

Race, Class, and Mobility in U.S. Marriage Markets

By Ariel J. Binder, Caroline Walker, Jonathan Eggleston, and Marta Murray-Close*

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We document racial-ethnic disparities in family income across generations by linking American Community Survey respondents born in 1978-87 to their parents' tax records. Conditional on childhood family income (CFI), Black non-Hispanic women obtain 60 percent less income from a romantic partner than do White non-Hispanic women, driven by a lower propensity to partner and a lower partner CFI rank. These marriage market dynamics account for 84-90 percent of the observed family income mobility gap. Mobility gaps are larger in birth areas with greater CFI inequality and racial-ethnic segregation. We develop a segmented matching model to interpret our findings.

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* U.S. Census Bureau, Center for Economic Studies. Binder: ariel.j.binder@census.gov, Walker: caroline.walker@census.gov, Eggleston: jonathan.s.eggleston@census.gov, Murray-Close: marta.murray.close@census.gov. Thanks to Kendall Houghton, Maggie R. Jones, Kate Pennington, and other seminar participants at the U.S. Census Bureau for helpful comments and discussion. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the Census Bureau or the Internal Revenue Service. The Census Bureau has reviewed this data product for unauthorized disclosure of confidential information and has approved the disclosure avoidance practices applied to this release. DRB approval numbers: CBDRB-FY2021-CES010-022, CBDRB-FY2022-CES005-010, CBDRB-FY-2022-CES005-011, and CBDRB-FY2022-CES010-028.

I. Introduction

More than 250 years after the end of slavery, large racial-ethnic differences in income persist in the United States. The relative income of Black Americans improved with the inclusion of paid Black labor in the industrial economy, migration out of the South, greater schooling completion, and civil-rights-era programs,¹ but has stagnated since 1970 (Bound and Freeman 1992; Bayer and Charles 2018). The absence of meaningful convergence over this long horizon has motivated recent research that analyzes racial disparities from an intergenerational perspective (e.g. Akee et al. 2019; Chetty et al. 2020; Collins and Wanamaker 2022; Derenoncourt 2022). This research has shown that Black and White men who come from families of a given income level earn very different personal incomes throughout their adult lives.²

The focus of prior research on personal income is important, but it does not offer a complete picture of racial income disparities and how they shift across generations. During the recent period in which the racial gap in men's incomes stagnated, the United States experienced a massive decline in marriage rates (Cherlin 2014; Lundberg et al. 2016; Binder and Bound 2019) that occurred unevenly across racial-ethnic groups (Tucker and Mitchell-Kernan 1995; Wilson 1996; McLanahan and Percheski 2008; Raley et al. 2015). By 2019, the share of White non-Hispanic women aged 25-54 currently married was 60.0%, whereas the share for Black non-Hispanic women was only 31.1%.³ Romantic partners often pool resources to invest in education, homeownership, and children; to insure each other against income shocks; and to consume household public goods. Adopting a family income, rather than personal income, perspective can shed new light on racial-ethnic inequality and its driving forces. This is particularly the case for women, who exhibit small disparities in personal income (Chetty et al. 2020), but who confront a wide distribution of potential male incomes in searching for a partner.

In this paper, we generate new estimates of family income mobility for different racial-ethnic groups of women, and analyze the marriage market forces underlying the disparities we find. To do so, we merge the universe of Internal Revenue Service (IRS) 1040 income tax forms to household data from the 2011-2019 American Community Survey (ACS). The resultant dataset allows us to observe childhood family income (CFI), race-ethnicity, adulthood income, and union formation outcomes for more than one million adults born between 1978 and 1986. We use ACS relationship identifiers to consider unmarried as well as married couples in our analysis. We also

¹ Myrdal (1944) first reported on the persistence of racial disparities in the U.S. economy. For research documenting and explaining partial convergence, see Smith and Welch (1989); Donohue and Heckman (1991); Aaronson and Mazumder (2011); Collins and Wanamaker (2014); Margo (1995, 2016); Derenoncourt and Montialoux (2021).

