Blundell et al. (2016)

Table 5 summarizes the main parameters estimated from the data. Preferences for consumption, parenting, and the time cost of work are estimated using SMM, while human capital accumulation parameters are identified using wage growth moments. Wage shock parameters and child human capital production function parameters are also estimated using SMM or nonlinear GMM, as indicated. This approach allows the model to closely match observed labor supply, wage dynamics, and parenting patterns in the data

Table 5: Main parameters estimated or calibrated

Parameter	Description	How/Where Estimated
ν	Preference for consumption	SMM, labor supply
α	Preference for parenting	SMM, parenting
ψ	Time cost of work	SMM, Ratio of parenting
γ	Risk aversion (CRRA)	Calibrated
β	Discount factor	Calibrated
ξ	Wage accumulation	GMM, wage growth moments
τ	Age effect accumulation	GMM, wage growth moments
δ	Depreciation	SMM, labor supply
ρ	Persistence of wage shocks	SMM, wage CV
σ_{ϵ^f}	Std. dev. of wage shocks	SMM, wage CV
σ_θ	Var of high-productivity	SMM, cross-sectional wage
dist_θ	Prob. of high-productivity	SMM, cross-sectional wage

7 Results

Table 6 presents the main parameter estimates from the Simulated Method of Moments (SMM). The estimates for preferences, human capital depreciation, and wage process parameters are precise and consistent with values found in the literature. These parameters govern the trade-offs between consumption, parenting, and labor supply, as well as the persistence and volatility of wage shocks. The standard errors indicate that the estimates are statistically meaningful.

Table 6: Parameter estimates from Simulated Method of Moments (SMM)

Parameter	Description	Estimate	Std. Error
ν	Consumption weight	0.41	0.05
α	Parenting weight	0.23	0.04
ψ	Work time cost	0.24	0.03
δ	HC depreciation	0.74	0.08
ρ	Wage shock AR(1)	0.85	0.06
σ_{ϵ^f}	Female wage shock std.	0.22	0.02
σ_θ	Type spread	0.35	0.07
dist_θ	Type probability	0.48	0.09

Table 7 compares key moments from the data to those generated by the model simulation for both White and Black women. The model closely matches employment rates, parenting time, and the distribution of wages and labor income across age groups and family statuses, indicating a good fit to the observed data. This close fit supports the model's ability to replicate the main empirical patterns in the data.

Table 7: Comparison of Key Moments: Data vs. Simulation

	White Women		Black Women	
Moment	Data	Simulation	Data	Simulation
Employment Rate (all ages)	0.697	0.675	0.675	0.650
Employment Rate, Age 20–25	0.683	0.660	0.625	0.604
Employment Rate, Age 26–30	0.673	0.650	0.663	0.631
Employment Rate, Before 1st Child	0.864	0.830	0.800	0.780
Employment Rate, After 1st Child	0.609	0.580	0.654	0.641
Employment Rate, 1st Marriage (In)	0.673	0.653	0.685	0.661
Employment Rate, 1st Marriage (Out)	0.747	0.702	0.664	0.623
Active Parenting (weekday, employed)	4.10	4.00	4.10	4.05
Active Parenting (weekday, not employed)	5.50	5.40	5.50	5.45
CV of Wage, Age 20–25	0.60	0.67	0.62	0.70
CV of Wage, Age 26–30	0.59	0.65	0.61	0.68
CV of Wage, All Ages	0.62	0.69	0.65	0.73
CV of Labor Income, Age 20–25	1.00	1.10	1.05	1.18
CV of Labor Income, Age 26–30	0.98	1.08	1.03	1.15
CV of Labor Income, All Ages	1.05	1.13	1.10	1.22

Figure 6 shows the overall goodness of fit for the model, comparing simulated and observed event study profiles. The close alignment between the model and data across key outcomes further supports the validity of the model structure and parameter estimates. Additional model validation, including comparisons of simulated versus observed shares of women with children and in first marriage by race, is provided in Appendix Figure C.46.

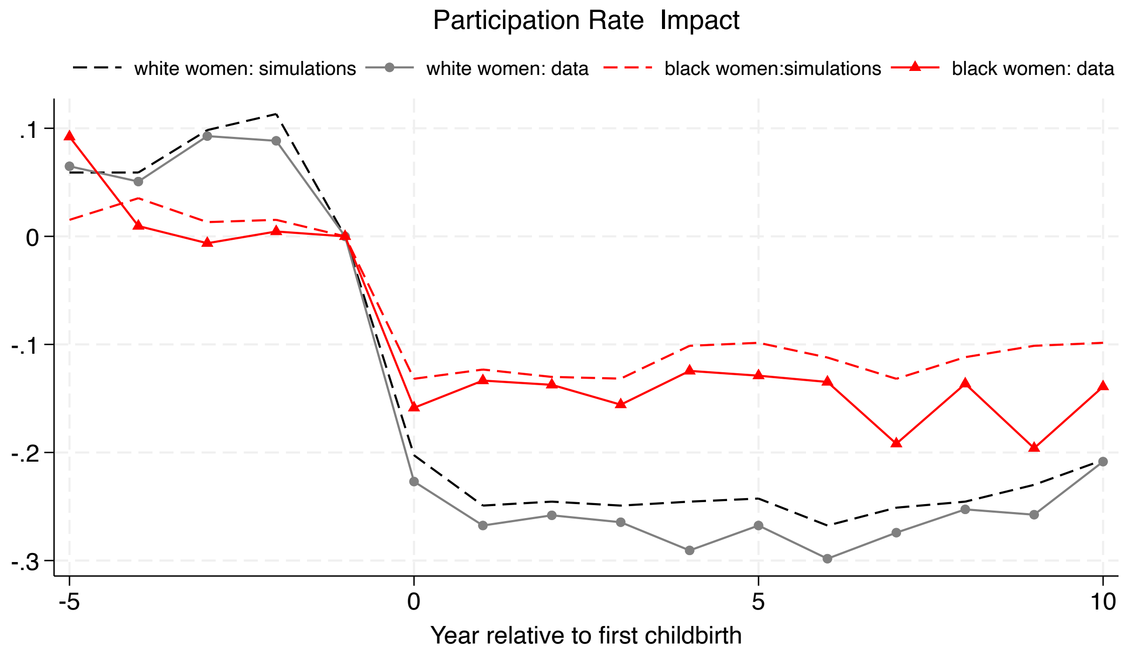

Figure 6: Goodness of fit: Simulated vs. observed event study profiles

7.1 Unobservable Heterogeneity : Policy function

The figures below illustrate the lifecycle policies as functions of age and assets, comparing Black and White individuals with children. Figure 7 displays the labor supply policy functions for married women with children, highlighting differences in optimal labor supply choices by group and ability. This illustrates how the model captures heterogeneity in labor supply responses.

This subsection examines the female labor supply policy functions under unobservable heterogeneity, comparing Black and White individuals across different ability types (Low Ability and High Ability). The figures below illustrate the lifecycle labor supply policies as functions of age and assets.

The differences in policy functions between Black and White women across ability types (low vs. high) can be explained by the interaction between unobservable ability, human capital, and the economic environment they face. For White women, higher ability (high type) leads to greater returns to human capital accumulation, which incentivizes them to reduce labor supply in favor of investing more time in activities like childcare or leisure, as their higher wages allow them to smooth consumption with less labor market participation. In contrast, for Black women, higher ability amplifies the need to work more due to structural factors such as lower expected returns to human capital for their children (due to discrimination) and higher economic uncertainty, including greater divorce risk and lower spousal income. These factors push high-ability Black women to increase labor supply as a precautionary measure to accumulate savings and maintain labor market attachment, ensuring financial stability and mitigating future risks. This divergence highlights how structural inequalities shape labor supply decisions differently for Black and White women, even when they share similar ability levels.

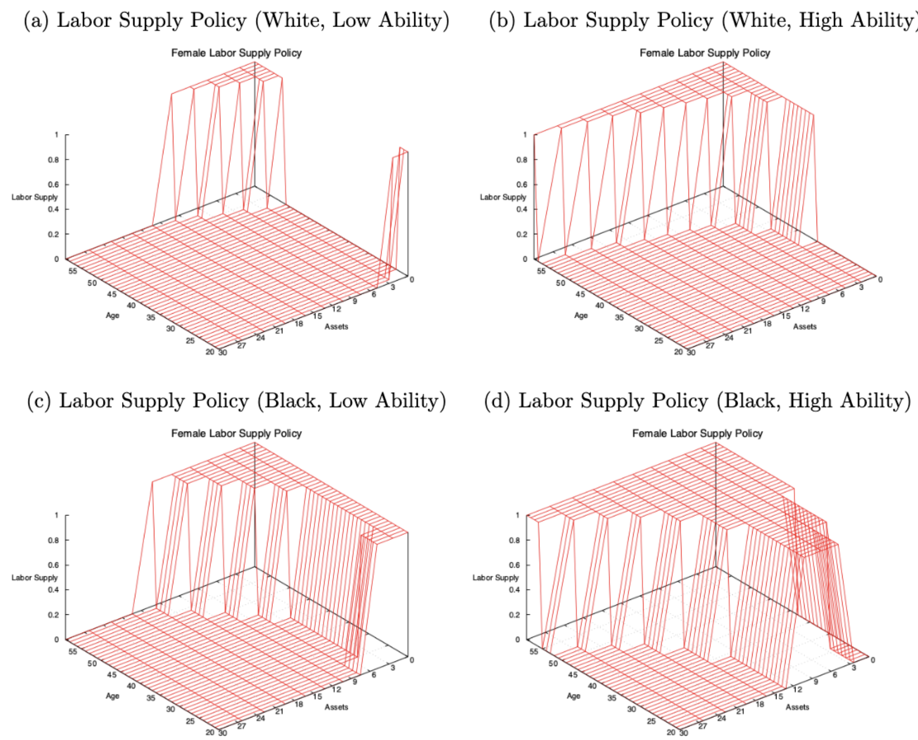

Figure 7: Labor supply policy functions of married women with children

Counterfactual simulations further assess the impact of equalizing marriage and husband income dynamics across groups. Figure 8 shows that aligning these processes substantially narrows the racial gap in female labor supply and child outcomes, highlighting the importance of family structure and spousal earnings in explaining observed disparities.

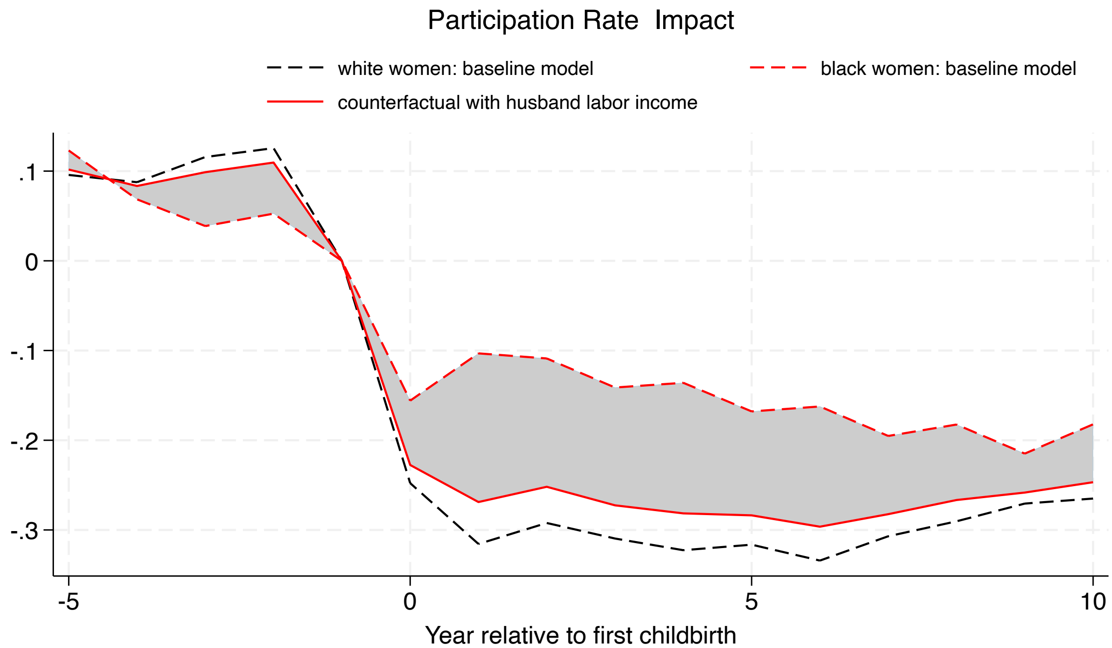

Figure 8: Counterfactuals: Simulated outcomes when marriage and husband income dynamics are equalized

As utility is not cardinaly scaled, to derive a meaningful quantative measure, we derive the relative increase (or decrease) in income necessary to reach the same utility, Δ, which is the income equivalent variation (Hicksian equivalent variation, HEV). Because utility function is homothetic,

$$\Delta = ((\frac{U_1}{U_0})^{\frac{1}{1-\frac{1}{\gamma}}} - 1) * 100 \tag{44}$$

Therefore, welfare is measured in lifetime consumption monetary unit in percent term. We then use a utilitarian social welfare criterion where we aggregate over each individual's lifetime utility given equal weight to each individual.

As utility is not cardinally scaled, to derive a meaningful quantitative measure, we compute the relative increase (or decrease) in income necessary to reach the same utility, Δ, known as the income equivalent variation (Hicksian equivalent variation, HEV). Because the utility function is homothetic,

$$\Delta = \left(\left(\frac{U_1}{U_0}\right)^{\frac{1}{1-\frac{1}{\gamma}}} - 1\right) \times 100, \tag{45}$$

where U_1 and U_0 denote the lifetime utility in the counterfactual and baseline scenarios, respectively. Therefore, welfare is measured in terms of lifetime consumption, expressed as a percentage. We then use a utilitarian social welfare criterion, aggregating each individual's lifetime utility with equal weight.

Table 8: Decomposition of Welfare Gain (% of Lifetime Consumption)

Component	Welfare Gain (%)
Consumption	4.2
Leisure	7.8
Parenting	1.7
Total	**13.7**

Notes: The table decomposes the total welfare gain for Black women from equalizing marriage and husband wage transitions, measured as a percentage of lifetime consumption. Each row shows the gain from increasing only that component to its counterfactual path.

8 Conclusion

This study shows striking differences in child penalties between black and white women in the US. This paper largely rules out the main explanation of single parenthood, family structure, and homeownership. Furthermore, most economics, demographic, and work-related gender attitude variables do not explain most of the racial gap in child penalty.

Heterogeneity analysis shows that the racial gap is primarily driven by women in the South with high wages. Consistently, the structural model of lifecycle modeling of employment produces very similar empirical patterns of child penalties between Black and white women, using only racial difference in marriage rate with identical parameters for Black and white women. This suggests that Black women stay in the labor market to keep human capital from depreciation to self-sure against future divorce shock.

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A Appendix

Table A.1: Cross-tabulation of own and spouse race

	Male race		
Female race	White	Black	Total
White	12,125	0	12,125
Black	0	6,534	6,534
Total	12,125	6,534	18,659

Notes: All psid individuals using family matrix relationship data. Married couples can be legally married or cohabiting for at least 1 year.

Table A.2: Share of first births occurring before or after marriage, by race

	Race		
First birth timing	White	Black	Total
Childbirth before marriage	7.93%	37.70%	16.22%
Childbirth in marriage	92.07%	62.30%	83.78%
Total	100.00%	100.00%	100.00%

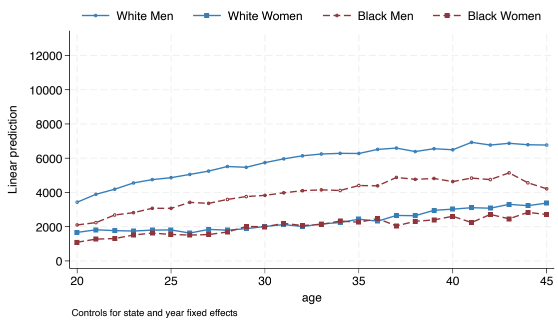
Table A.3: Share with prior wage above or below the median, by race and gender

Panel A: Women			
	White	Black	Total
Prior wage below median	33.66%	51.21%	37.89%
Prior wage above median	66.34%	48.79%	62.11%
Total	100.00%	100.00%	100.00%
Panel B: Men			
	White	Black	Total
Prior wage below median	47.37%	72.38%	53.11%
Prior wage above median	52.63%	27.62%	46.89%
Total	100.00%	100.00%	100.00%

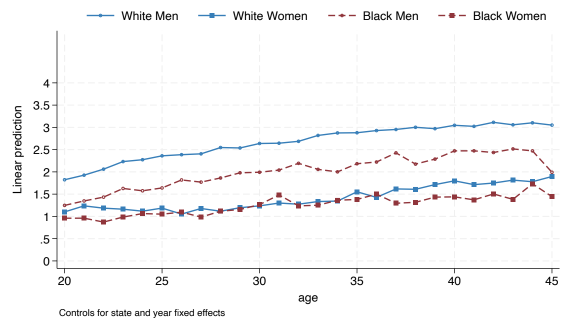
Notes: Cell entries are column percentages.

A.1 Stylized Facts: Labor Market and Marriage Market

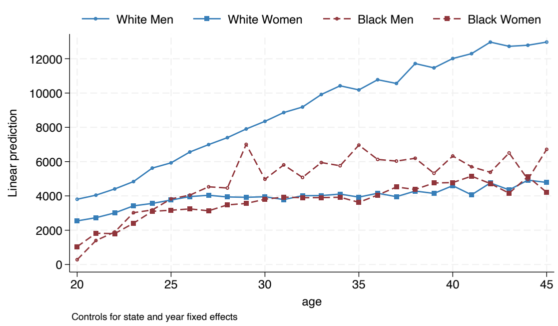
(a) Annual labor income: below high school graduate



(b) Hourly wage: below high school graduate



(c) Annual labor income: high school graduate and above



(d) Hourly wage: high school graduate and above

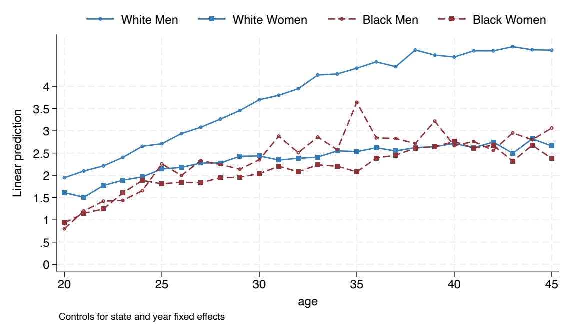
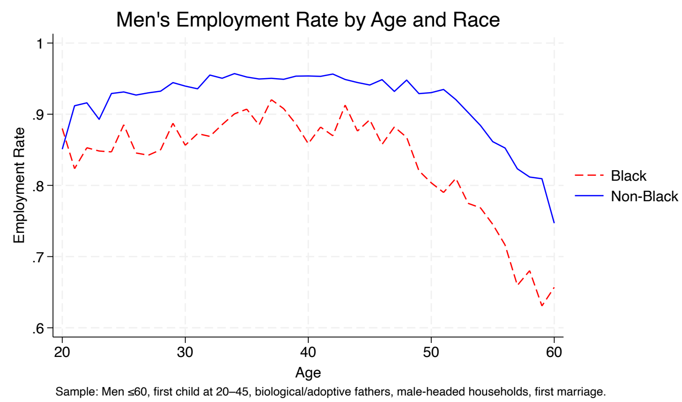


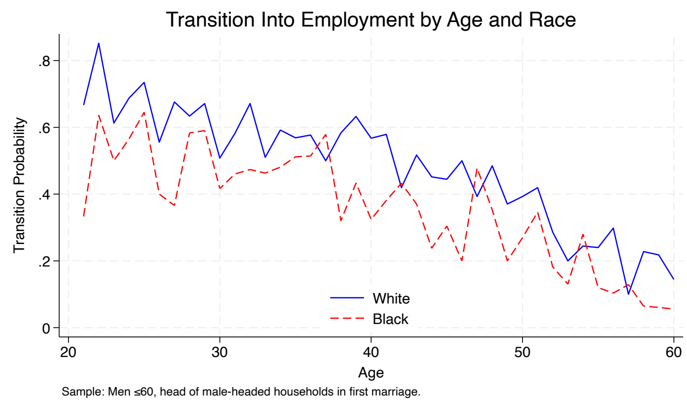
Figure A.1: Racial differences in age profiles of labor income and hourly wage, by education.

Notes: The sample consists of married women in male-headed households with their first child between 20 and 45. Income and wage adjusted by inflation index (1960 price). Source: Panel Study of Income Dynamics, 1967 to 2017.

(a) Employment Rate by Age and Race



(b) Transition into Employment by Age and Race



(c) Transition out of Employment by Age and Race

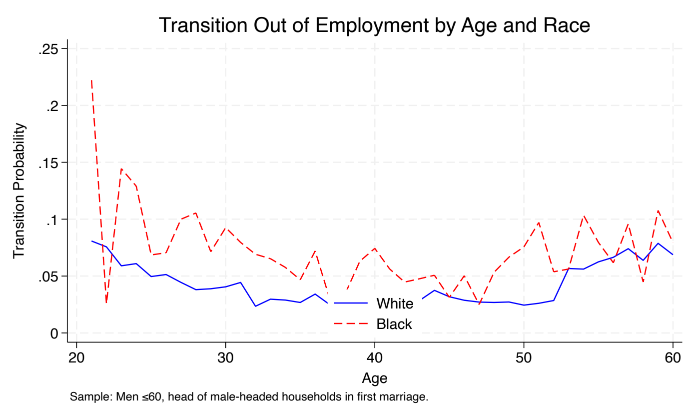


Figure A.2: Employment Rate and Transitions by Age and Race

Notes: These figures show the employment rate, transition into employment (from not employed to employed), and transition out of employment (from employed to not employed) for men by age and race. The sample consists of women aged 20–60, with their first child between ages 20–45, in male-headed households.

Table A.4: Subjective expectation: probability laid off in next 12 months, by gender and education

	(1)	(2)	(3)	(4)	(5)	(6)
	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
black	6.541	7.624***	5.988**	-5.847	5.954**	7.201***
	(14.602)	(2.675)	(2.429)	(5.001)	(2.335)	(1.920)
Grades of schooling FE	Yes	Yes	Yes	Yes	Yes	Yes
Occupation(3 digit) FE	Yes	Yes	Yes	No	No	No
Occupation(3 digit) FE	No	No	No	Yes	Yes	Yes
N	58	699	1036	298	1094	1494

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard error clustered at individual level. This table reports the subjective probability (0–100%) being laid off in the next 12 months, by race. Source: PSID, 1994.

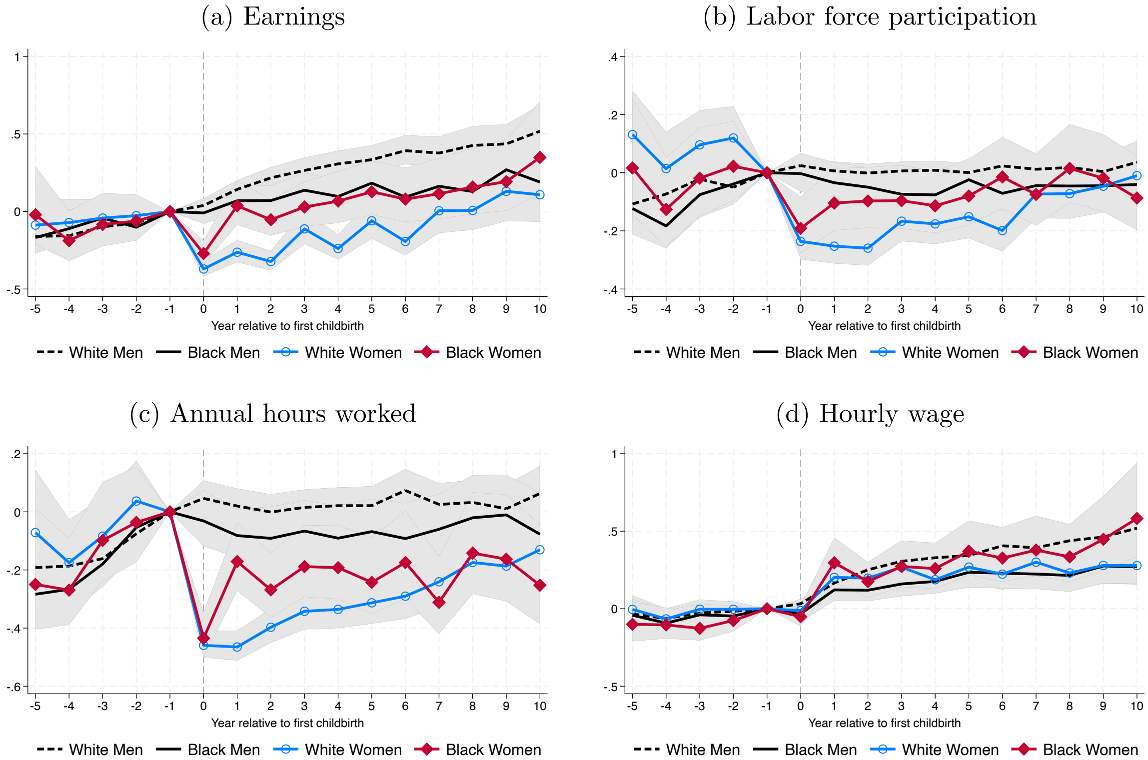


Figure A.3: Racial differences in the child penalties with prior childbirth (**wage never above the median**)

Notes: The sample consists of women with prior childbirth wage never above the median (wage distribution by gender and year), with their first child between ages 20 and 45. Income and wage are adjusted by the inflation index (1960 price). Wage and income are transformed by inverse hyperbolic sine. Annual hours worked are conditional on being employed. Source: Panel Study of Income Dynamics, 1967 to 2017.

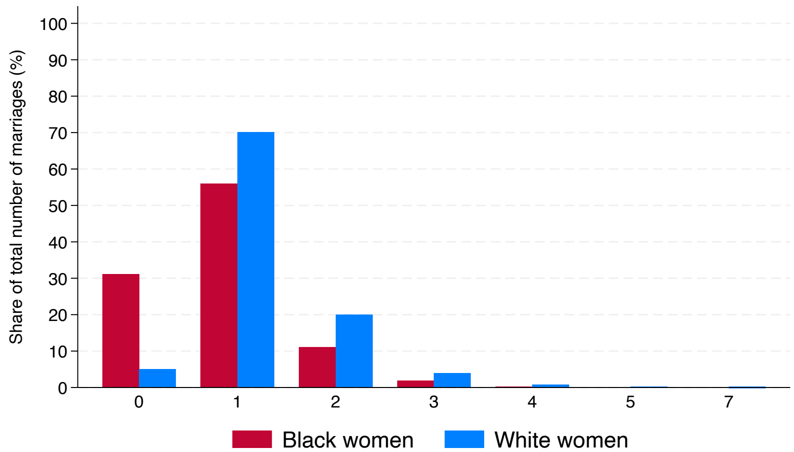
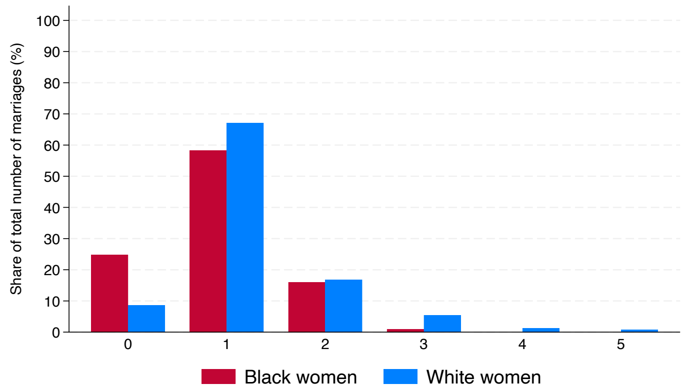


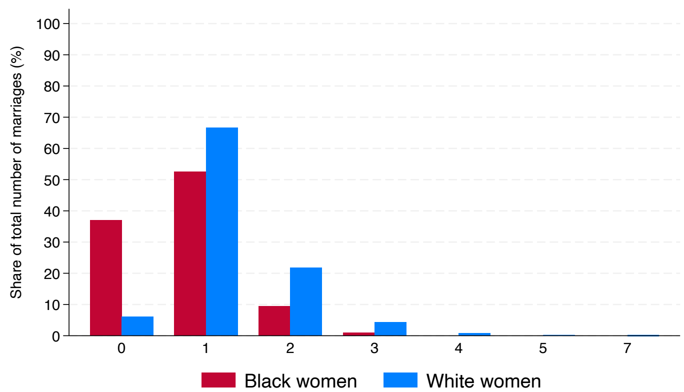
Figure A.4: Total number of marriage by race

Notes: Source: Panel Study of Income Dynamics. This is not a panel variable but an individual-level variable for the entire sample. Each individual has a unique value over the entire survey period.

(a) High school dropout



(b) High school diploma



(c) College and above

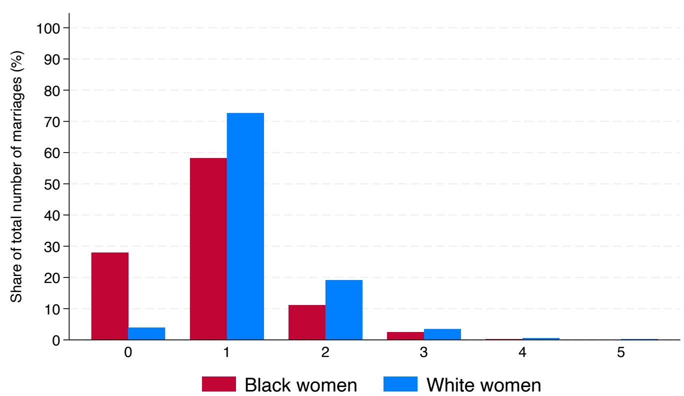


Figure A.5: Total marriage rates by race and education group

Notes: Source: Panel Study of Income Dynamics. This is not a panel variable but an individual-level variable for the entire sample. Each individual has a unique value over the entire survey period.

Table A.5: First marriage match of female and male education by race (Cell Percentages)

	Male education (%)			
Panel A: White, First Marriage				
Female education	High school dropout	High school diploma	College and above	Row total
High school dropout	6.47	3.68	1.27	11.42
High school diploma	6.21	17.18	10.92	34.31
College and above	2.22	12.45	39.59	54.26
Total	14.90	33.32	51.78	100.00
Panel B: Black, First Marriage				
	Male education (%)			
Female education	High school dropout	High school diploma	College and above	Row total
High school dropout	10.65	4.49	1.57	16.72
High school diploma	8.04	19.47	9.00	36.51
College and above	3.62	17.46	25.69	46.77
Total	22.31	41.42	36.27	100.00

Notes: Cell entries are percentages. 1 = low education, 2 = medium education, 3 = high education. Sample include individual ever in first marriage, having childbirth between age 20 and 45, PSID. Panel A: White; Panel B: Black.

Table A.6: Second marriage match of female and male education by race (Cell Percentages)

Panel A: White, Second Marriage				
		Male education (%)		
Female education	High school dropout	High school diploma	College and above	Row total
High school dropout	3.24	4.09	1.55	8.88
High school diploma	4.44	18.68	11.21	34.32
College and above	2.18	19.94	34.67	56.80
Total	9.87	42.71	47.43	100.00
Panel B: Black, Second Marriage				
		Male education (%)		
Female education	High school dropout	High school diploma	College and above	Row total
High school dropout	4.33	4.15	1.26	9.75
High school diploma	7.58	18.59	5.78	31.95
College and above	3.97	27.44	26.90	58.30
Total	15.88	50.18	33.94	100.00

Notes: Cell entries are percentages. 1 = low education, 2 = medium education, 3 = high education. Sample include individual ever in second marriage, having childbirth between age 20 and 45, PSID. Panel A: White; Panel B: Black.

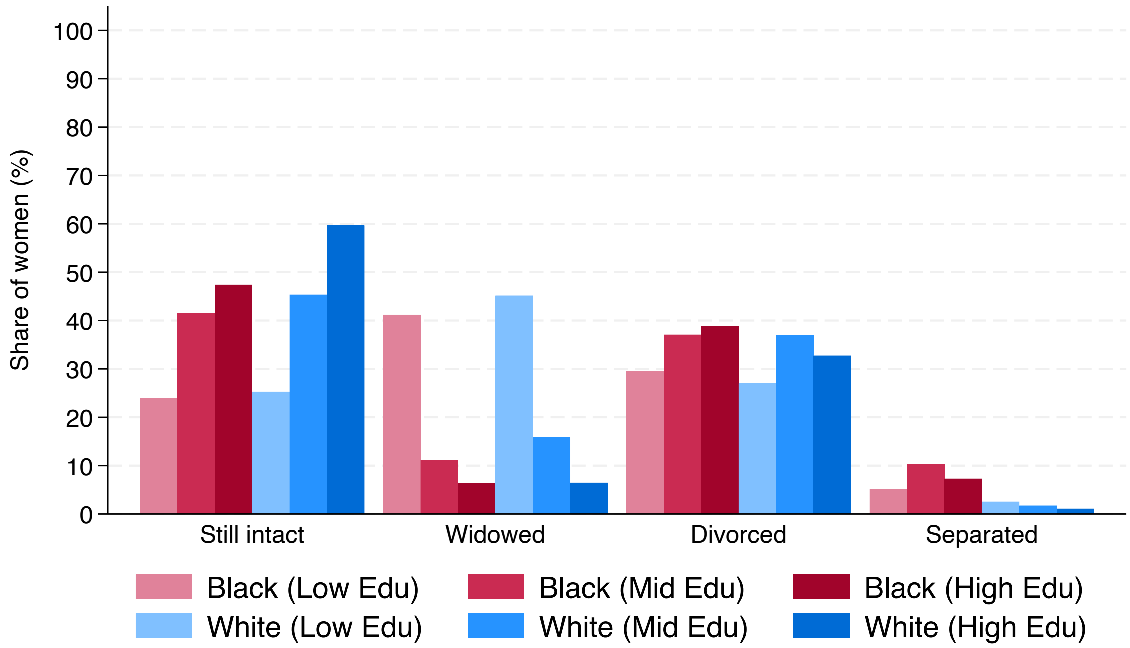


Figure A.6: Marriage exit rates by race and education group

Notes: Sample include individual ever in first marriage, having childbirth between age 20 and 45, PSID. Panel A: White; Panel B: Black.

Table A.7: Subjective probability of divorce by gender and education

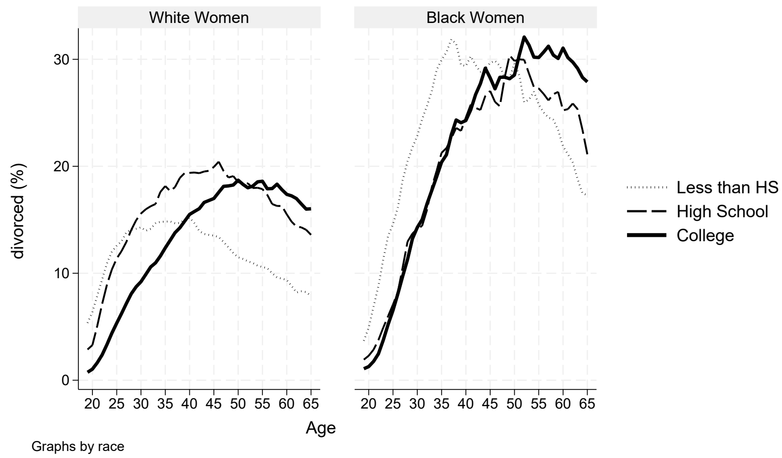
	(1)	(2)	(3)
	Low Edu	Mid Edu	High Edu
black	7.486	-3.721	4.081**
	(4.795)	(2.799)	(1.858)
Year FE	Yes	Yes	Yes
N	85	389	630

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Standard error clustered at individual level. Table reports the average subjective probability (0–1) of divorce, by race and education, among those who predict positive probabilities of getting married. Source: PSID.

(a) Divorced individuals



(b) Married individuals

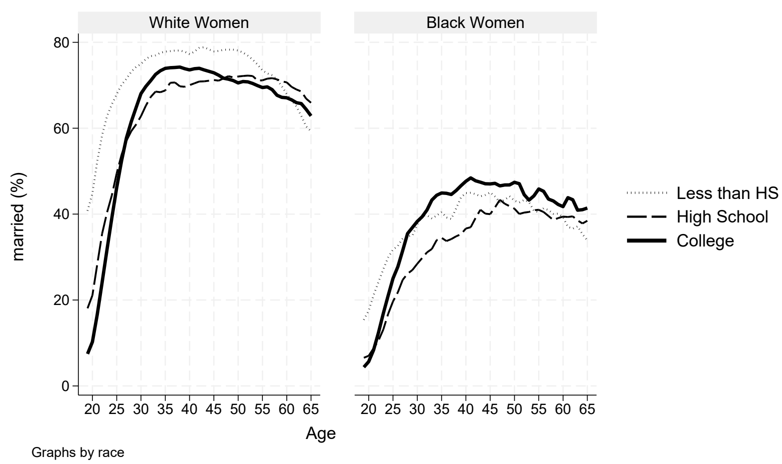
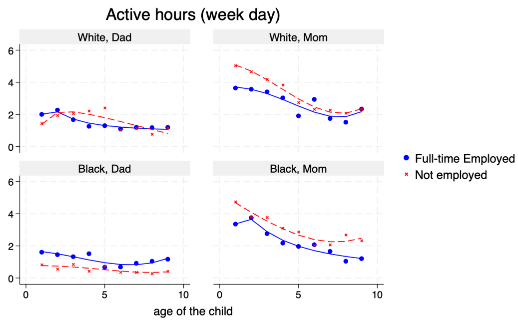


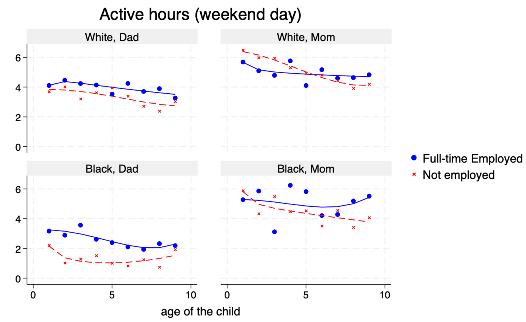
Figure A.7: Age trends in marital status by education (CPS, 1970–2020).

Notes: Age between 20 and 65. Source: Current Population Survey (CPS) Annual Social and Economic Supplements, 1970 to 2020. Weighted by CPS annual social and economic supplement weight.

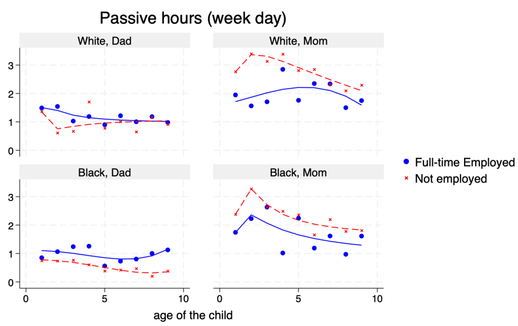
(a) Active Weekday Parenting



(b) Active Weekend Parenting



(c) Passive Weekday Parenting



(d) Passive Weekend Parenting

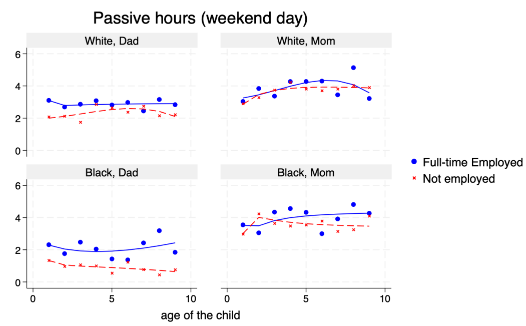


Figure A.8: Parenting time (active and passive) by age, race, and parental status, with employment overlay. Each panel overlays employed (blue) and not employed (red) within race and parent groups.

Notes: Each panel shows the relationship between age and parenting time (active or passive) on weekdays and weekends, by race and parental status, with employment status overlaid. Blue: employed; red: not employed. Circles/X's are data, lines are fitted values.

A.2 Marriage

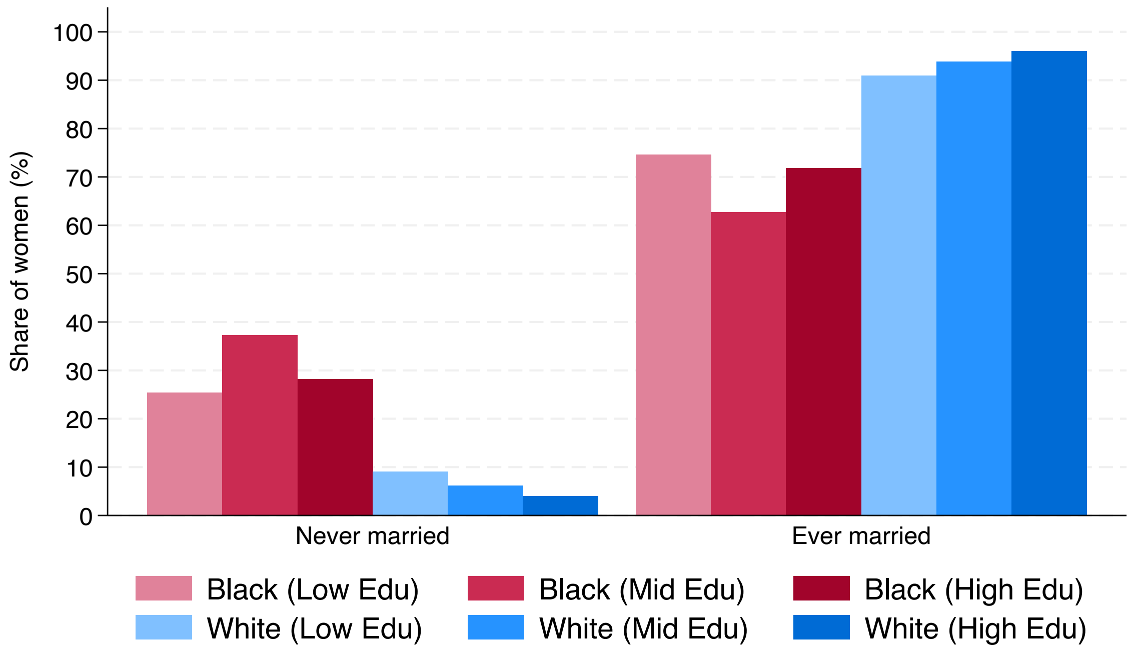


Figure A.9: Marriage entry rates by race

Duration of first marriage The t-test compares the duration of first marriages between Black and white individuals. The results show that white individuals (group 0) have a mean first marriage duration of 18.1 years, while Black individuals (group 1) have a mean of 14.95 years. The difference in means is 3.14 years $(95\%CI : 1.91to4.37)$, which is statistically significant ($p < 0.001$). This indicates that first marriages tend to last significantly longer for white individuals compared to Black individuals in the sample.

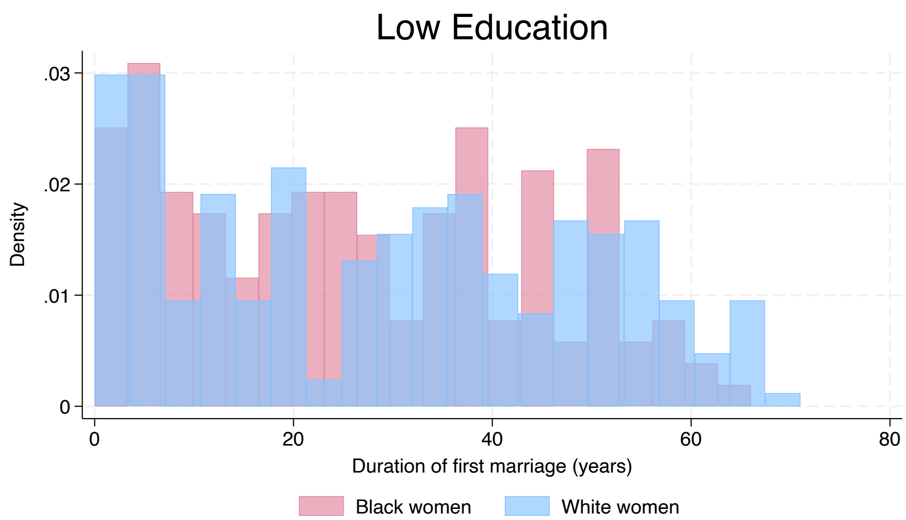
High school dropout: White women have an average first marriage duration of 29.41 years $(95\%CI : 26.87, 31.95)$, while Black women have an average of 26.36 years $(95\%CI : 23.59, 29.14)$. The difference is 3.04 years (95% CI: -0.80, 6.88), which is not statistically significant ($p = 0.12$).

High school diploma: White women's first marriages last on average 19.32 years (95% CI: 18.08, 20.56), compared to 13.67 years (95% CI: 12.21, 15.14) for Black women. The difference is 5.65 years (95% CI: 3.32, 7.98), which is statistically significant ($p < 0.001$).

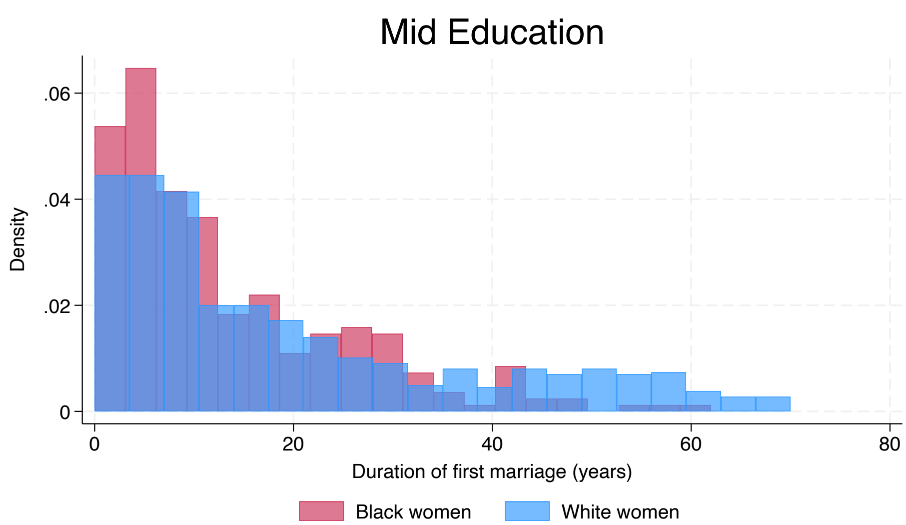
College and above: White women have an average first marriage duration of 14.67 years (95% CI: 13.89, 15.46), while Black women average 11.84 years (95% CI: 10.92, 12.76). The difference is 2.83 years (95% CI: 1.47, 4.19), also statistically significant ($p < 0.001$).

Summary: White women have longer first marriages than Black women across all education groups. The difference is largest and most significant among those with a high school diploma, while the gap among high school dropouts is not statistically significant.

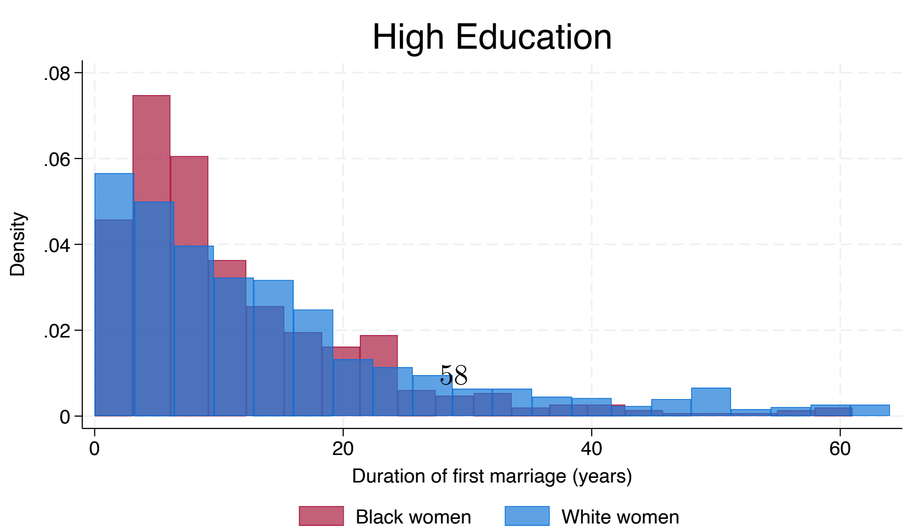
(a) High school dropout



(b) High school diploma



(c) College and above



A.3 CPS: Time Trend

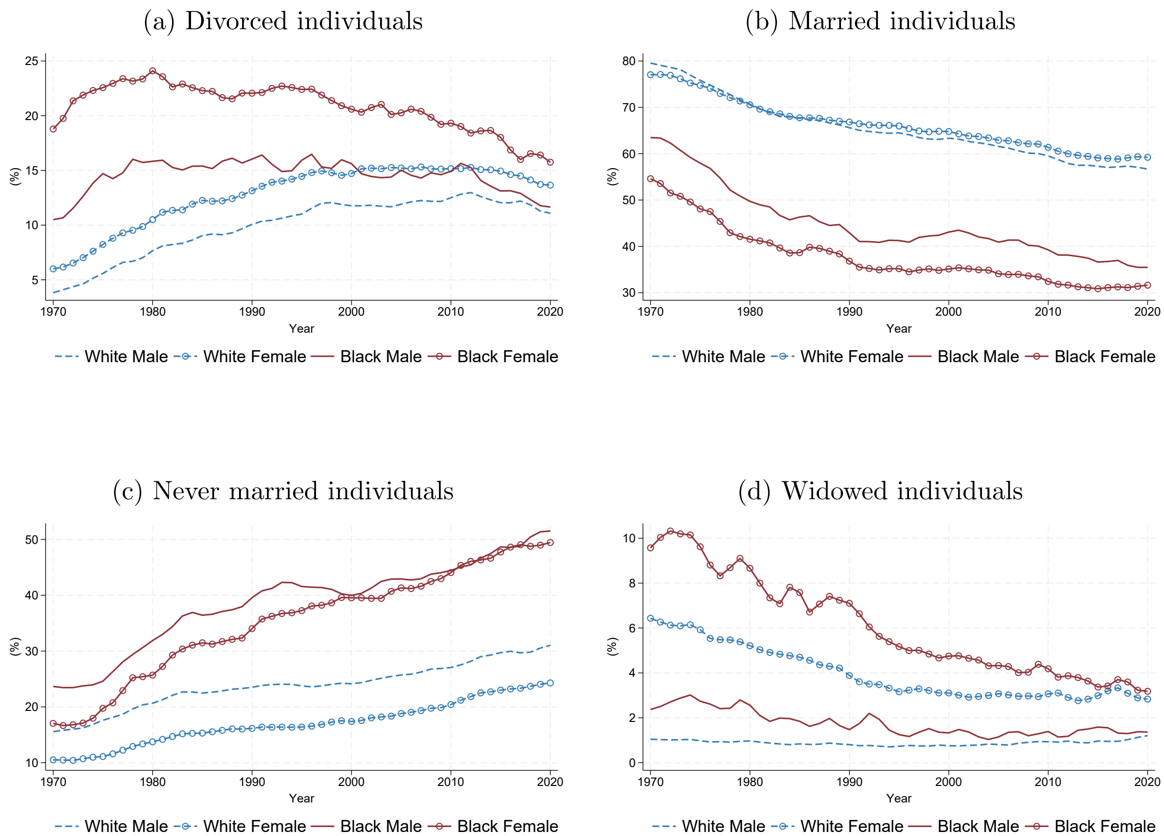


Figure A.11: CPS Year trend

Notes: Age between 19 and 49. Source: Current Population Survey (CPS) Annual Social and Economic Supplements, 1970 to 2019. Weighted by CPS annual social and economic supplement weight