² See Killewald and Bryan (2018) and Pfeffer and Killewald (2018) for similar findings regarding personal wealth.

³ Percentages were computed by the authors using public-use microdata from the American Community Survey. Some of these massive differences are offset by higher rates of non-marital cohabitation among Black non-Hispanic women, but cohabitations in the U.S. that do not turn into marriages tend to dissolve within a few years (e.g., Smock and Schwartz, 2020). Among those ages 40-54, an age range in which most stable cohabitations would have turned into marriages, the share of White non-Hispanic women currently married (66.4%) still greatly exceeded the share for Black non-Hispanic women (38.6%). We make efforts in this paper to capture marriage-like relationships that are not yet legal marriages and that are not always identifiable in the ACS, based on our ACS-IRS data linkage described in the next section.

identify a subset of couples that are not identifiable in the ACS alone, by observing individuals living in the same ACS household who filed their taxes as a married couple or will file as married in the future.

Our analysis consists of two parts. First, we present statistics across the CFI distribution and racial-ethnic groups on i) union formation propensities (extensive margin), and ii) average partner income, conditional on having formed a union (intensive margin). We also analyze assortative matching patterns on CFI. We summarize this information with a concept we call expected income from partner (*EIFP*), which is the product of i) and ii) and describes how much non-wage income individuals belonging to a given CFI-race group can expect from participating in the marriage market. These *EIFP* differences directly translate into inequality in family income mobility, in ways that we quantify for the first time.

This part of the analysis finds large *EIFP* gaps, driven by both the extensive and the intensive margins. We associate the intensive margin gaps with disparate patterns of assortative matching on CFI: the tendency to match within CFI rank is particularly strong at the top of the distribution for White non-Hispanic individuals and relatively weaker for Black non-Hispanic individuals, while the reverse is true at the bottom of the distribution. Among women from the 10th percentile of the CFI distribution, the gap in *EIFP* between White non-Hispanic women and Black non-Hispanic women is roughly \$16,000 (or 62% of White non-Hispanic women's *EIFP*). At the 90th percentile, the gap rises to \$29,000 (57%). We assess the implications of these disparities by computing intergenerational mobility statistics on a counterfactual dataset in which each woman's observed partner income is replaced with that of a randomly selected White non-Hispanic woman from the same CFI percentile. This counterfactual eliminates 84% of the observed White-Black gap in upward mobility and 90% of the observed Black-White gap in downward mobility, highlighting the central role of marriage market forces in determining the persistence of racial-ethnic income inequality across generations.

In the second part of the paper, we set out to explain these disparities in terms of proximate marriage market mechanisms. Prior literature has examined cross-sectional disparities by taking a local marriage markets approach, revealing correlations between area-level marriage patterns and demographic variables such as race-specific economic status and sex ratios (e.g., Lichter et al. 1991, 1992; Harris and Ono 2005; Charles and Luoh 2010; Qian et al. 2018; Washington and Walker 2022). Our data allow us to expand this literature in two ways. First, we classify local marriage markets according to birth location rather than adulthood location. This controls for the possibility that individuals selectively migrate to better marriage markets. Second, the tax data allow us to construct detailed measures of area-level CFI inequality and residential segregation, which we append to the standard demographic variables examined by the literature. We test how general exposure to socioeconomic stratification, on top of demographic disparities, shape racial-ethnic inequality in adulthood marriage market outcomes.

Our regressions reveal striking patterns of inequality. Consistent with the existing literature, we find that women's *EIFP* benefits from increases in the own-race CFI distribution and sex ratio. However, White non-Hispanic women benefit more from these advantages than do Black non-Hispanic women. We also find that exposures to CFI inequality and racial-ethnic segregation substantially reduce Black non-Hispanic women's *EIFP* relative to White non-Hispanic women's

EIFP. For example, a one-standard-deviation increase in area-level inequality exerts basically zero effect on White non-Hispanic women's *EIFP*, but reduces Black non-Hispanic women's *EIFP* by 6.1 log points. A one-standard-deviation increase in segregation reduces White non-Hispanic women's *EIFP* by 1.9 log points, but reduces Black non-Hispanic women's *EIFP* by 5.9 log points. We consider a counterfactual simulation in which we equalize race-specific sex ratios, eliminate racial-ethnic segregation, and reduce income inequality to that of Sweden. This counterfactual eliminates 40 percent of the observed mobility gap in *EIFP*, and we explain that this estimate is likely a lower bound. It also more than triples the rate of intermarriage.