A.4 CPS: Age Trend by Education

A.5 CPS: Age Trend by Education

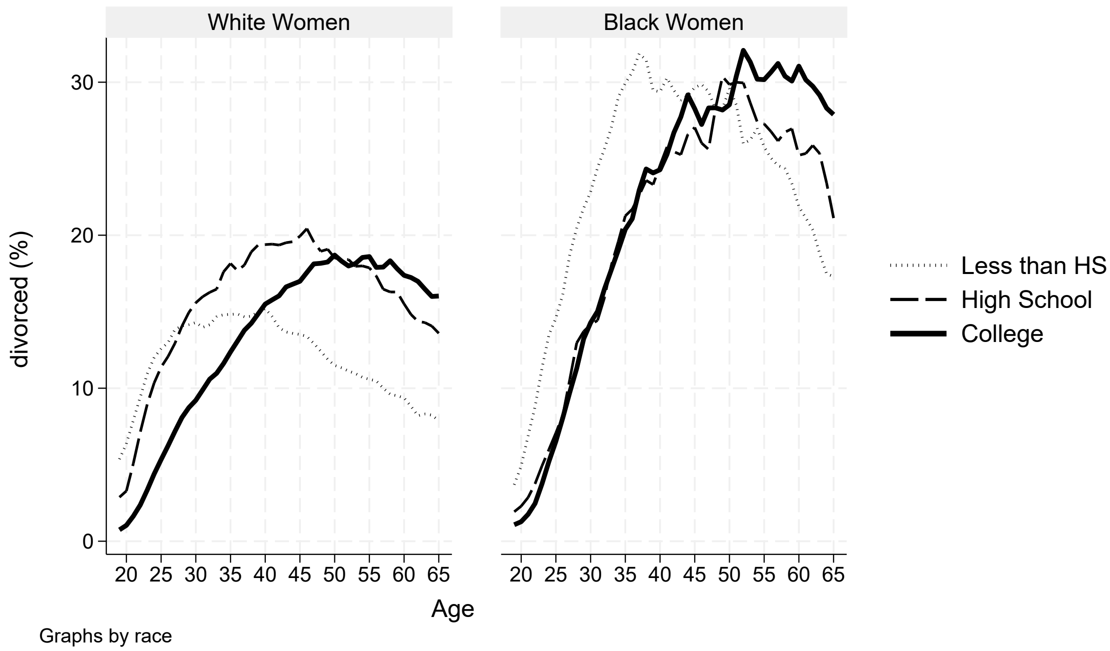
A.6 CPS: Age Trend by Education (continued)

A.7 CPS: Men

A.8 Empirical

Sample selection follows Kleven et al. (2019a) 1) We drop sample with missing or incomplete data on birth year of first children; no birth history was collected for this individual in 1985-2021; no children; 2) I keep

(a) Divorced individuals



(b) Married individuals

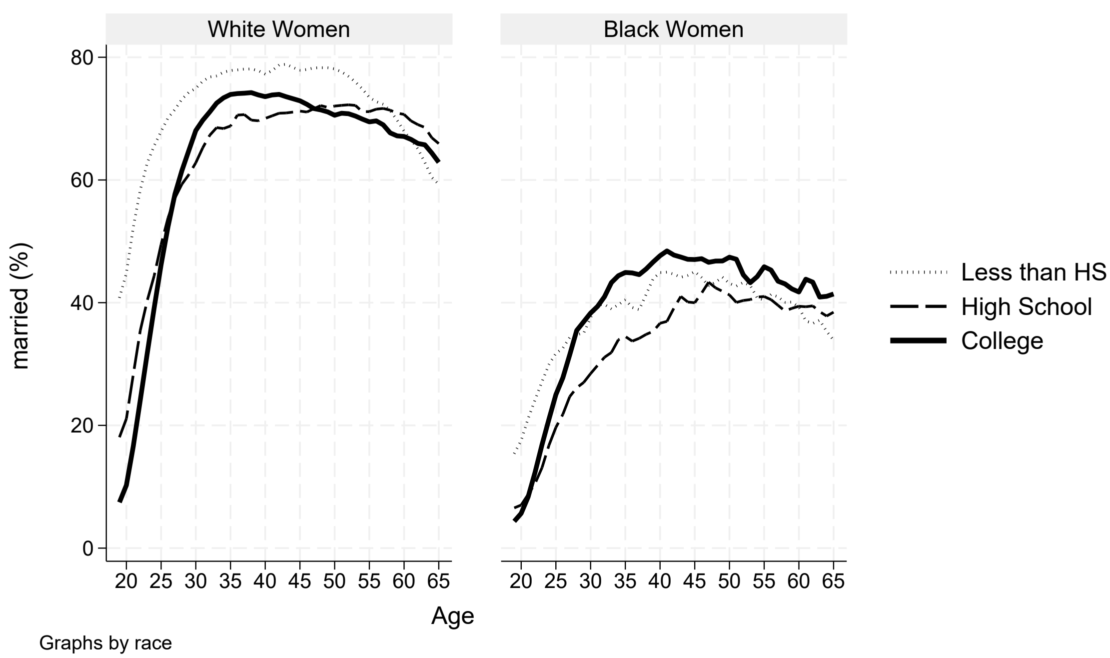
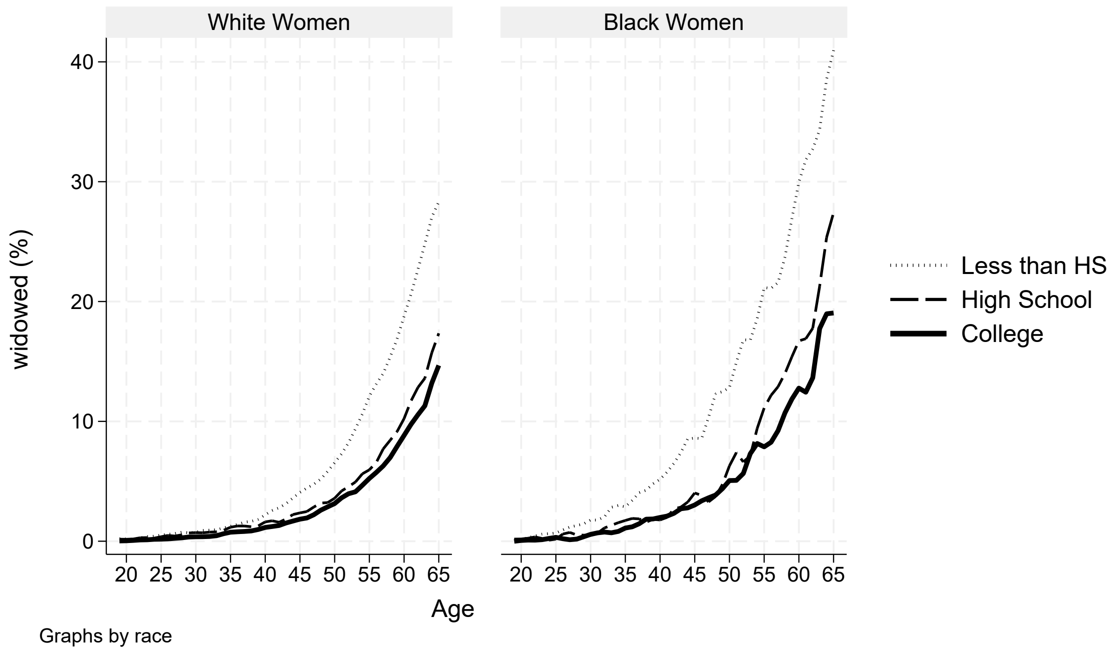


Figure A.12: Age trends in marital status by education (CPS, 1970–2020).

Notes: Age between 20 and 65. Source: Current Population Survey (CPS) Annual Social and Economic Supplements, 1970 to 2020. Weighted by CPS annual social and economic supplement weight.

(a) Widowed individuals



(b) Never married individuals

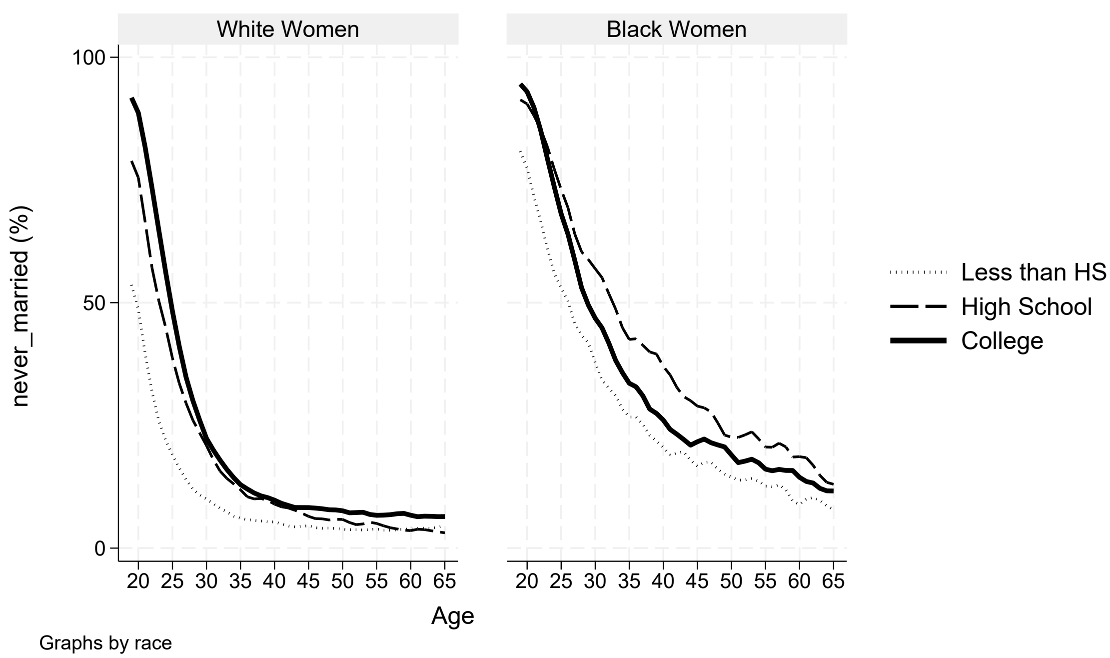


Figure A.13: Age trends in marital status by education (CPS, 1970–2020).

Notes: Age between 20 and 65. Source: Current Population Survey (CPS) Annual Social and Economic Supplements, 1970 to 2020. Weighted by CPS annual social and economic supplement weight.

Table A.8: White–Black Ln(Income) Gaps by Age Group

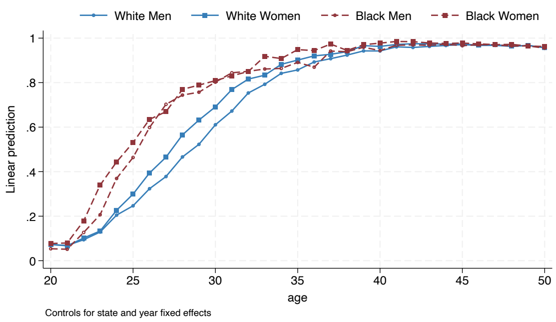
	(1) ln(income)	(2) ln(income)	(3) ln(income)
white=1	0.148***	0.152***	0.126***
	(0.036)	(0.036)	(0.038)
white × Age 20–24	0.013	-0.051	0.045
	(0.039)	(0.039)	(0.041)
White × Age 25–29	0.156***	0.088**	0.201***
	(0.038)	(0.038)	(0.039)
White × Age 30–34	0.213***	0.135***	0.253***
	(0.038)	(0.038)	(0.039)
White × Age 35–39	0.231***	0.153***	0.275***
	(0.038)	(0.038)	(0.039)
White × Age 40–44	0.229***	0.146***	0.272***
	(0.038)	(0.038)	(0.039)
White × Age 45–49	0.221***	0.141***	0.271***
	(0.038)	(0.038)	(0.040)
White × Age 50–54	0.244***	0.168***	0.294***
	(0.039)	(0.039)	(0.040)
White × Age 55–59	0.168***	0.091**	0.219***
	(0.041)	(0.041)	(0.042)
White × Age 60–64	0.079*	0.011	0.140***
	(0.045)	(0.044)	(0.046)
Observations	833,328	833,328	833,328

Notes: Sample includes men with education higher than a high school diploma. This table reports the racial gap in the age profile of annual income by age group. The first column reports the raw racial gap. The second column controls for the age profile across 13 detailed education categories. The third column allows for state-specific age profiles. Source: Current Population Survey (CPS) Annual Social and Economic Supplements, 1970 to 2020. Weighted by CPS annual social and economic supplement weight.

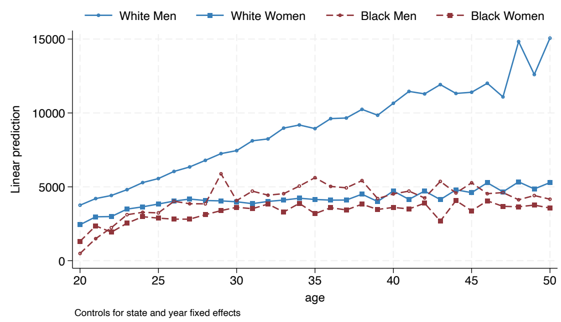
individuals if their first childbirth is between age 20 and 45. In the final sample, average age of first childbirth is 25.04, 25.64 for white and 23.93 for black.

A.8.1 Age profile by gender and race

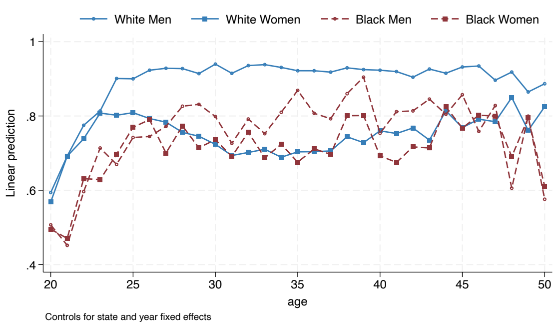
(a) Fraction of individuals with first child born



(c) Annual labor income



(b) Annual employment



(d) Hourly wage rate

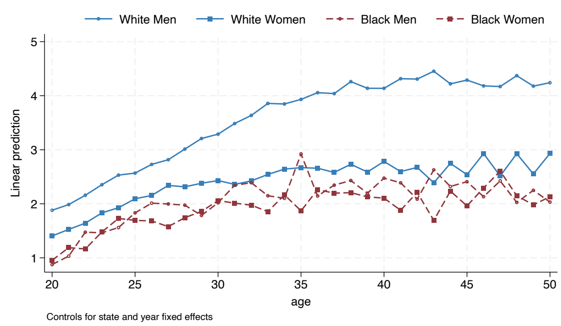
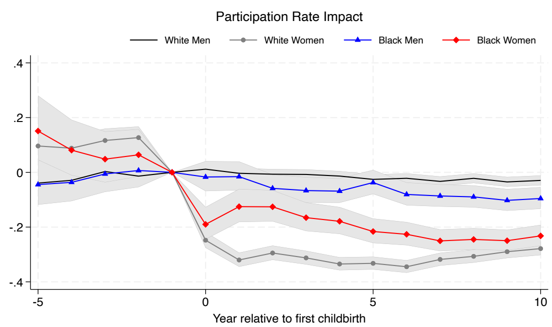


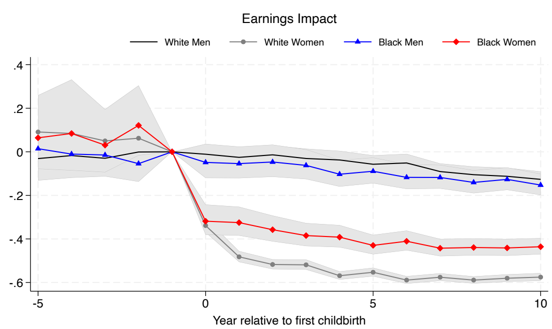
Figure A.14: Age profiles by gender and race

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017. Dollar values adjusted to 1960 using CPI.

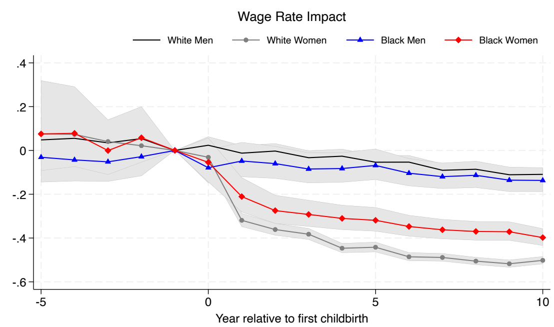
(a) Annual employment



(b) Annual labour income



(c) Annual hourly wage rate



(d) Annual hours worked

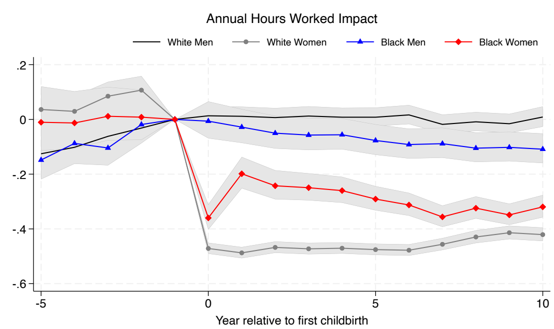


Figure A.15: Racial differences in the child penalty with individual

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017.

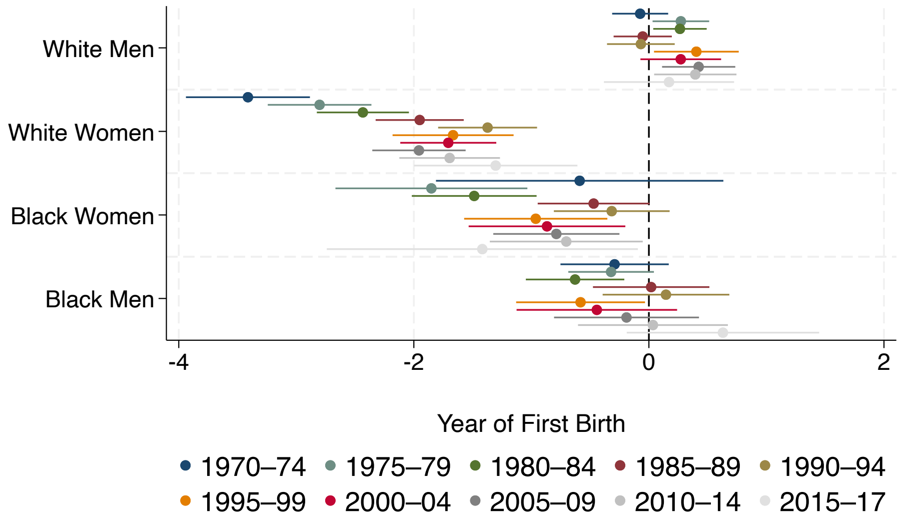


Figure A.16: Child penalty by birth cohort and race

Notes: The sample consists of individuals having their first child between 20 and 45. Child penalty is estimated using event study methodology for each birth cohort bin (1930-1939, 1940-1949, 1950-1959, 1960-1969, 1970-1979). Weighted using PSID Longitudinal weights. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.8.2 Marriage

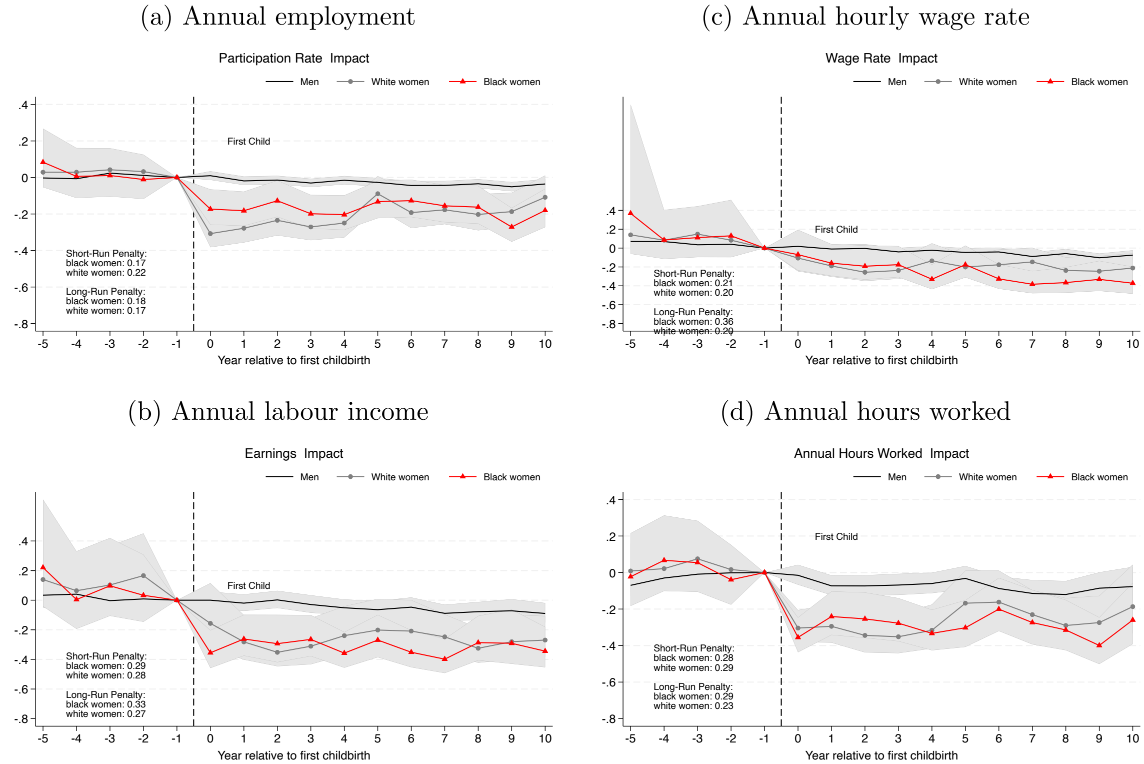


Figure A.17: Racial differences in the child penalty among single individuals

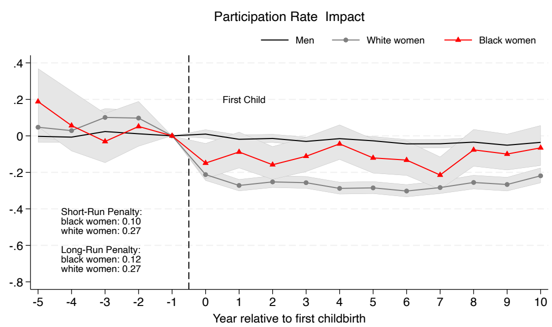
Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017.

Martial Status In PSID, no distinction was made between those legally married and those who merely cohabited in measurement in marital status from 1968-1976 data (Are you married, single, widowed, divorced, or separated?). Since 1977, cohabitation was observed if cohabitor who has lived with Head for 12 months or more.

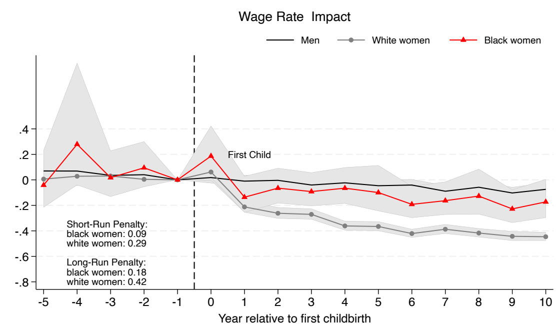
Here, marriage is defined as being the spouse in the legal marriage or cohabitation with the head of the households.

Another measure in PSID is the start and end of first marriage.

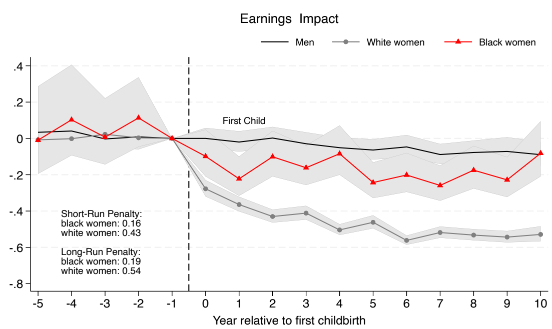
(a) Annual employment



(c) Annual hourly wage rate



(b) Annual labour income



(d) Annual hours worked

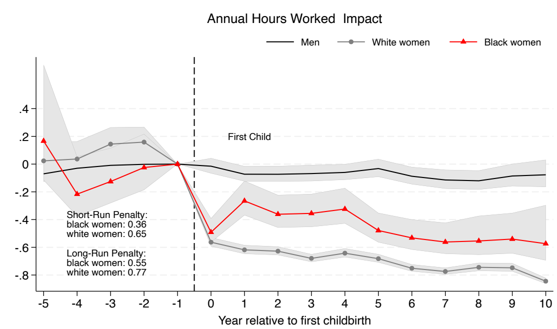
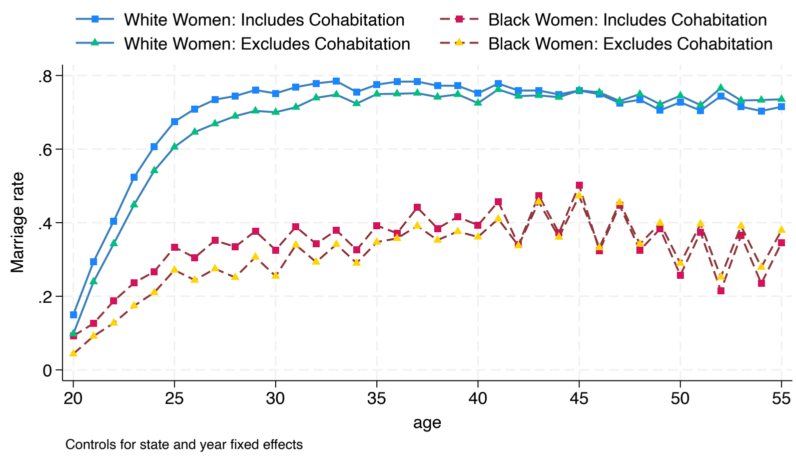


Figure A.18: Racial differences in the child penalty among married individuals

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017.

(a) Marriage rate (edu0)



(b) Marriage rate (edu1)

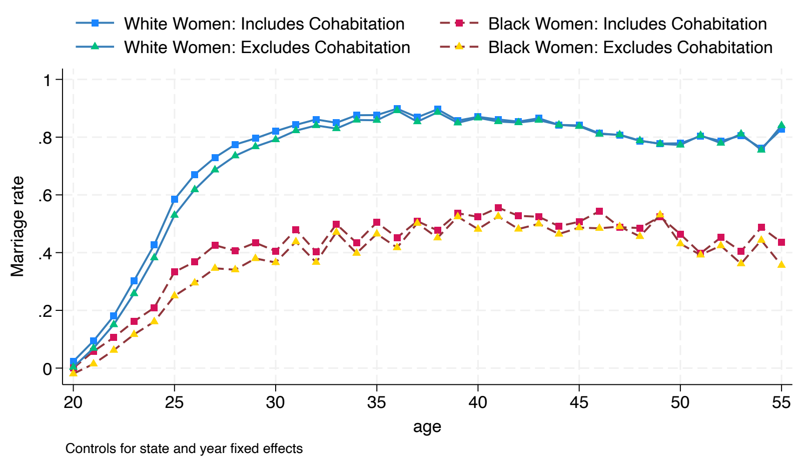


Figure A.19: Racial differences in the age profiles of women

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

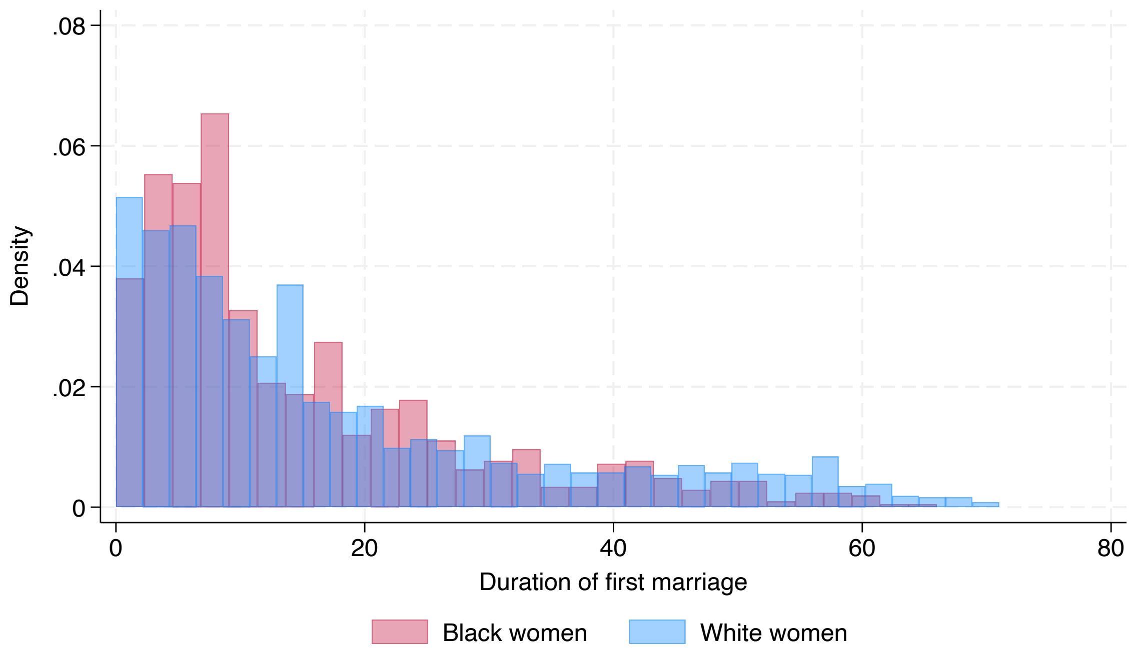
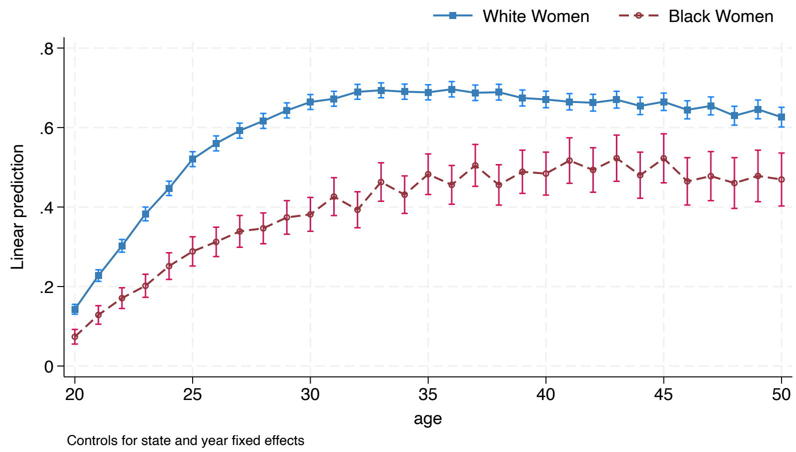


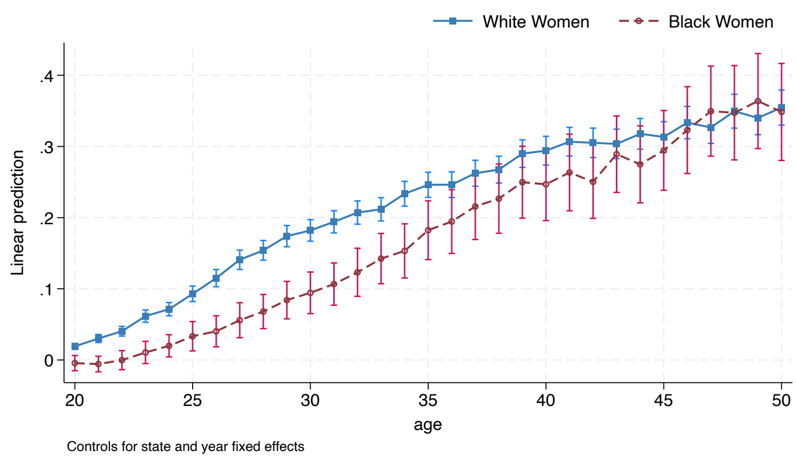
Figure A.20: Duration of first year marriage(conditional sample(married and divorced))

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

(a) In first marriage



(b) Divorced, widowed or separated from first marriage



(c) Never married

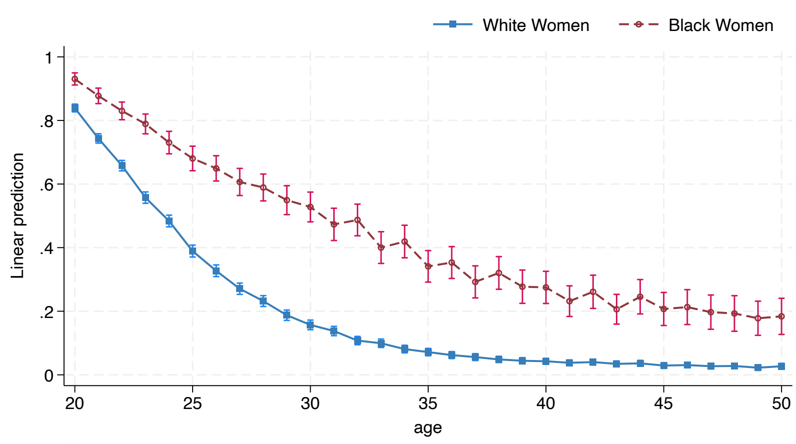
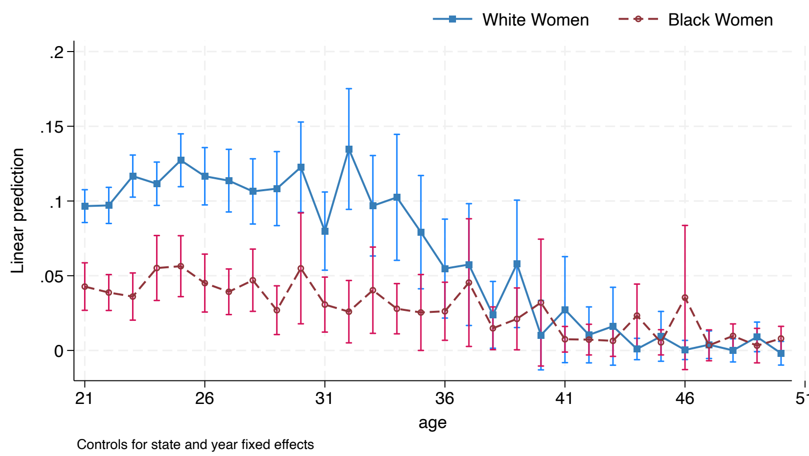


Figure A.21: Racial differences in the age profiles of women

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

(a) Transition into first marriage



(b) Transition out of first marriage

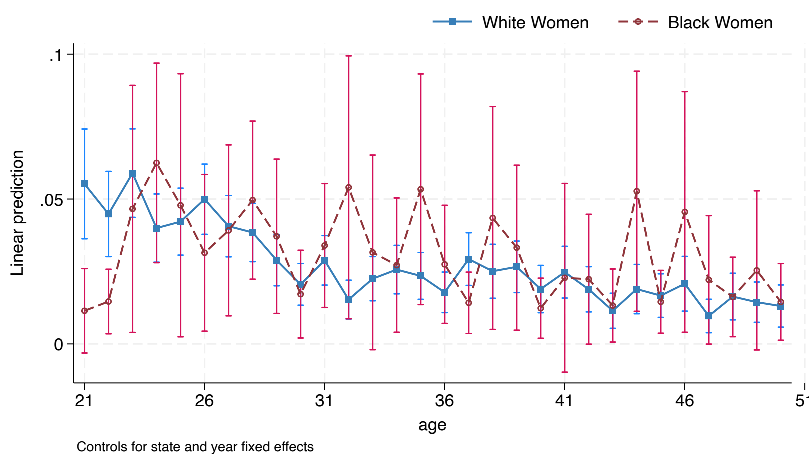


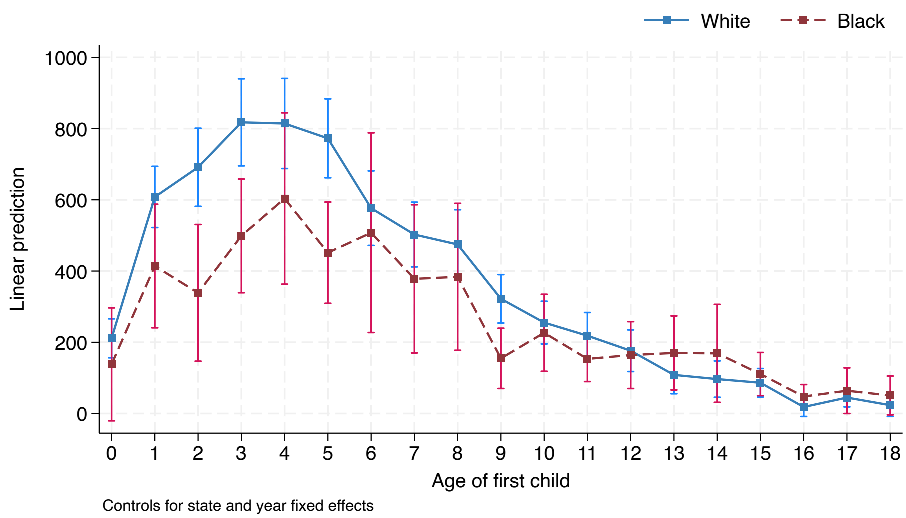
Figure A.22: Racial differences in the age profiles of women

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.9 Stylized fact 4: Childcare Expenditure and Transfer by Age of the Child

Figure A.37 shows that childcare expenditure and transfer by age of the child among full-time employed mothers. The figure shows that childcare expenditure is higher for White mothers than Black mothers, especially for children aged 1-6. This suggests that while Black mothers may spend less on childcare, they receive more support through transfers, which may help offset the costs of childcare. However, there is no statistically racial difference in the transfer received.

(a) Childcare expenditure



(b) Transfer

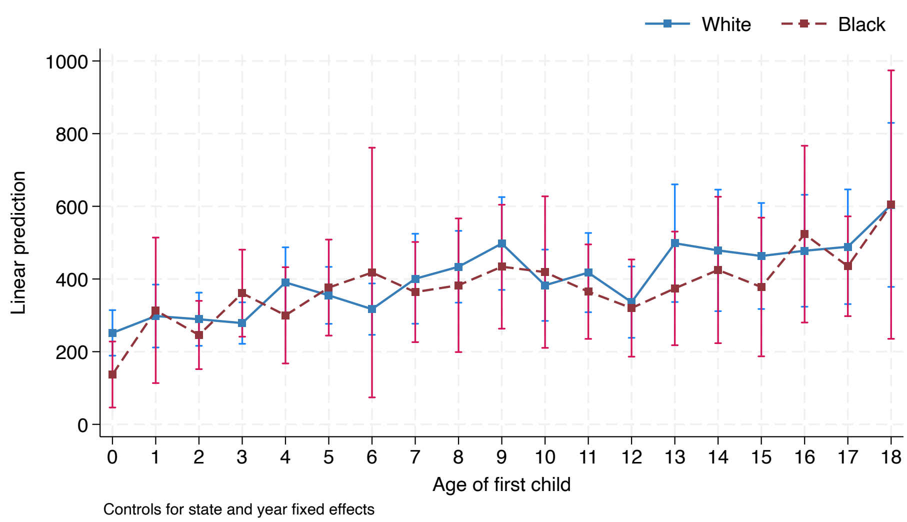


Figure A.23: Racial differences in the age profiles of children

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.10 Education

PSID data shows disparities in educational attainment by race and gender. Among White males, 47.88% have attained education beyond high school, with an average maximum degree level of 13.13 years. For Black males, this figure is significantly lower, with only 29.63% achieving education beyond high school, and an average maximum degree level of 12.32 years. White females show higher attainment, with 53.86% having education levels above high school and an average maximum degree of 13.46 years, compared to 45.89% of Black females, whose average maximum degree is 12.91 years. These results underscore substantial racial and gender disparities in post-secondary educational outcomes.

However, the level of assortative mating by education is similar between black and white population as show in figure A.24.

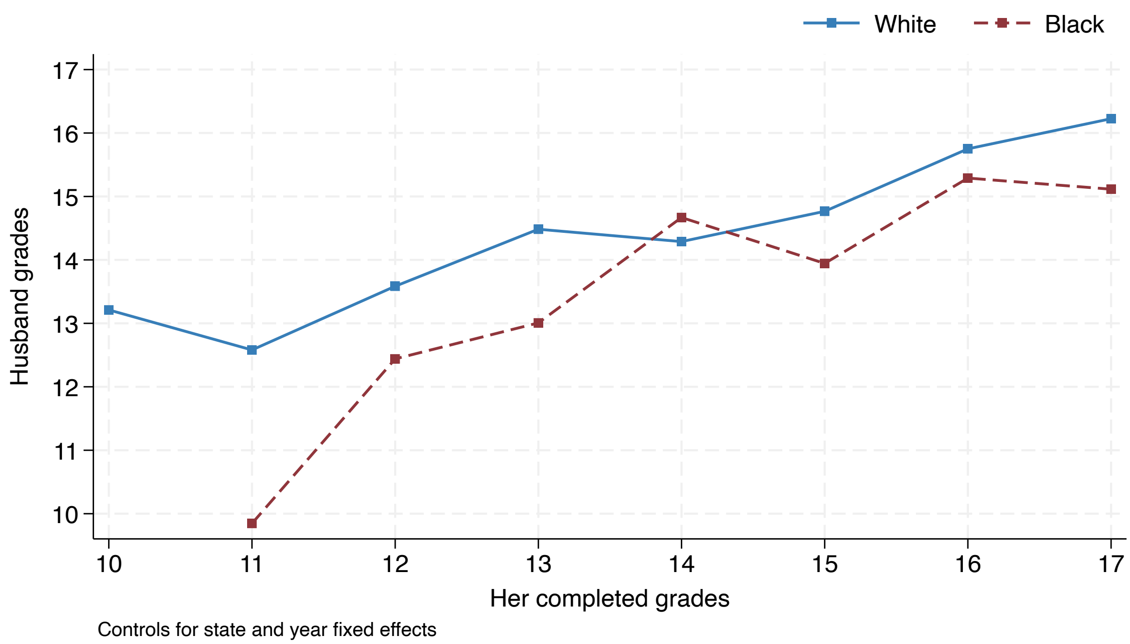


Figure A.24: Assortative mating of education by race

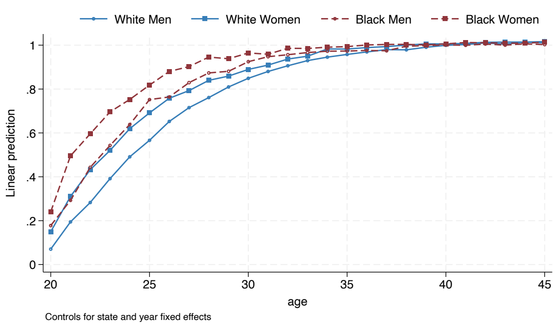
Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.10.1 Age profile by own education

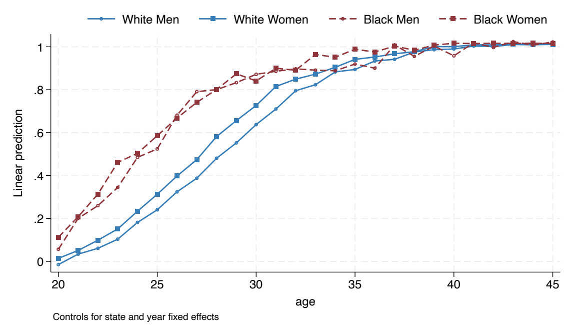
A.11 Age profile by spouse education

The data examines spousal educational attainment before the age of 26, focusing on degrees exceeding high school graduation in PSID. Among White males, 65.84% have spouses who attained education beyond high school by age 26, with an average spousal schooling of 14.12 years. For Black males, the percentage is lower

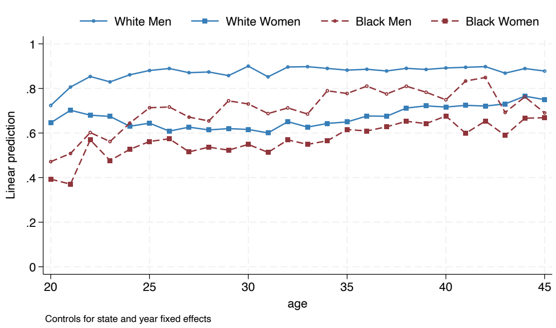
(a) Fraction of individuals with first child born (below high school graduate)



(c) Fraction of women with first child born (high school graduate and beyond)



(b) Annual employment (below high school graduate)



(d) Annual employment (high school graduate and beyond)

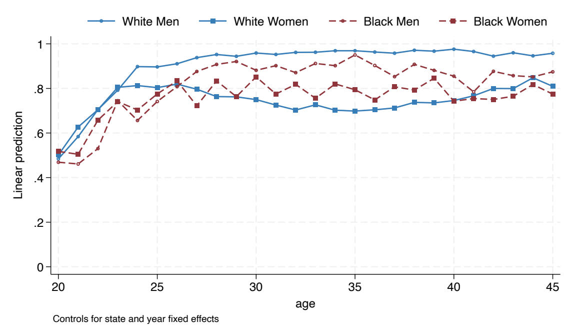
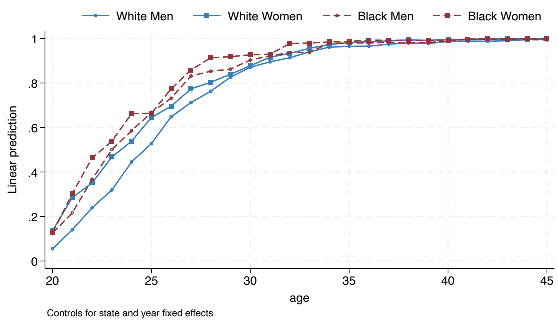


Figure A.25: Racial differences in the age profiles by education level

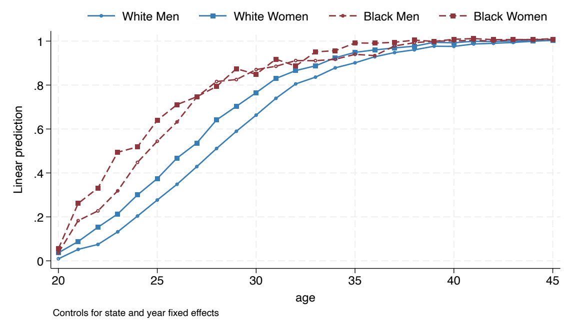
Notes: The sample consists of individuals having their first child between 20 and 45. Weights for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017.

at 61.04%, with an average spousal schooling of 13.63 years. Among females, 62.54% of White women have spouses with education beyond high school, averaging 14.01 years of schooling, while only 45.10% of Black women have similarly educated spouses, with an average spousal schooling of 12.88 years. These findings highlight significant racial disparities in spousal educational attainment for couples by age 26.

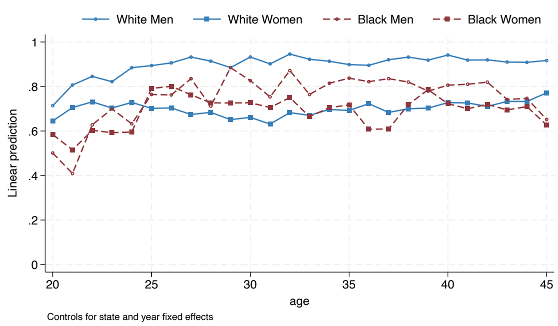
(a) Fraction of women with first child born (edu0)



(c) Fraction of women with first child born (edu1)



(b) Annual employment (edu0)



(d) Annual employment (edu1)

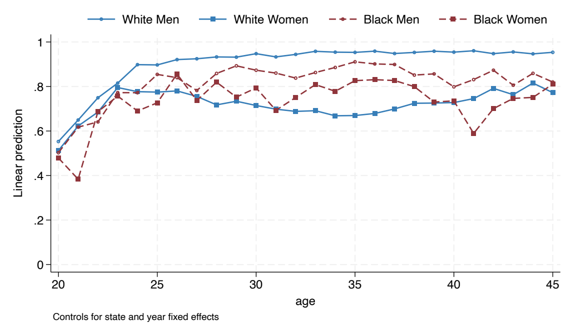
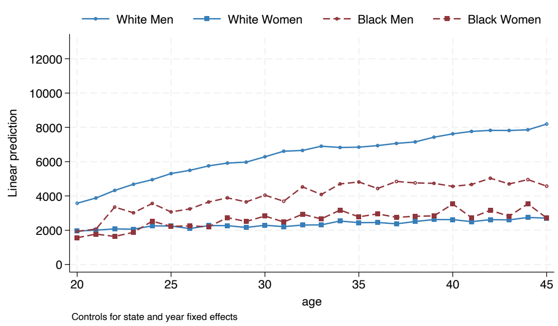


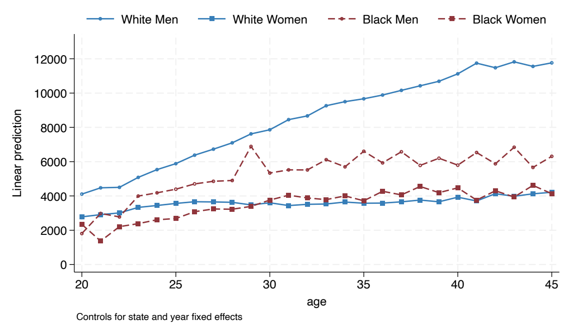
Figure A.26: Racial differences in the age profiles

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017.

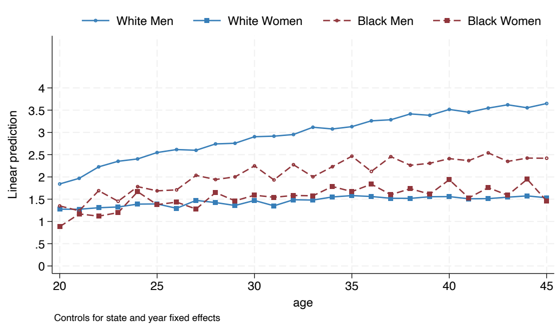
(a) Annual labor income (edu0)



(c) Annual labor income (edu1)



(b) Hourly wage rate (edu0)



(d) Hourly wage rate (edu1)

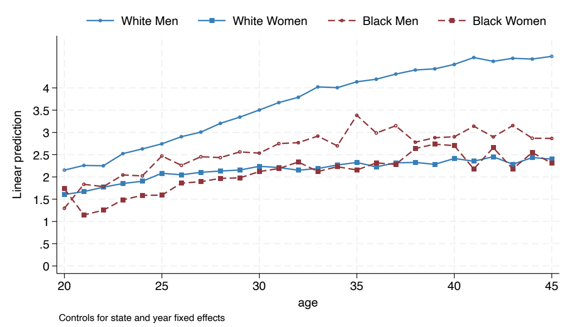
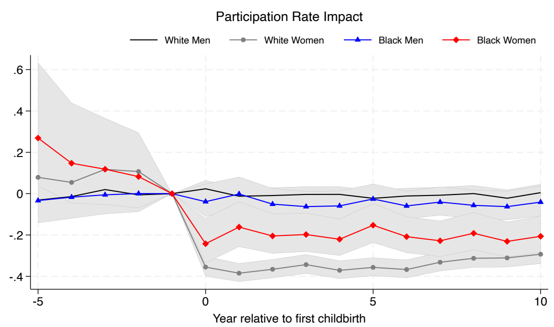


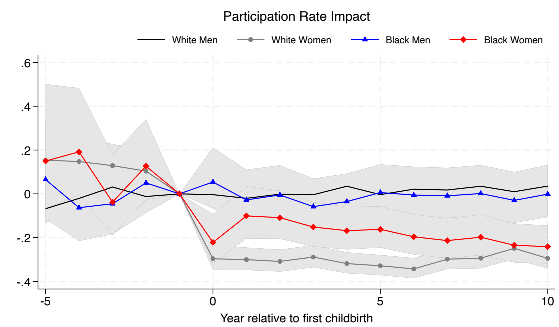
Figure A.27: Racial differences in the age profiles

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal weight are used. Source: Panel Study of Income Dynamics, 1967 to 2017.

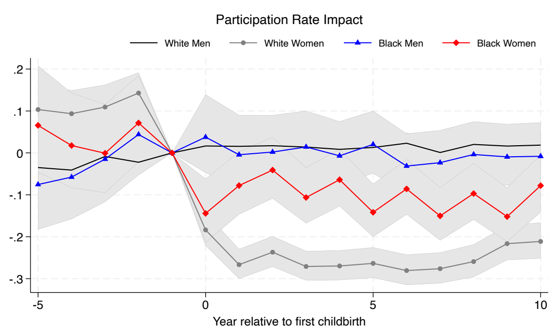
(a) Employment (own education: below high school graduation)



(b) Employment (spouse education: below high school graduation)



(c) Employment (own education: high school graduation and above)



(d) Employment (spouse education: high school graduation and above)

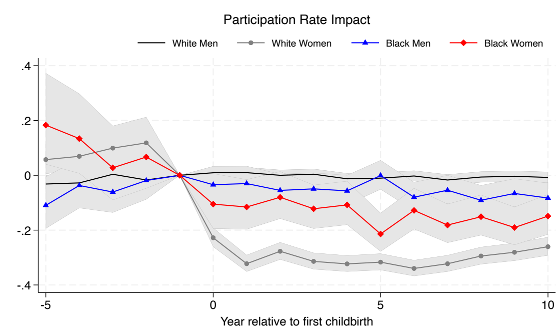


Figure A.28: Racial differences in the child penalties

Notes: The sample consists of individuals having their first child between 20 and 45. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.12 Different wage growth

Table A.9: Wage growth

	Men		Women	
	White	Black	White	Black
	(1)	(2)	(3)	(4)
Age	0.006***	0.005***	0.009***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Age × High school graduate	0.009***	0.005**	0.001	0.005***
	(0.001)	(0.002)	(0.001)	(0.001)
Constant	-0.247***	-0.290***	-0.491***	-0.606***
	(0.018)	(0.027)	(0.019)	(0.026)
N	36935	12903	29009	12816
R^2	0.066	0.021	0.050	0.066

Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

A.13 Variable description

Total labor income This is the sum of the actual amounts of labor part of farm income and business income, bonuses, overtime, commissions, professional practice, trade.

This variable is the sum of several labor income components from the raw data, including, in addition to wages and salaries (ER20425), any separate reports of bonuses (ER20427), overtime (ER20429), tips (ER20431), commissions (ER20433), professional practice or trade (ER20435), market gardening (ER20437), miscellaneous labor income (ER20439), and extra job income (ER20441).

Childbirth The values for this variable indicate the total number of children born to this individual as of the wave indicated in ER32021. For a detailed description of the types of people about whom birth history information was gathered, see the 1985-2021.

Institutionalization ER32002(All Years) "WTR EVER CODED INSTITUTIONAL"

Whether Individual Was Ever Institutionalized While Connected to a Responding Family

The values for this variable represent the actual number of individuals (1-9) who were incarcerated in penal institutions. Such individuals must conform to the rule at V13653, and their values for V30552 must equal 12. Count 6,999 99.73 % 0 None

This variable is generated by selecting individuals whose sequence numbers have been in the range 51-59 in any year from 1969 through the present and/or whose person numbers are in the range 020-026 (thus indicating institutionalization in 1968 if core, 1990 if Latino, 1997/1999 if 97 Immigrant or 2017/2019 if 17 Immigrant). If such individuals had income during the portion of the year preceding their move out, this part-year income is included in the family-level data of the family whence they departed. In years following their institutionalization, no income questions were asked about them until they rejoined the family or split off.

6.63 percent 1 This individual has been in an institution while connected to a responding family for at least one year during the study.

Table A.10: Racial differences in annual labor income of women

	(1) Labor income	(2) Labor income	(3) Labor income	(4) Labor income
Childbirth	-1487.787***	-1262.568***	-1259.395***	-1171.749***
	(46.832)	(46.853)	(46.962)	(50.795)
Black X Childbirth	982.783***	835.814***	847.043***	764.934***
	(83.759)	(82.174)	(82.762)	(88.995)
Hisband labor income		-0.033***	-0.035***	-0.034***
		(0.006)	(0.006)	(0.006)
Hisband wage		-38.929***	-36.569***	-38.092***
		(12.837)	(12.826)	(13.909)
Married		-778.385***	-766.066***	-630.831***
		(53.194)	(53.412)	(58.508)
Non labor income			-0.036***	-0.036***
			(0.004)	(0.004)
Grades completed				250.998***
				(31.016)
year FE	Yes	Yes	Yes	Yes
age FE	Yes	Yes	Yes	Yes
N	41798	40397	40091	34949
R^2	0.035	0.055	0.056	0.050

Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

A.14 Data: Women

Table A.11: Female employment changes relative to childbirth controlled for age year and individual fixed effect

	(1) Employment	(2) transition_in	(3) transition_out
Childbirth	-0.283***	-0.403***	0.247***
	(0.009)	(0.038)	(0.014)
Black X Childbirth	0.173***	0.207***	-0.105***
	(0.019)	(0.070)	(0.031)
year FE	Yes	Yes	Yes
age FE	Yes	Yes	Yes
individual FE	Yes	Yes	Yes
N	27504	6554	10675
R^2	0.045	0.043	0.043

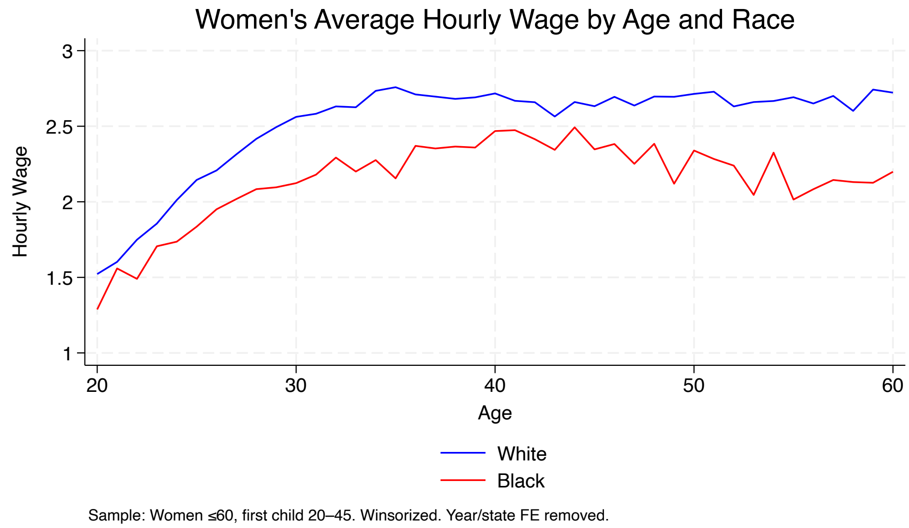
Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

Table A.12: Female employment changes relative to childbirth controlled individual fixed effect

	(1) Employment	(2) transition_in	(3) transition_out
Childbirth	-0.276***	-0.392***	0.245***
	(0.009)	(0.037)	(0.014)
Black X Childbirth	0.174***	0.212***	-0.104***
	(0.019)	(0.069)	(0.031)
year FE	Yes	Yes	Yes
individual FE	Yes	Yes	Yes
N	27504	6554	10675
R^2	0.042	0.037	0.040

Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

(a) Average Hourly Wage by Age and Race



(b) Coefficient of Variation (CV) of Hourly Wage by Age and Race

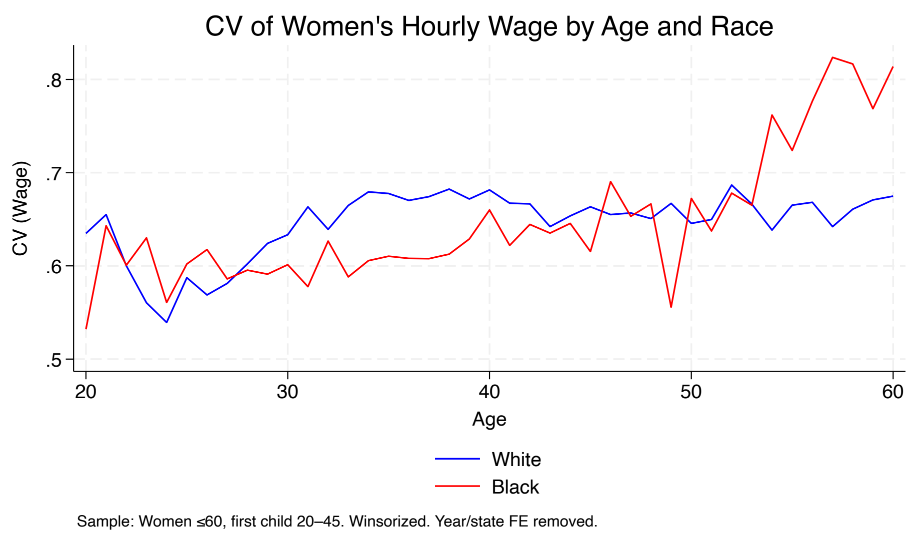
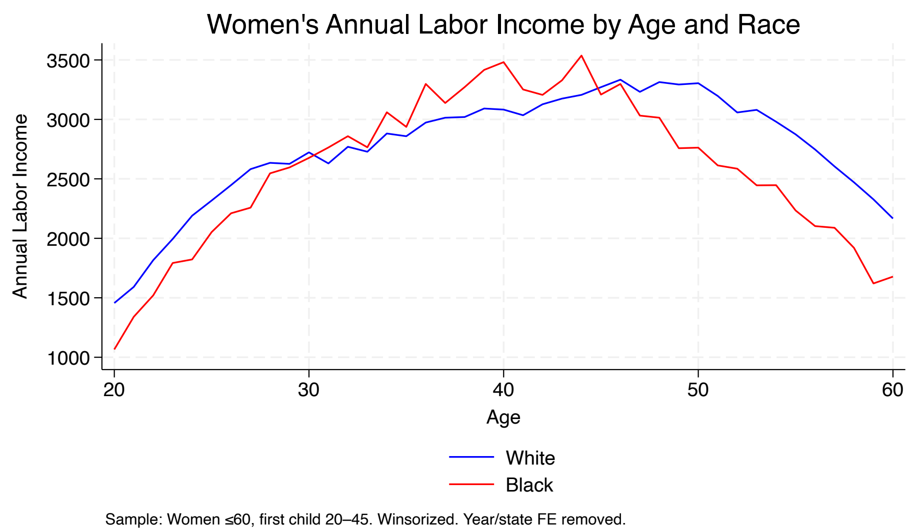


Figure A.29: Hourly Wage and its Variability by Age and Race

Notes: These figures show the average hourly wage and its coefficient of variation (CV) for women by age and race. The CV is calculated as the standard deviation divided by the mean. The sample consists of women aged 20–60, with their first child between ages 20–45, in male-headed households. CPI Deflated. Winsorized. Year & state FE removed.

(a) Average Annual Labor Income by Age and Race



(b) Coefficient of Variation (CV) of Annual Labor Income by Age and Race

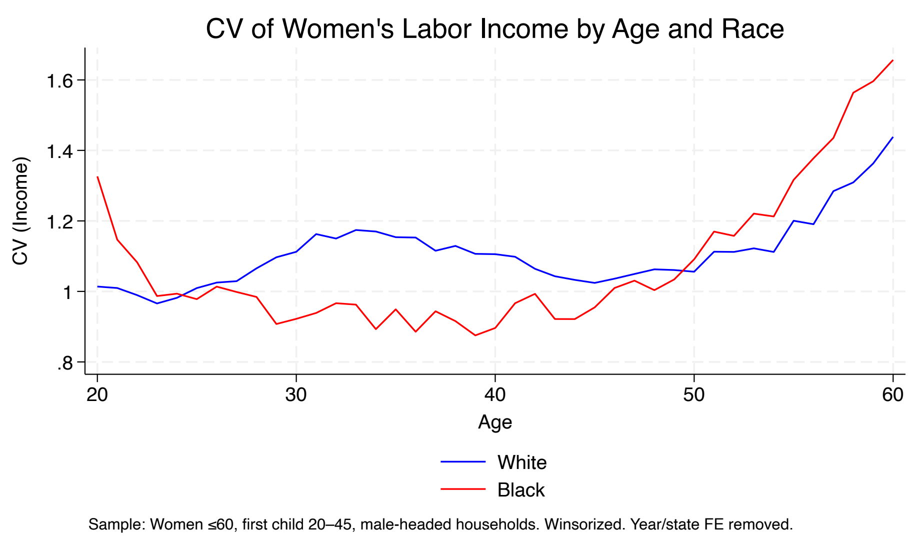
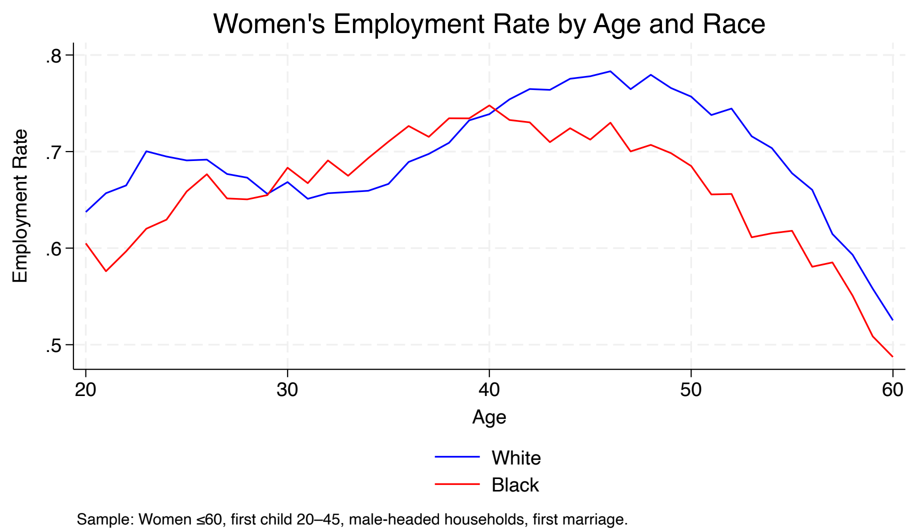


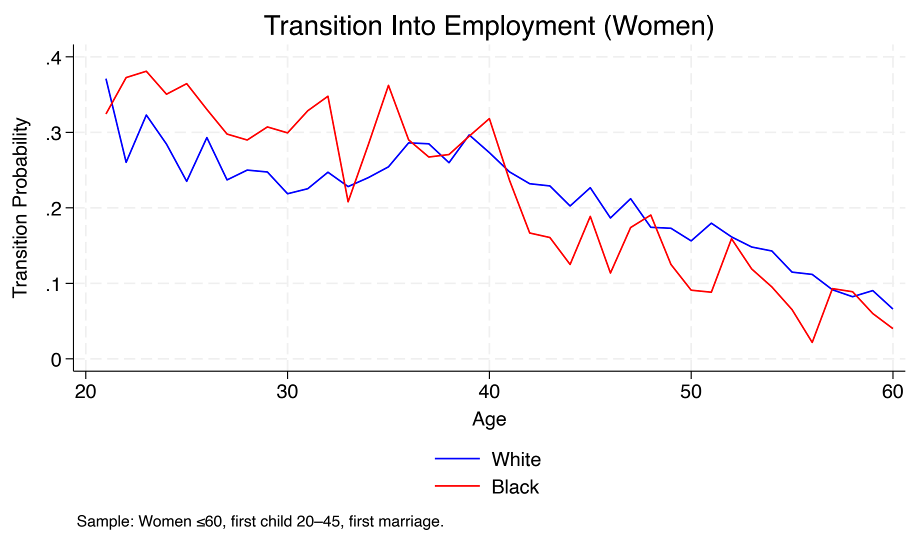
Figure A.30: Annual Labor Income and its Variability by Age and Race

Notes: These figures show the average annual labor income and its coefficient of variation (CV) for women by age and race. The CV is calculated as the standard deviation divided by the mean. The sample consists of women aged 20–60, with their first child between ages 20–45, in male-headed households. CPI Deflated. Winsorized. Year & state FE removed.

(a) Employment Rate by Age and Race



(b) Transition into Employment by Age and Race



(c) Transition out of Employment by Age and Race

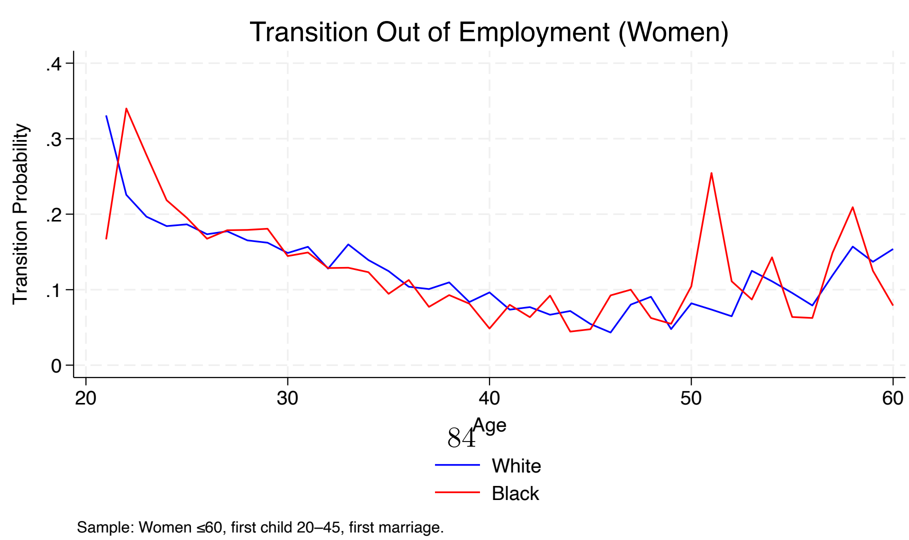


Figure A.31: Employment Rate and Transitions by Age and Race

Table A.13: Female employment changes relative to childbirth controlled for year fixed effects

	(1) Employment	(2) transition_in	(3) transition_out
Childbirth	-0.252***	-0.285***	0.113***
	(0.008)	(0.025)	(0.010)
Black X Childbirth	0.076***	0.083***	-0.031***
	(0.007)	(0.013)	(0.009)
year FE	Yes	Yes	Yes
N	27504	6554	10675
R^2	0.057	0.030	0.018

Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

A.15 Data: Men

Table A.14: Male employment changes relative to childbirth controlled for age and year fixed effects

	(1) Employment	(2) transition_in	(3) transition_out
Childbirth	0.010*	0.117	0.000
	(0.006)	(0.110)	(0.007)
Black X Childbirth	-0.056***	-0.318*	0.043**
	(0.012)	(0.190)	(0.017)
year FE	Yes	Yes	Yes
age FE	Yes	Yes	Yes
N	29012	1414	16836
R^2	0.010	0.089	0.012

Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

Table A.15: Male employment changes relative to childbirth controlled for year fixed effects

	(1) Employment	(2) transition_in	(3) transition_out
Childbirth	0.014**	0.114	-0.002
	(0.006)	(0.107)	(0.007)
Black X Childbirth	-0.056***	-0.305	0.044***
	(0.012)	(0.188)	(0.017)
year FE	Yes	Yes	Yes
N	29012	1414	16836
R^2	0.007	0.043	0.008

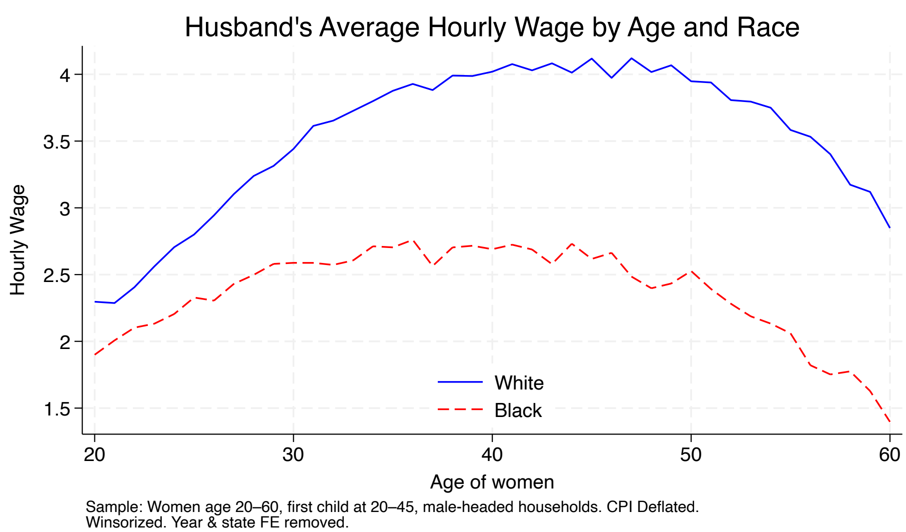
Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

Table A.16: Male employment changes relative to childbirth without fixed effects

	(1) Employment	(2) transition_in	(3) transition_out
Childbirth	0.016***	-0.029	-0.006
	(0.004)	(0.046)	(0.005)
Black X Childbirth	-0.079***	-0.131***	0.040***
	(0.004)	(0.028)	(0.004)
year FE	Yes	Yes	Yes
N	29012	1414	16836
R^2	0.021	0.031	0.013

Notes: Sample: PSID individuals first child between the ages of 20 and 45. Standard errors are in parentheses. PSID Longitudinal weights applied. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Source: PSID.

(a) Average Hourly Wage by Age and Race



(b) Coefficient of Variation (CV) of Hourly Wage by Age and Race

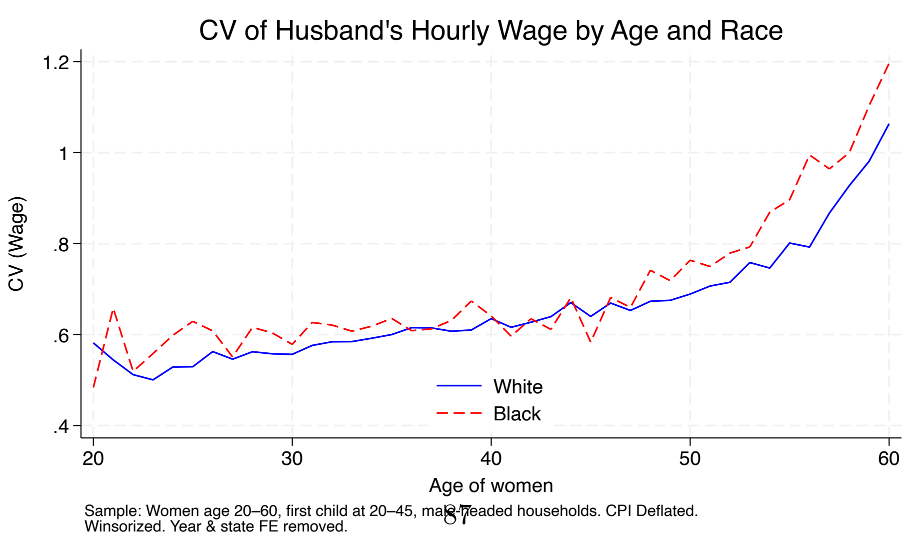
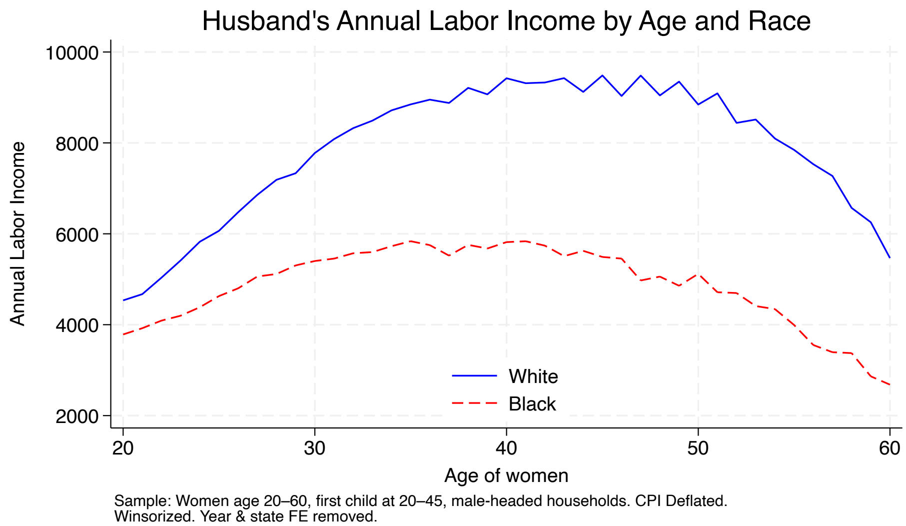


Figure A.32: Hourly Wage and its Variability by Age and Race

Notes: These figures show the average hourly wage and its coefficient of variation (CV) for men by age and

(a) Average Annual Labor Income by Age and Race



(b) Coefficient of Variation (CV) of Annual Labor Income by Age and Race

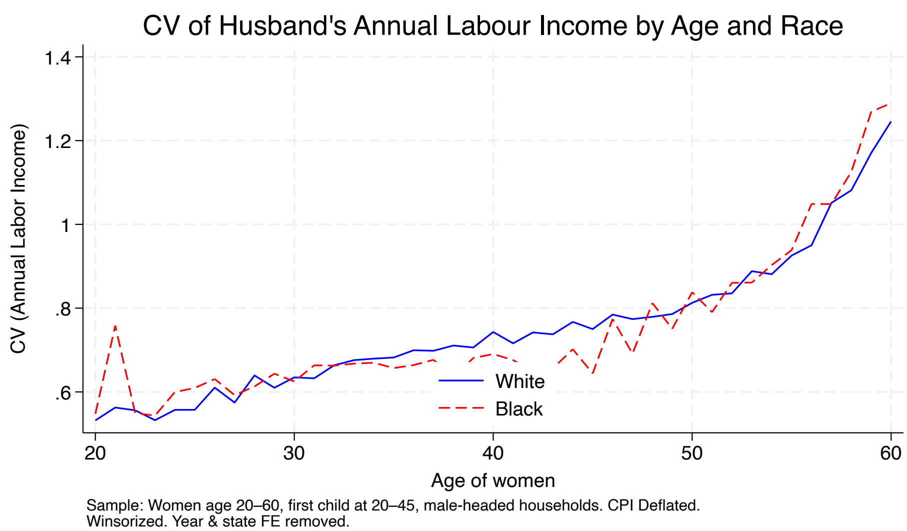


Figure A.33: Annual Labor Income and its Variability by Age and Race

Notes: These figures show the average annual labor income and its coefficient of variation (CV) for men by age and race. The CV is calculated as the standard deviation divided by the mean. The sample consists of women aged 20–60, with their first child between ages 20–45, in male-headed households. CPI Deflated. Winsorized. Year & state FE removed.

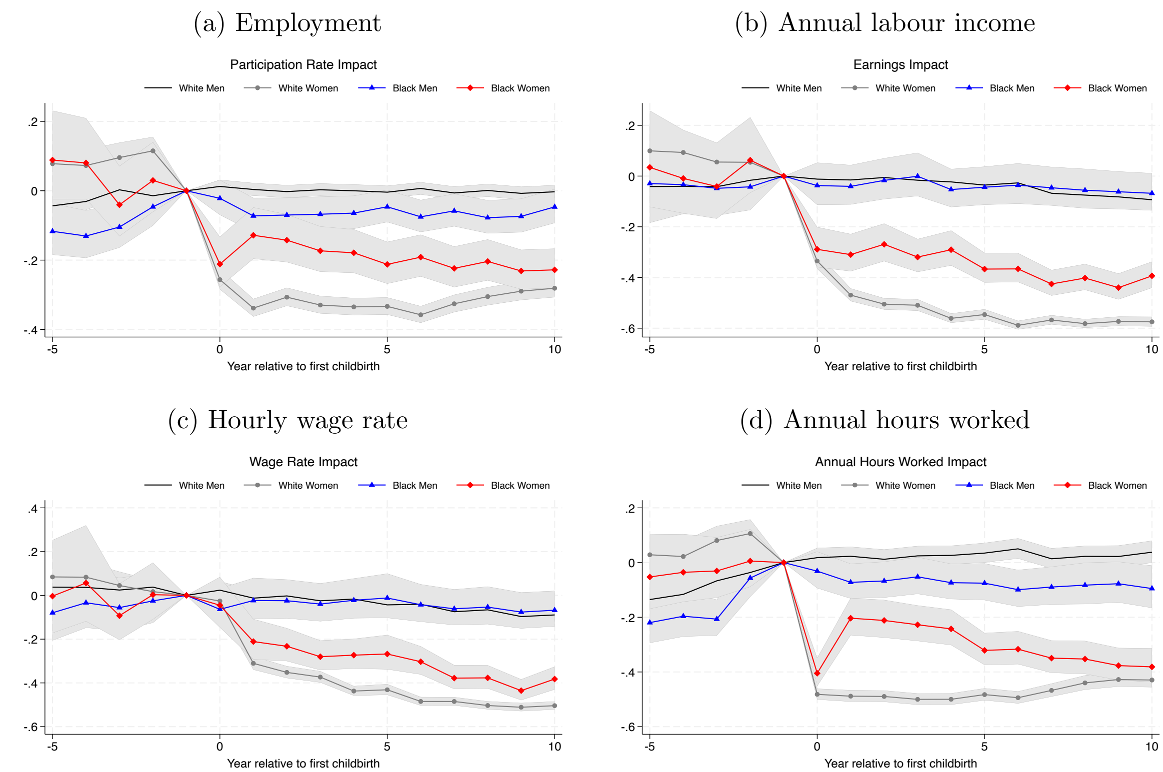


Figure A.34: Racial differences in the child penalties

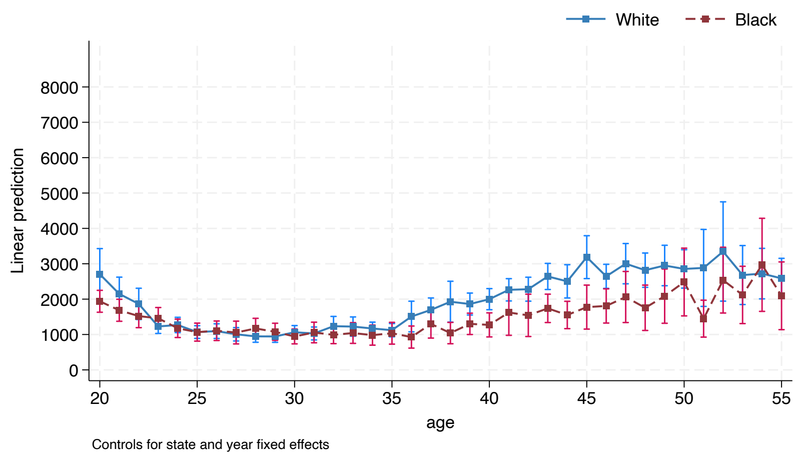
Notes: The sample consists of individual having their first child between 20 and 45. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.16 Event study among children born in first marriage

A.17 Assets

In the PSID, total household assets are constructed by summing the values of six key asset types and adjusting for liabilities and home equity. These asset types include ownership in any farm or business, liquid financial assets such as money in checking and savings accounts, money market funds, certificates of deposit, government savings bonds, treasury bills, and retirement accounts. Additionally, the value of any real estate other than the primary home, such as second homes, land, or rental properties, is included. Shares in publicly held corporations, mutual funds, investment trusts, and stocks held in retirement accounts are also factored into the total. The net value of vehicles and recreational assets like cars, motor homes, trailers, and boats, after subtracting any remaining debt on them, is added to the calculation, along with other savings or assets such as bond funds, cash value in life insurance policies, valuable collections, or rights in trusts or estates. After summing all these assets, the household's total debt, including credit card balances, student loans, medical debts, and other personal liabilities, is subtracted. Lastly, home equity is added, calculated as the difference between the current market value of the primary residence and the outstanding mortgage balance. This process results in a comprehensive measure of total net wealth, incorporating various assets, debts, and real estate equity.

(a) Non labor income (edu0)



(b) Non labor income (edu1)

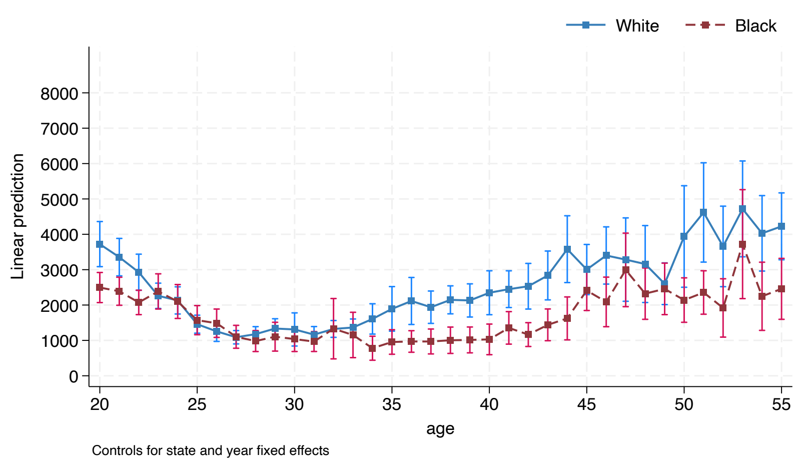
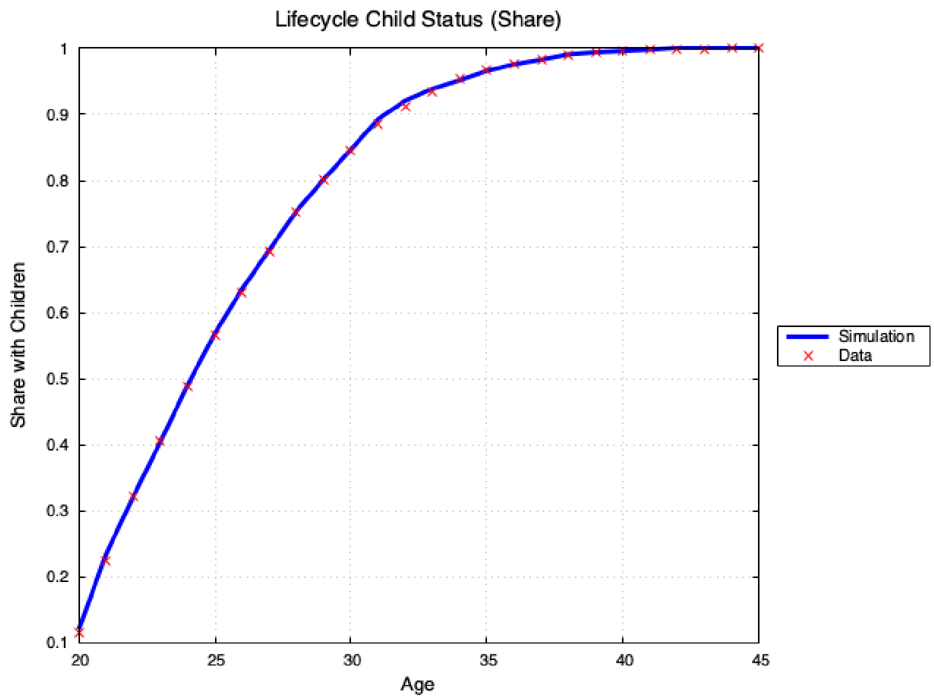


Figure A.35: Racial differences in the age profiles of women

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

(a) Simulation



(b) Transfer

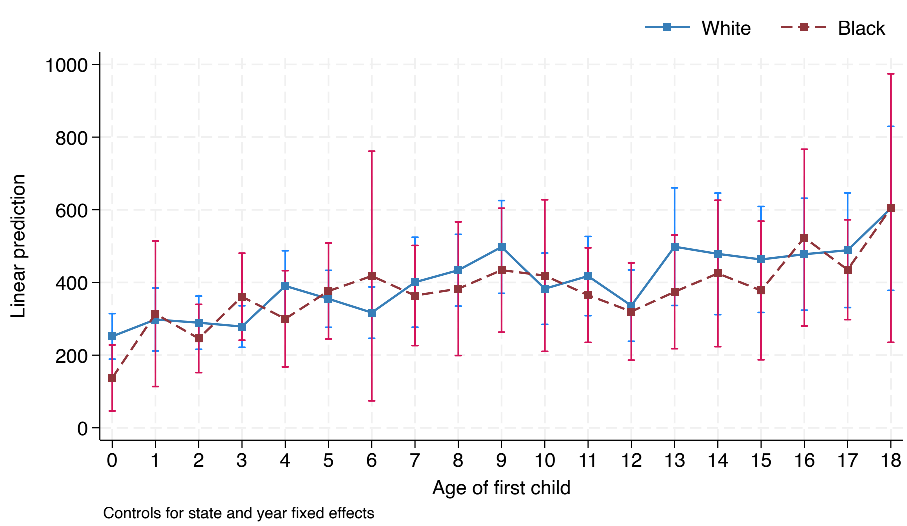


Figure A.36: Racial differences in the age profiles of children

Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

(a) Wealth

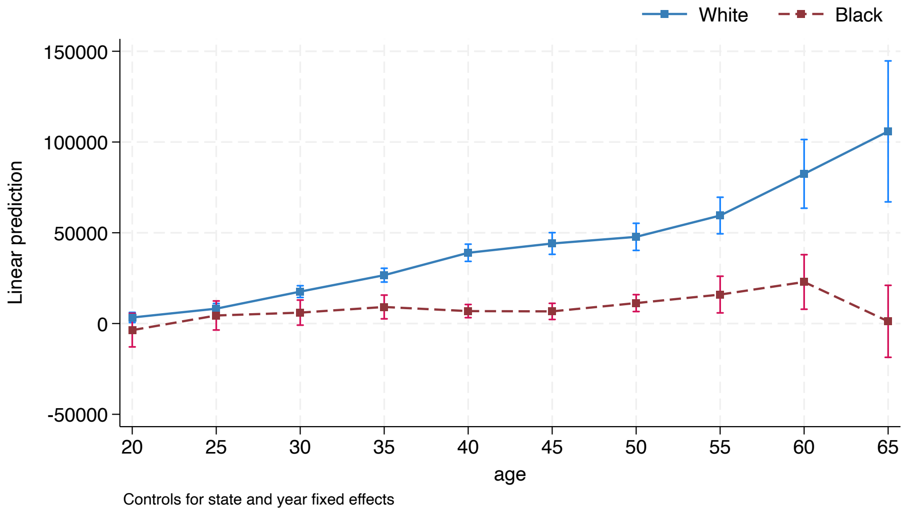
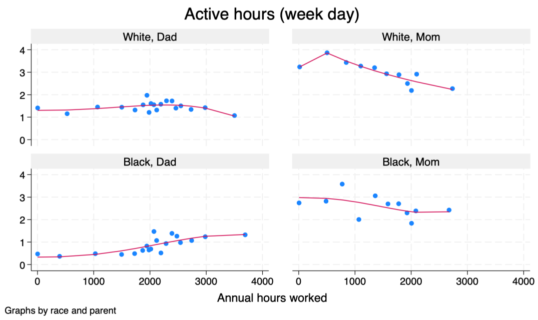


Figure A.37: Racial differences in the age profiles of women

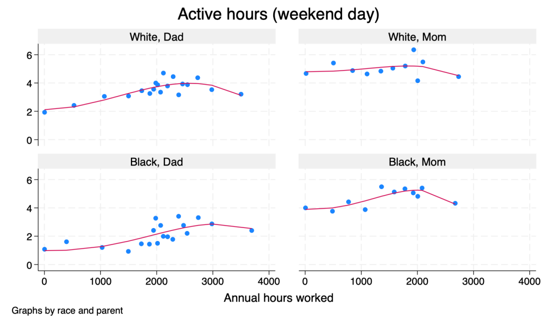
Notes: The sample consists of individual having their first child between 20 and 45. Weightes for PSID Longitudinal Weight used. Source: Panel Study of Income Dynamics, 1967 to 2017.

A.18 Parenting Time by Race and Parental Work Hours

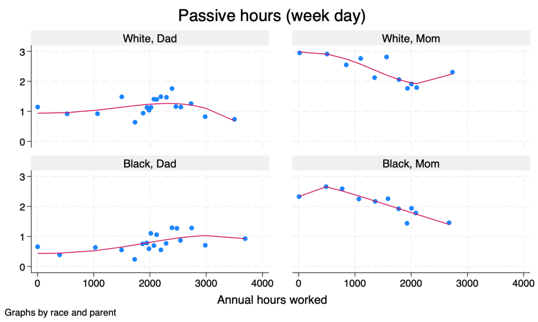
(a) Active Weekday Parenting



(b) Active Weekend Parenting



(c) Passive Weekday Parenting



(d) Passive Weekend Parenting

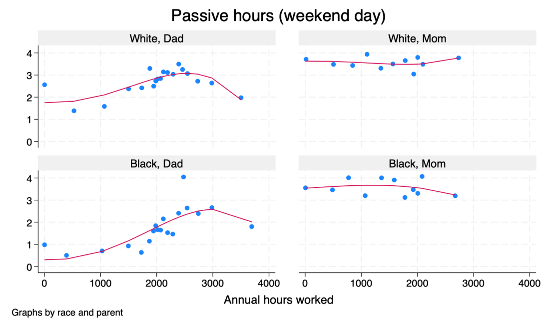
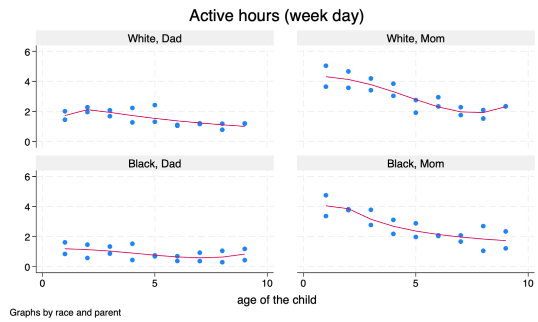


Figure A.38: Parenting time (active and passive) by race and parental work hours, weekdays and weekends

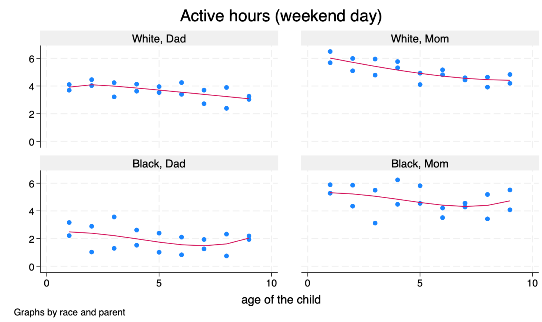
Notes: Each panel shows the relationship between parental work hours and parenting time (active or passive) on weekdays and weekends, by race. Fitted lines are from fractional polynomial regression.

A.19 Parenting Time by Age, Race, and Parental Status (No Employment Overlay)

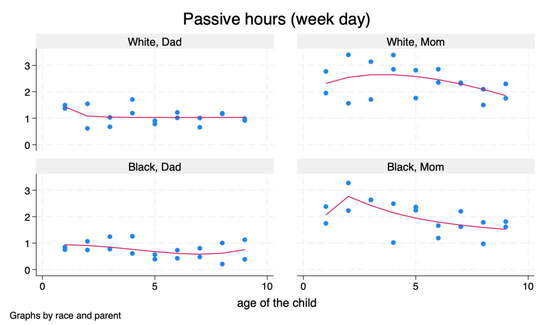
(a) Active Weekday Parenting



(b) Active Weekend Parenting



(c) Passive Weekday Parenting



(d) Passive Weekend Parenting

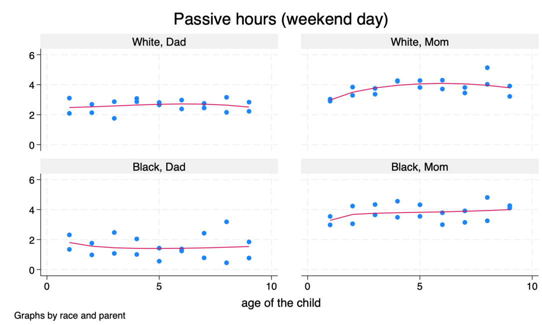


Figure A.39: Parenting time (active and passive) by age, race, and parental status. Each panel shows the relationship without employment overlay.

B A simple model of household specification and differential wage growth

How differential wage growth may influence female and male labor supply in the households? To fix ideas, a two period model of labor supply is presented here. This model is very stylzed in order to bring economic insight in a sharp way. In the next step, a full life cycle model in later section will be used to quantify the contribution of wage growth in explaining the racial gap in child penalties alongside uncertainty in other dimensions household facing, such as divorce risk, fertility risk, husband income risk, and employment risk.

The economy is populated by married couples living for two periods. Household utility is derived from consumption, husband leisure and wife leisure.

$$U = \alpha \ln(c) + (1-\alpha)\ln(1-l_m) + (1-\alpha)\lambda \ln(1-l_f) \tag{46}$$

The variable c is consumption, l_m is husband leisure, l_f is wife leisure. The parameter α is the weight of consumption in the utility function. The parameter λ is the weight of wife leisure in the utility function across households following some cumulative distribution function $F(\lambda)$.

There are wage growth. If a woman decides to work in the first period, then second period wage will be $(1+x)w_f$. Different from Greenwood et al. (2017) in which there is no returns to experience for a man, there we allow male wage to also have wage growth that in the second period is $(1+y)w_m$. Child exists in the first period. Household discount the future at rate $\beta \in (0,1)$.

The household utility if the wife does not work in the first period is

$$\begin{aligned} V^{NW} =& \alpha \ln(w_m l_m) + (1-\alpha)\ln(1-l_m) + (1-\alpha)\lambda \ln(1-l_f) \\ &+ \beta\big[\alpha \ln(w_m(1+x)l_m + w_f l_f) + (1-\alpha)\ln(1-l_m) \\ &+ (1-\alpha)\lambda \ln(1-l_f)\big]. \end{aligned} \tag{47}$$

The household utility if the wife works in the first period is

$$\begin{aligned} V^{W} =& \alpha \ln(w_m l_m + w_f l_f - l_f p_c) + (1-\alpha)\ln(1-l_m) + (1-\alpha)\lambda \ln(1-l_f) \\ &+ \beta\big[\alpha \ln(w_m(1+x)l_m + w_f(1+y)l_f) + (1-\alpha)\ln(1-l_m) \\ &+ (1-\alpha)\lambda \ln(1-l_f)\big]. \end{aligned} \tag{48}$$

To search for the threshold of λ that makes the wife not work in the first period, we compare V^{NW} and V^{W}. The threshold is

$$V^{NW} \leq V^{W} \tag{49}$$

$$\begin{aligned} \hat{\gamma} =& \frac{\alpha}{1-\alpha}\Big[\frac{1}{\ln(1-I_c) - \ln(1-I_c-l_f)}\Big]\big[\ln(w_m l_m + w_f l_f - p_c l_f) - \ln(w_m I_m)\big] \\ &+ \beta\frac{\alpha}{1-\alpha}\Big[\frac{1}{\ln(1-I_c) - \ln(1-I_c-l_f)}\Big]\big[\ln(w_m(1+x)l_m + w_f(1+y)l_f) \\ &- \ln(w_m(1+x)I_m + w_f l_f)\big] \end{aligned} \tag{50}$$

PROPOSITION 1: married female labor force participation $(F(\hat{\lambda}))$is increasing in the husband wage growth rate x, increasing in gender gap of wage growth$(1+x)/(1+y)$ and decreasing in the wife wage growth rate y.

Proof:

$$\begin{aligned} \frac{\partial \hat{\gamma}}{\partial x} =& \frac{\alpha}{1-\alpha}\Big[\frac{1}{\ln(1-I_c) - \ln(1-I_c-l_f)}\Big]\big[-w_m l_m w_f l_f y\big] \\ & \frac{1}{\big[w_m(1+x)l_m + w_f(1+y)l_f\big]\big[w_m(1+x)l_m + w_f l_f\big]} < 0 \end{aligned} \tag{51}$$

Set gender gap in wage growth as $c = \frac{1+x}{1+y}$

$$\begin{aligned} \frac{\partial \hat{\gamma}}{\partial c} =& \frac{\alpha}{1-\alpha}\Big[\frac{1}{\ln(1-I_c) - \ln(1-I_c-l_f)}\Big]\big[-w_m l_m w_f l_f y(1+x)\big] \\ & \frac{1}{\big[w_m c(1+y)l_m + w_f(1+y)l_f\big]\big[w_m c(1+y)l_m + w_f l_f\big]} < 0 \end{aligned} \tag{52}$$

$$\frac{\partial \hat{\gamma}}{\partial y} = \frac{\alpha}{1-\alpha}\left[\frac{1}{\ln(1-I_c) - \ln(1-I_c-l_f)}\right] w_f l_f > 0 \tag{53}$$

This simple model explains that lower male wage growth in black households compared to white households lead to higher labor supply of women and less specialisation in household production.

C Distribution of Covariates Before and After IPW

This section presents the distribution of key covariates before and after inverse probability weighting (IPW), separately for Black and White women. The IPW procedure aims to balance the distribution of these covariates across groups, ensuring that the estimated racial gap in child penalties is not driven by differences in observable characteristics. The figures below show the distributions for each variable used in the IPW estimation.

Construction of Inverse Probability Weights (IPW):

Let X denote a covariate of interest (e.g., average annual mortgage payment, average husband hourly wage, etc.), measured as the individual-level lifetime mean. The IPW procedure is implemented as follows: The distribution of X is divided into K bins (here, $K = 100$), indexed by $k = 1, \ldots, K$. For each bin k, compute the empirical share of Black and White women:

$$b_k = \frac{\text{Number of Black women in bin } k}{\text{Total number of Black women}}$$

$$w_k = \frac{\text{Number of White women in bin } k}{\text{Total number of White women}}$$

For each individual i in bin k:

- If individual i is White, set $\text{IPW}_i = 1$.
- If individual i is Black, set

  $$\text{IPW}_i = \frac{w_k}{b_k}$$

  This reweights Black women so that their distribution of X matches that of White women.

The final IPW for each individual is the mean of the assigned weights across all observations for that individual:

$$\text{IPW}_{i,X} = \frac{1}{T_i}\sum_{t=1}^{T_i} \text{IPW}_{i,t}$$

where T_i is the number of observations for individual i.

C.0.1 Lifetime Average Annual Mortgage Payment

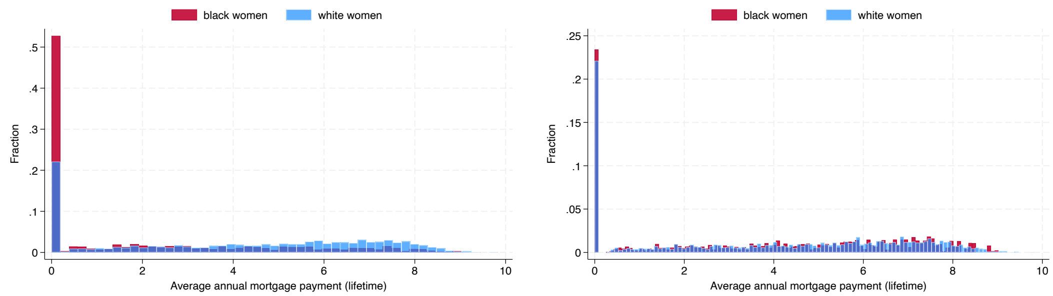


Figure C.1: Distribution of lifetime average annual mortgage payment before (left) and after (right) IPW, by race

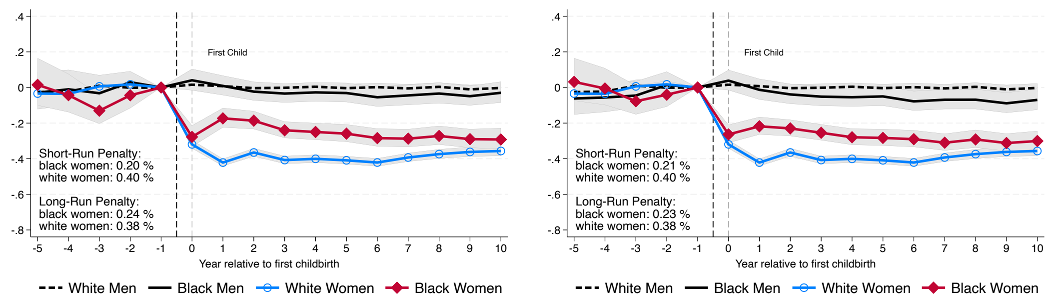


Figure C.2: Child penalty in employment, weights for mortgage applied (left: with weights, right: without weights)

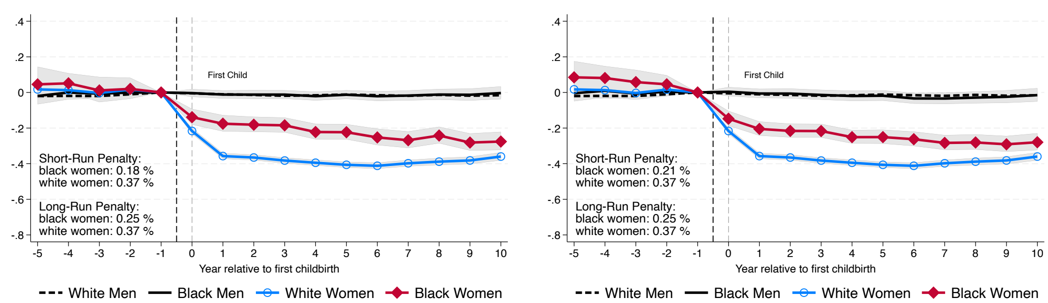


Figure C.3: Child penalty in labor income, weights for mortgage applied (left: with weights, right: without weights)

C.0.2 Lifetime Average Husband Hourly Wage

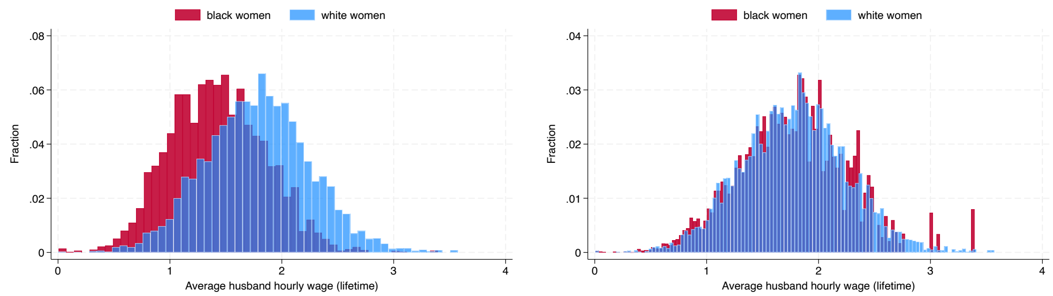


Figure C.4: Distribution of lifetime average husband hourly wage before (left) and after (right) IPW, by race

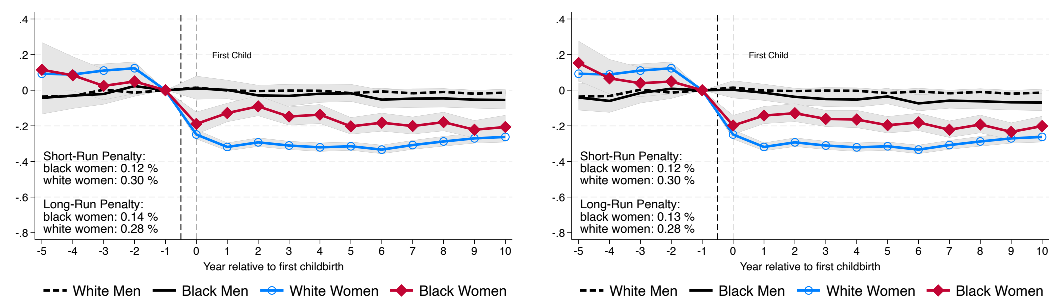


Figure C.5: Child penalty in employment, weights for `malwgrate` applied (left: with weights, right: without weights)

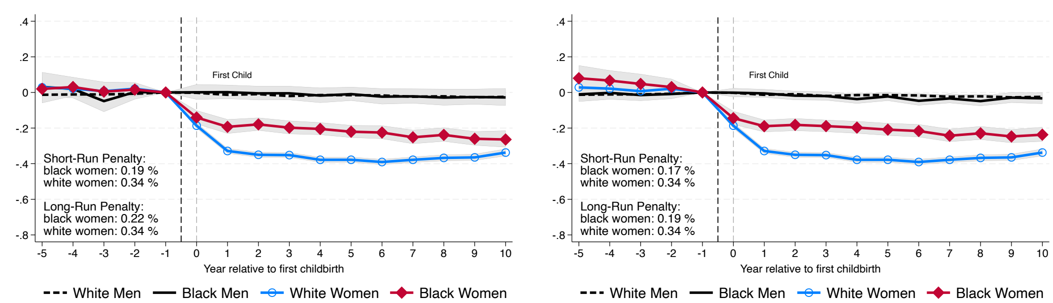


Figure C.6: Child penalty in labor income, weights for `malwgrate` applied (left: with weights, right: without weights)

C.0.3 Lifetime Average Husband Annual Labor Income

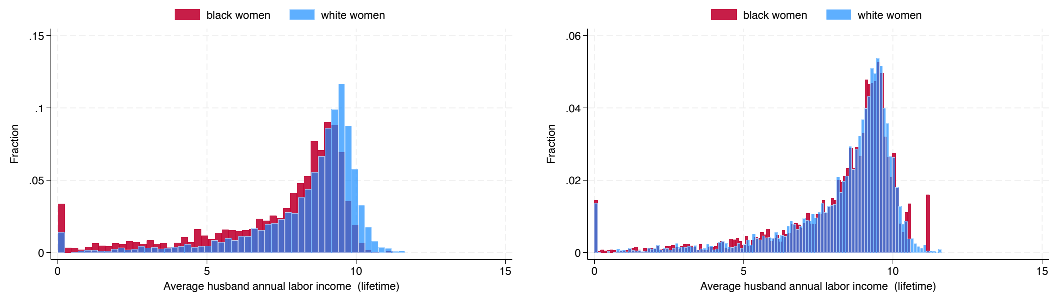


Figure C.7: Distribution of lifetime average husband annual labor income before (left) and after (right) IPW, by race

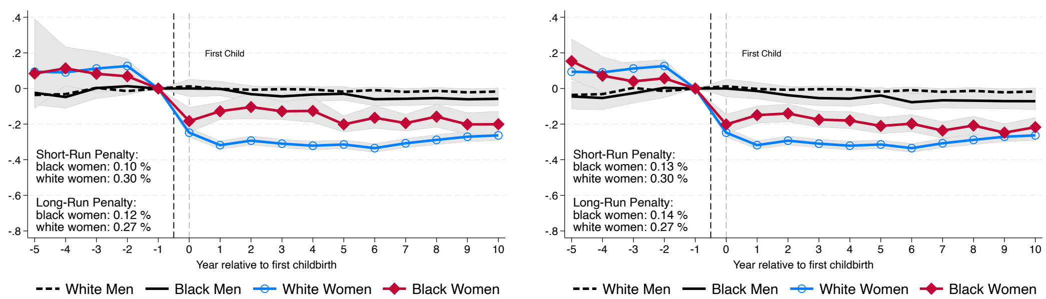


Figure C.8: Child penalty in employment, weights for `mallabinc` applied (left: with weights, right: without weights)

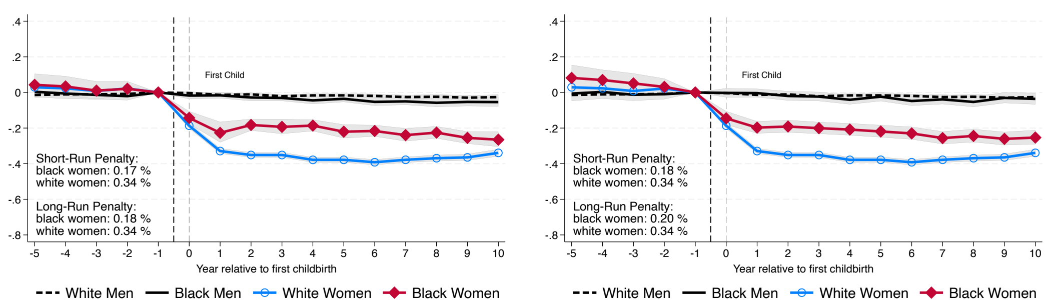


Figure C.9: Child penalty in labor income, weights for `mallabinc` applied (left: with weights, right: without weights)

C.0.4 Lifetime Average Non-Labor Income

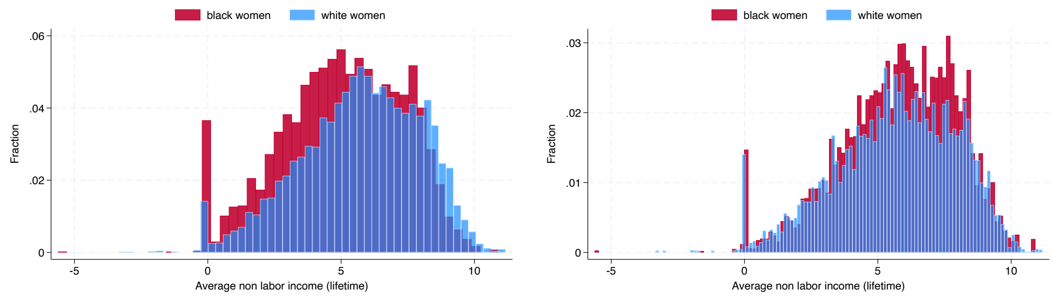


Figure C.10: Distribution of lifetime average non-labor income before (left) and after (right) IPW, by race

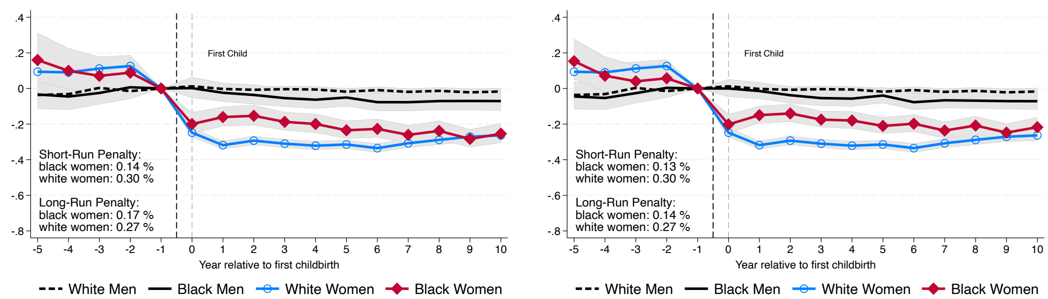


Figure C.11: Child penalty in employment, weights for `nonlabourinc2` applied (left: with weights, right: without weights)

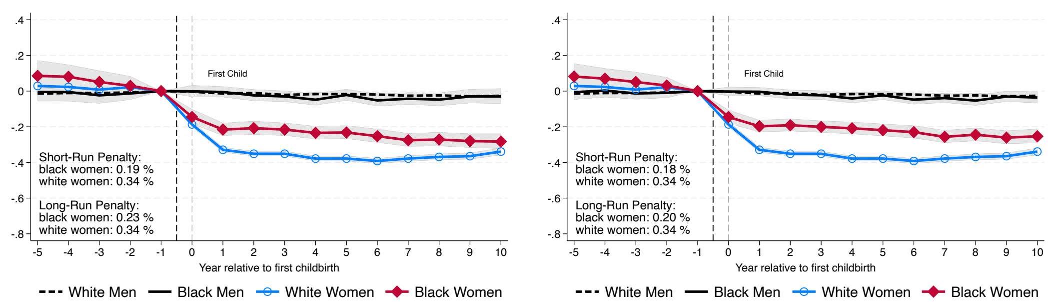


Figure C.12: Child penalty in labor income, weights for `nonlabourinc2` applied (left: with weights, right: without weights)

C.0.5 Lifetime Average Annual Debt

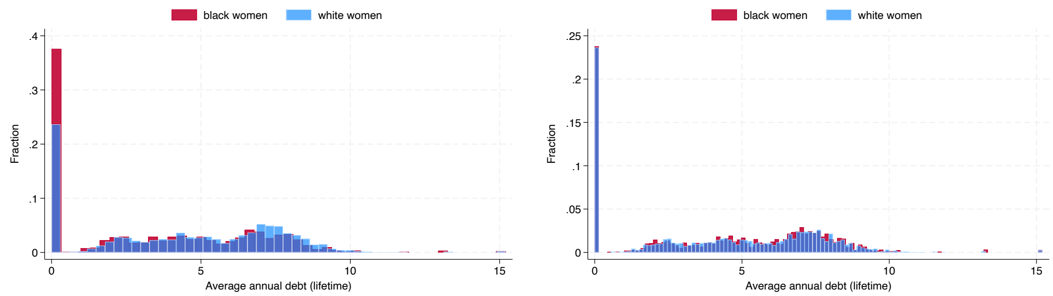


Figure C.13: Distribution of lifetime average annual debt before (left) and after (right) IPW, by race

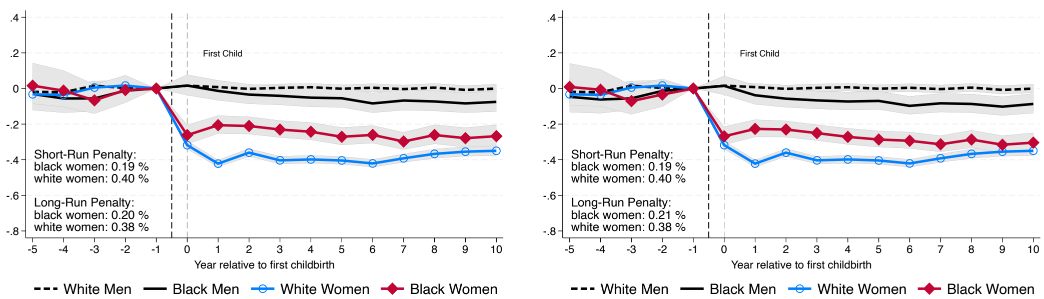


Figure C.14: Child penalty in employment, weights for `debt` applied (left: with weights, right: without weights)

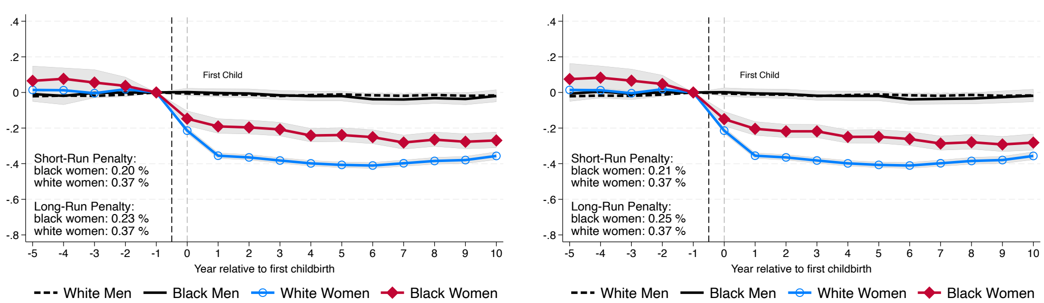


Figure C.15: Child penalty in labor income, weights for `debt` applied (left: with weights, right: without weights)

C.0.6 Years of Schooling

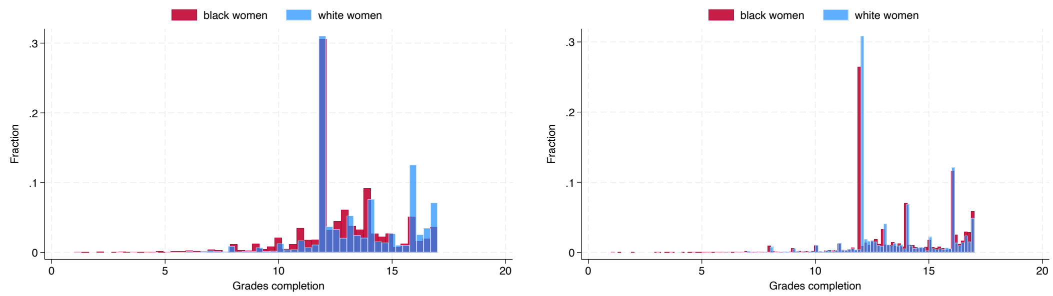


Figure C.16: Distribution of years of schooling before (left) and after (right) IPW, by race

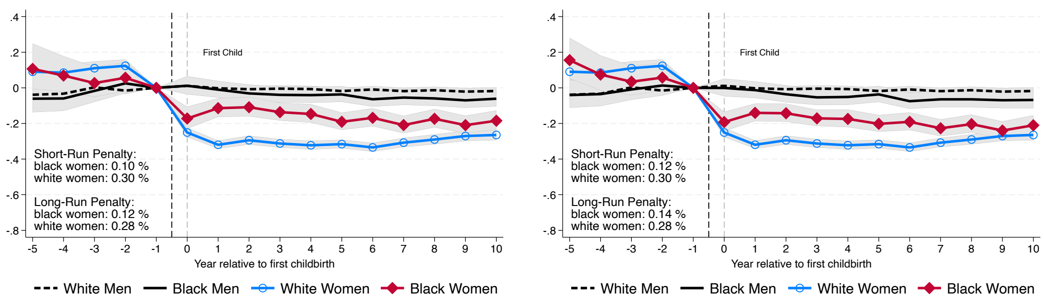


Figure C.17: Child penalty in employment, weights for schooling applied (left: with weights, right: without weights)

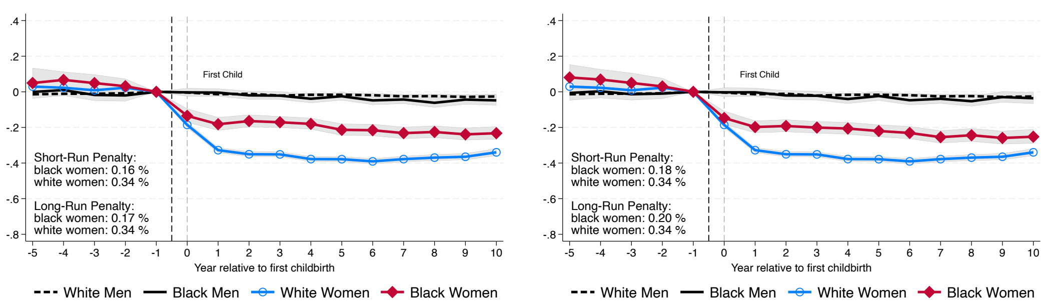


Figure C.18: Child penalty in labor income, weights for schooling applied (left: with weights, right: without weights)

C.0.7 Expectation of Children's Earnings

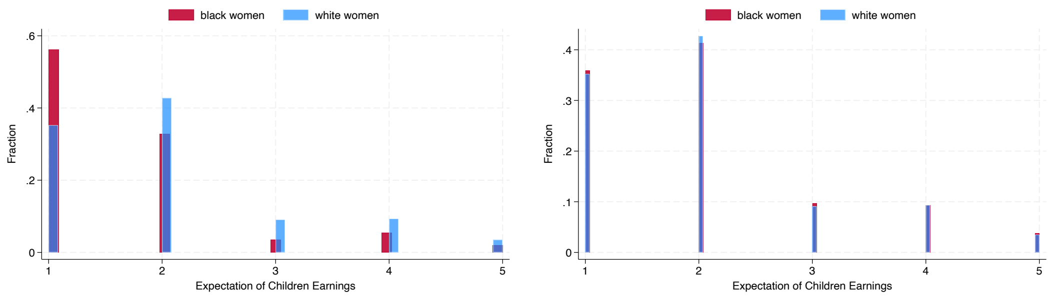


Figure C.19: Distribution of expectation of children's earnings before (left) and after (right) IPW, by race

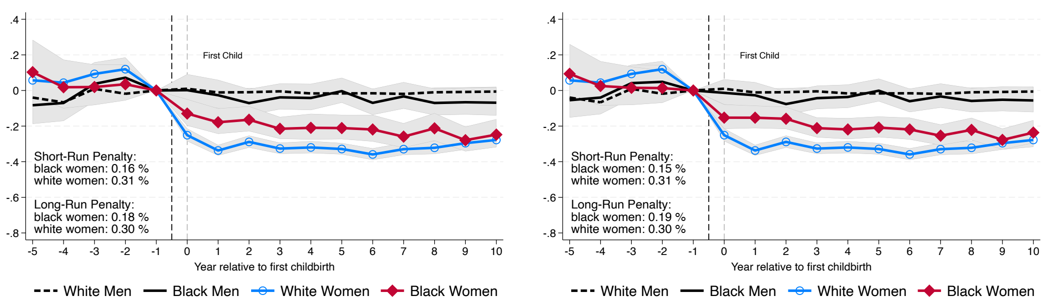


Figure C.20: Child penalty in employment, weights for expectation of children's earnings applied (left: with weights, right: without weights)

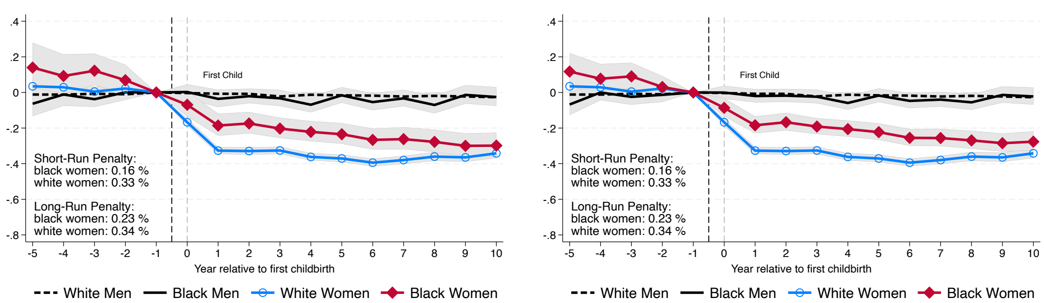


Figure C.21: Child penalty in labor income, weights for expectation of children's earnings applied (left: with weights, right: without weights)

C.0.8 Wife Job Insurance

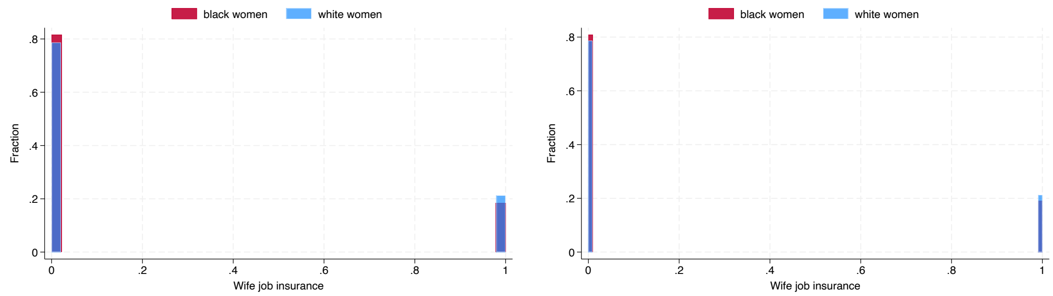


Figure C.22: Distribution of wife job insurance before (left) and after (right) IPW, by race

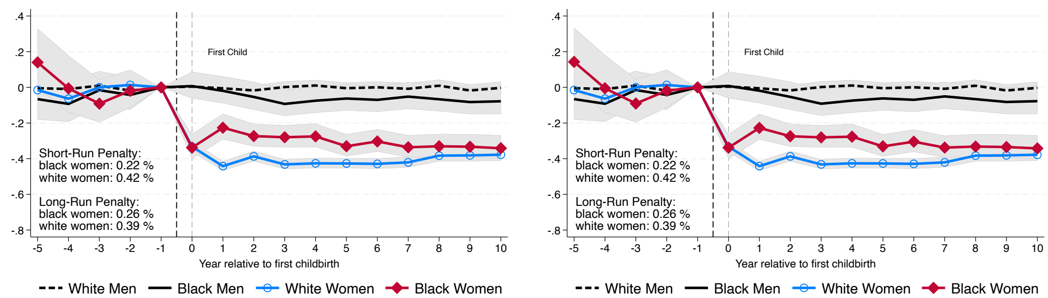


Figure C.23: Child penalty in employment, weights for job insurance applied (left: with weights, right: without weights)

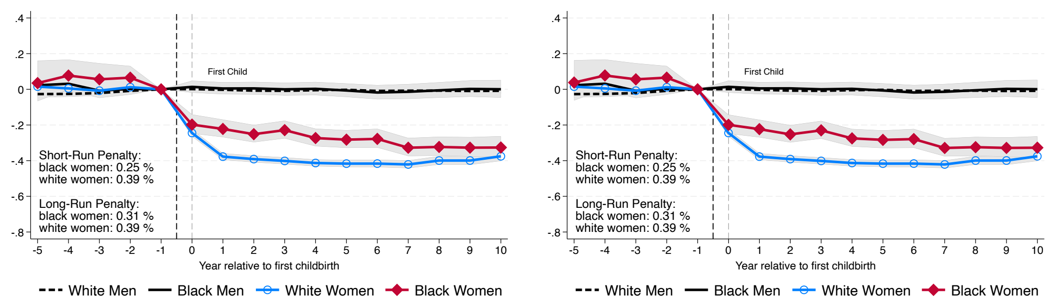


Figure C.24: Child penalty in labor income, weights for job insurance applied (left: with weights, right: without weights)

C.0.9 Number of Relatives Nearby

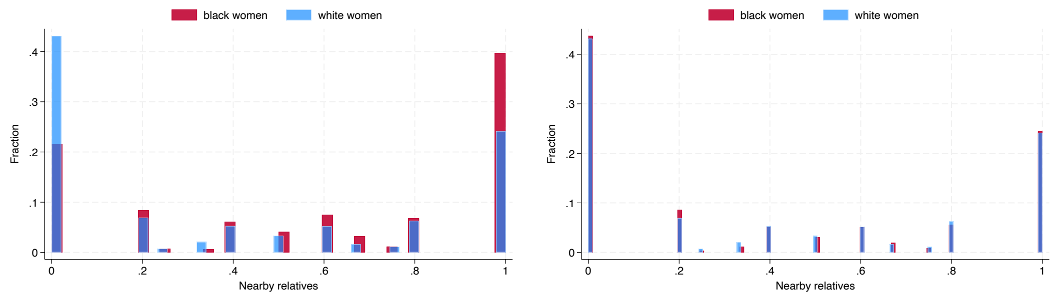


Figure C.25: Distribution of number of relatives nearby before (left) and after (right) IPW, by race

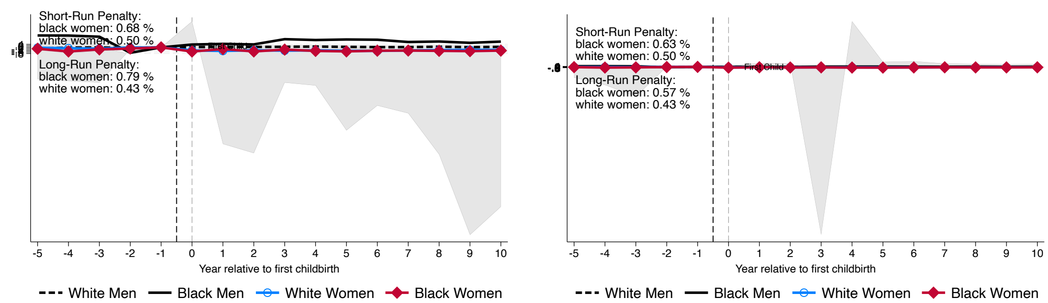


Figure C.26: Child penalty in employment, weights for number of relatives nearby applied (left: with weights, right: without weights)

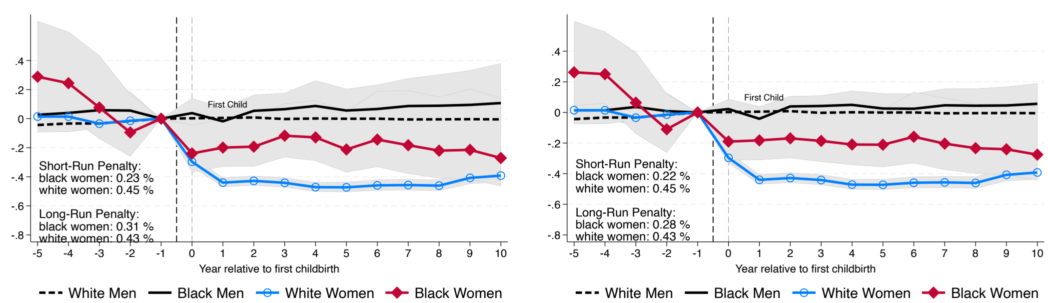


Figure C.27: Child penalty in labor income, weights for number of relatives nearby applied (left: with weights, right: without weights)

C.0.10 Female Occupation Indicator (`femocc`)

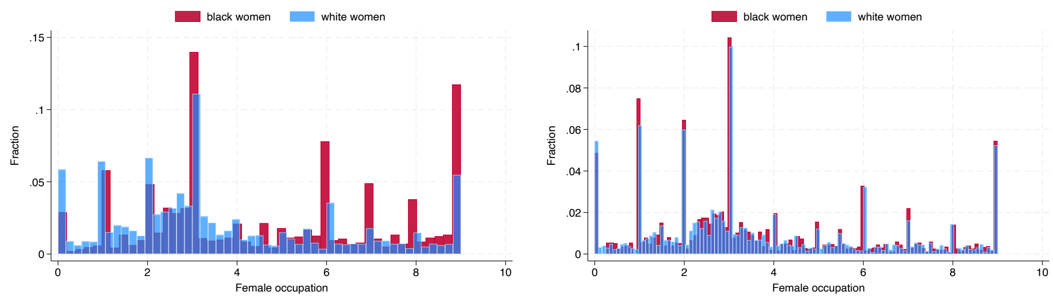


Figure C.28: Distribution of female occupation indicator before (left) and after (right) IPW, by race

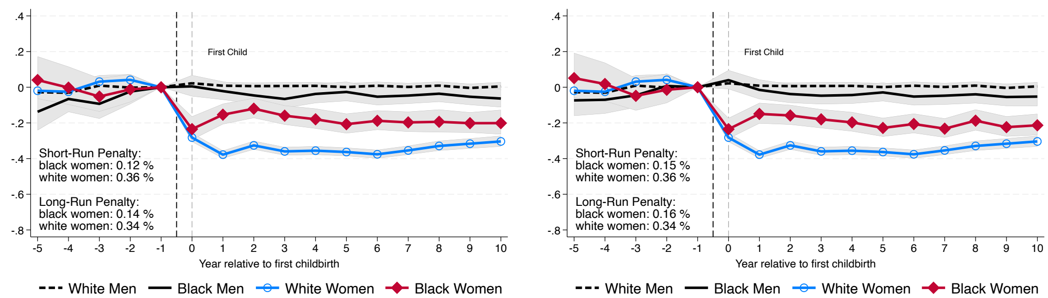


Figure C.29: Child penalty in employment, weights for occupation applied (left: with weights, right: without weights)

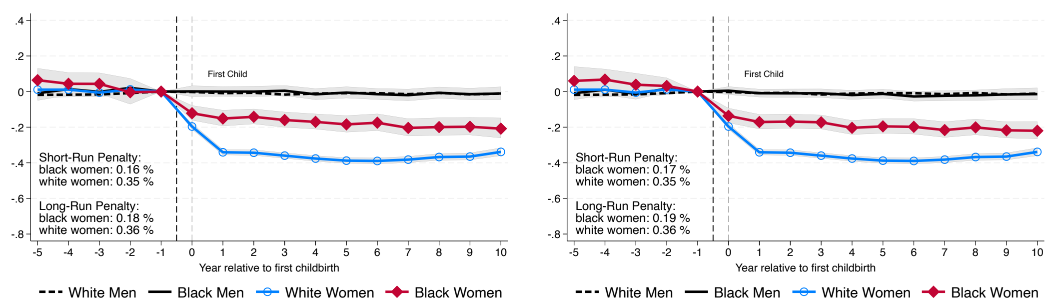


Figure C.30: Child penalty in labor income, weights for Occupation applied (left: with weights, right: without weights)

C.0.11 Husband's Gender Attitude (attitudehusb)

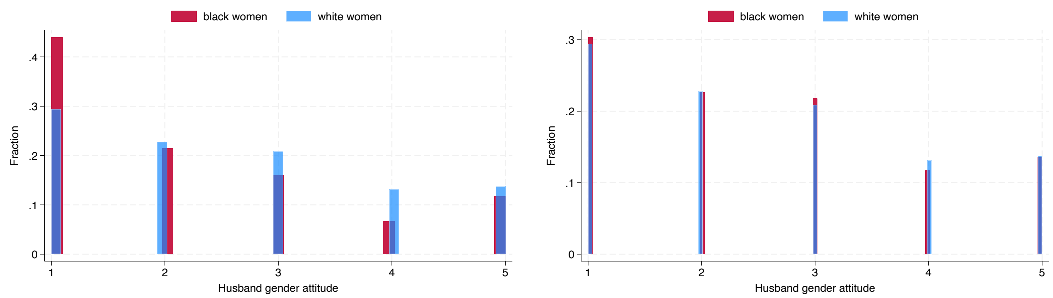


Figure C.31: Distribution of husband's gender attitude before (left) and after (right) IPW, by race

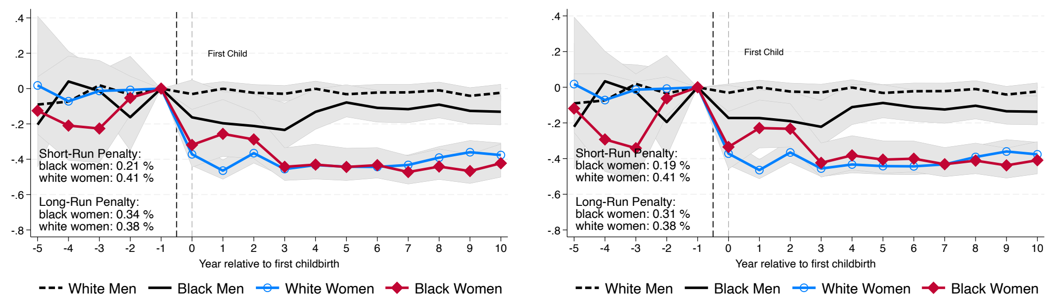


Figure C.32: Child penalty in employment, weights for husband's gender attitude applied (left: with weights, right: without weights)

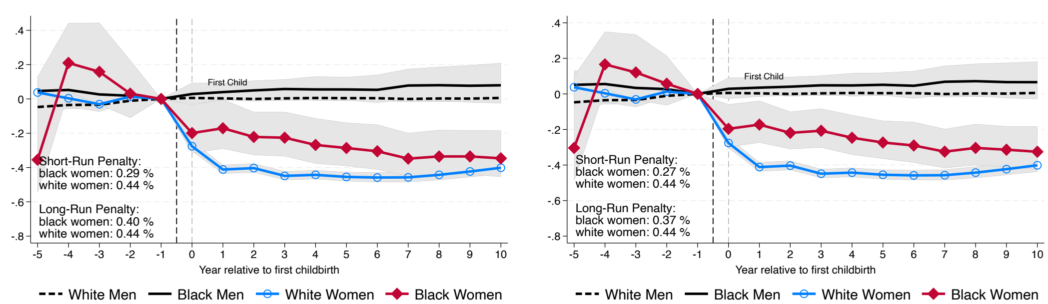


Figure C.33: Child penalty in labor income, weights for husband's gender attitude applied (left: with weights, right: without weights)

C.0.12 Wife's Gender Attitude (`attitudewife`)

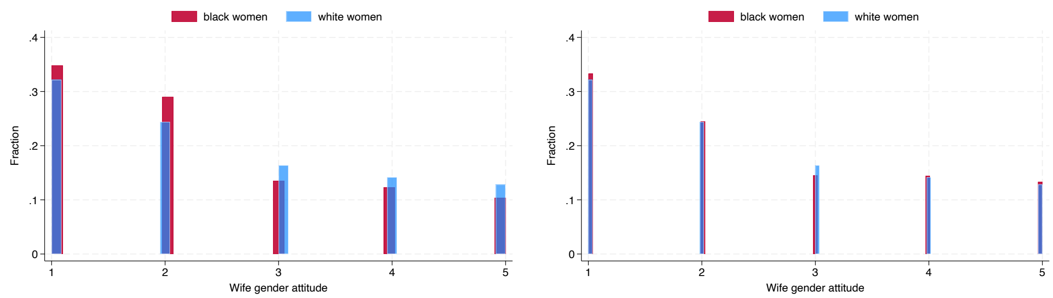


Figure C.34: Distribution of wife's gender attitude before (left) and after (right) IPW, by race

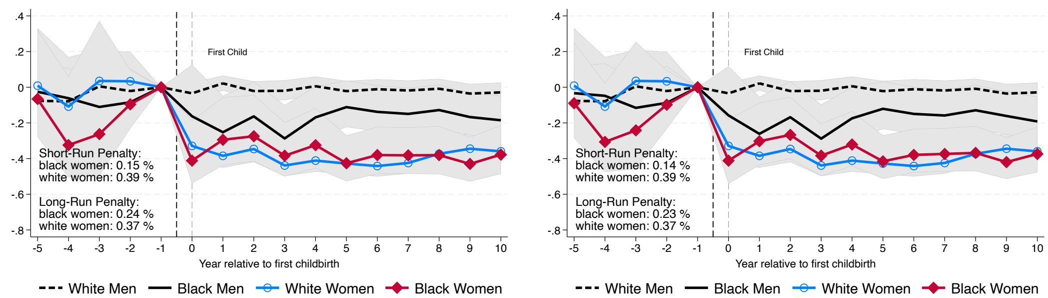


Figure C.35: Child penalty in employment, weights for Wife's Gender Attitude applied (left: with weights, right: without weights)

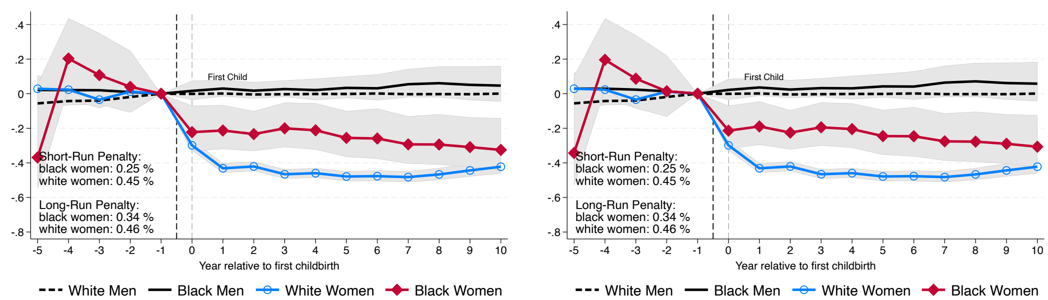


Figure C.36: Child penalty in labor income, weights for Wife's Gender Attitude applied (left: with weights, right: without weights)

C.0.13 Number of Sisters (sis_tot)

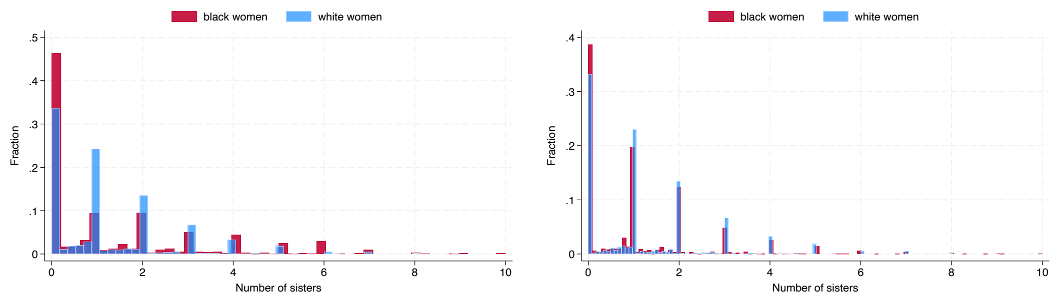


Figure C.37: Distribution of number of sisters before (left) and after (right) IPW, by race

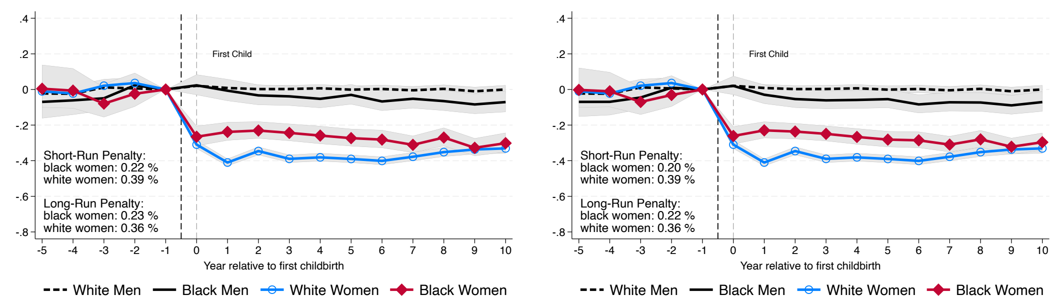


Figure C.38: Child penalty in employment, weights for number of sisters applied (left: with weights, right: without weights)

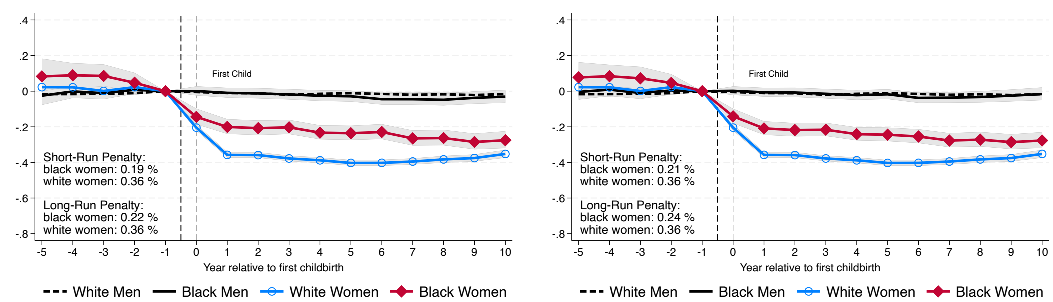


Figure C.39: Child penalty in labor income, weights for number of sisters applied (left: with weights, right: without weights)

C.0.14 Number of Children of Maternal Grandmother (`numchildofgrandma`)

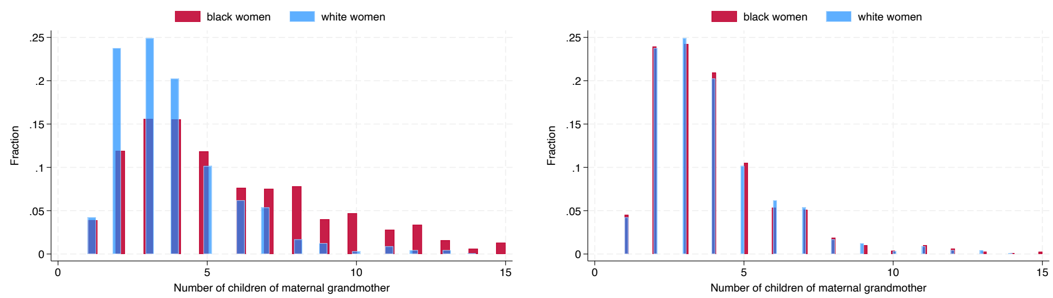


Figure C.40: Distribution of number of children of maternal grandmother before (left) and after (right) IPW, by race

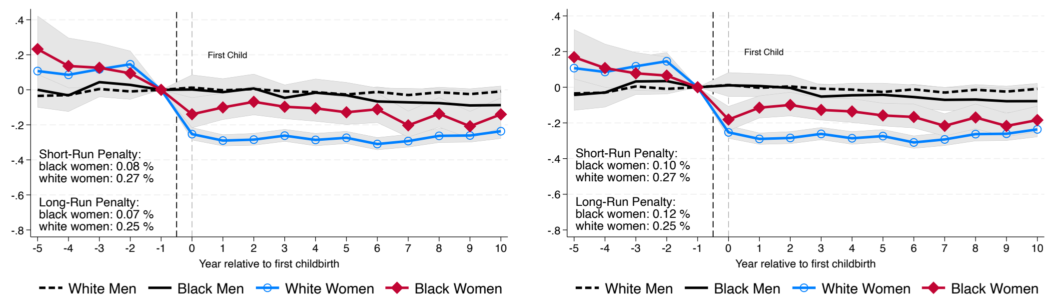


Figure C.41: Child penalty in employment, weights for number of children of maternal grandmother applied (left: with weights, right: without weights)

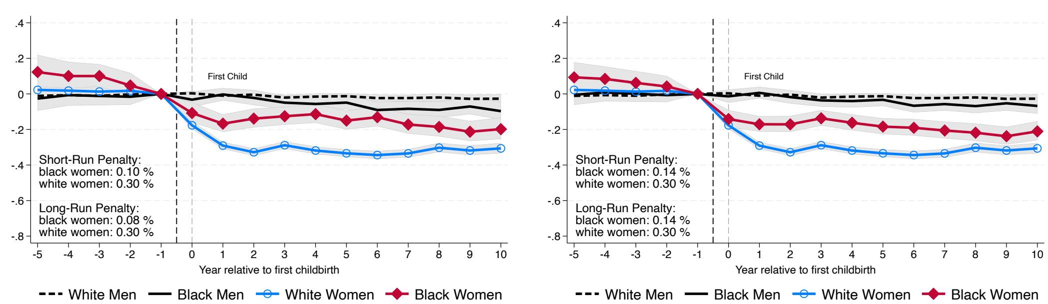


Figure C.42: Child penalty in labor income, weights for number of children of maternal grandmother applied (left: with weights, right: without weights)

C.0.15 Female Industry Indicator (femind_1d)

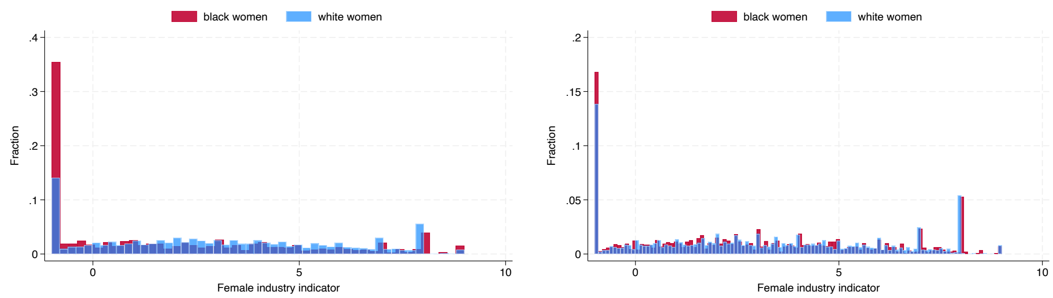


Figure C.43: Distribution of female industry indicator before (left) and after (right) IPW, by race

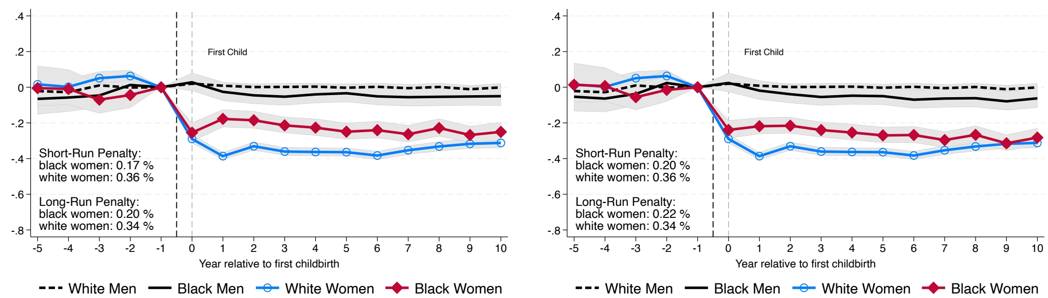


Figure C.44: Child penalty in employment, weights for industry applied (left: with weights, right: without weights)

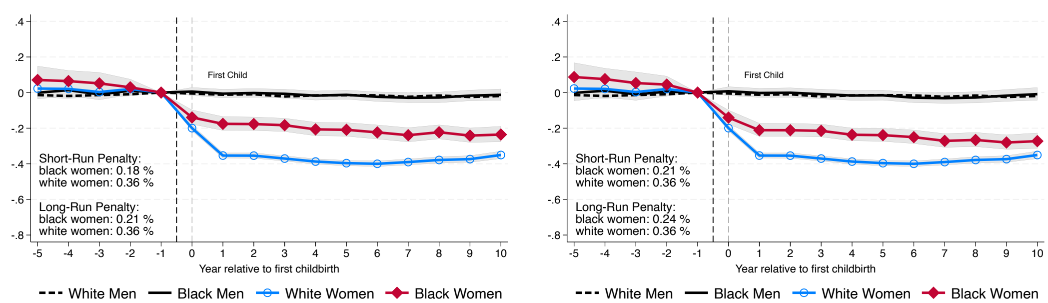
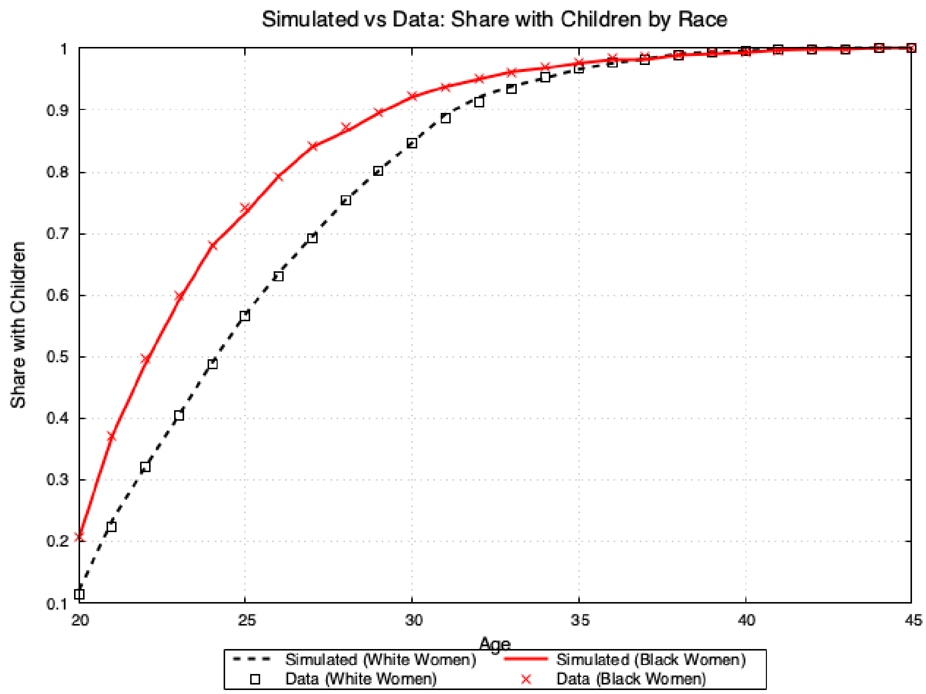


Figure C.45: Child penalty in labor income, weights for industry applied (left: with weights, right: without weights)

(a) Simulated vs Data: Share with Children by Race



(b) Simulated vs Data: Share in First Marriage by Race

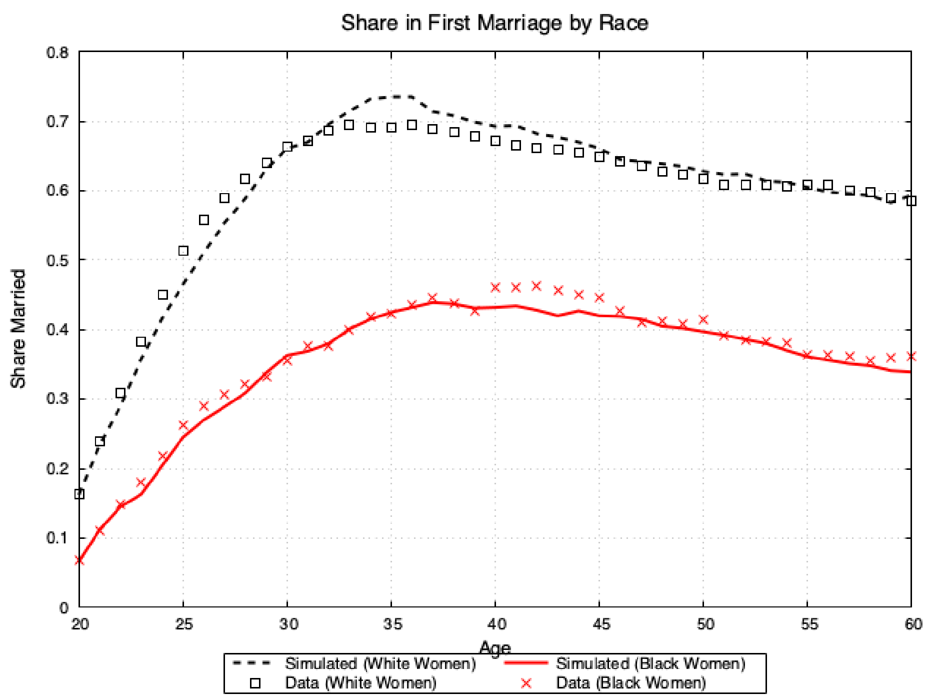


Figure C.46: Simulated vs Data: Share with Children and Share in First Marriage by Race

Notes: These figures compare the simulated and real data for the share of women with children and the share of women in their first marriage by age and race. The simulated data is shown with dashed lines, while the real data is represented by markers. The sample consists of women aged 20–45 for the share with children and women aged 20–60 for the share in first marriage.