We discuss our findings through the lens of a simple matching model. Individuals are characterized by social identity (White or Black) and parental economic status (Rich or Poor), where White individuals are Richer on average than Black individuals. We assume a penalty for a match between individuals of different identities, which captures preferences or frictions that cut against intermarriage (e.g. Baker 2022; Ciscato 2022). This segments the marriage market into an average-poorer and average-richer submarket, where Black individuals disproportionately find themselves in the poorer submarket. Unless there is perfect assortative matching on economic status within each submarket, segmentation creates a racial mobility gap, because an individual's marriage market outcome depends on their own economic status as well as the average status of their submarket. In addition, the greater economic assortativeness exhibited by Rich Whites exacerbates the racial gap in downward mobility of Rich individuals, relative to the benchmark case of equal assortativeness across groups.

Therefore, the racial gap in marriage market mobility can be understood as an interaction between market segmentation and imperfect (and unequal) assortative matching. An intervention to reduce economic assortativeness in the marriage market will improve mobility *within* a given submarket or racial-ethnic group. However, if this intervention does not also address race-based market segmentation, it can have the unintended consequence of increasing the mobility gap *across* groups. Our local marriage market regressions give us hope that these policy levers can naturally align: we find that a cross-CBSA reduction in income inequality—holding constant observed race-specific factors—makes White partnerships less economically assortative while also reducing the racial mobility gap. On the other hand, reducing racial segregation would reduce the racial mobility gap but also increase assortative matching for Rich Whites.

Our focus on racial-ethnic inequality expands a “race-neutral” literature that applies an intergenerational perspective to the study of marriage markets. We build on the seminal work of Chadwick and Solon (2002), which used the Panel Study of Income Dynamics to analyze the contribution of the marriage market to intergenerational family income mobility among women. Other studies have used similar data to study assortative matching on parental income or wealth (e.g., Ermisch et al. 2006, Charles et al. 2013; Choi et al. 2020). Our novel data linkage allows us to study a much larger sample than prior literature, which permits detailed examination of racial-ethnic differences and their proximate mechanisms via spatial analysis. Two related studies use

intergenerational administrative data to study assortative matching on wealth in Scandinavian countries, without attention to race (Wagner et al. 2020, Fagereng et al. 2022).⁴

The paper is structured as follows. Section II describes our data and our methodology for identifying couples. Section III presents statistics from our national samples concerning union formation, assortative matching, *EIFP*, and family income mobility. Section IV describes our local marriage market regressions and presents their results. Section V concludes the paper by discussing a simple matching framework that we use to interpret our results and the broader context of American marriage markets.

II. Data

The foundation of our dataset consists of household responses to the 2011-2019 American Community Surveys (ACS). The ACS is the largest household survey in the United States, sampling about 3.5 million addresses each year and eliciting information on a variety of individual economic, demographic, social, and housing characteristics. We supplement the ACS with intergenerational information on economic background and contemporary information on marital status from IRS 1040 Individual Income Tax Returns. These forms contain the income of all people in the United States who file taxes,⁵ along with information that allows us to identify parent-child and spousal relationships. We have access to 1040 forms for tax years 1994-1995 and 1998-2019.

This ACS-IRS data linkage is made possible by the internal data infrastructure at the Census Bureau. To facilitate survey and research operations, administrative and survey data are assigned harmonized personal identifiers called Protected Identification Keys (PIKs) using the Census Bureau's Person Identification Validation System (PVS), as described in Wagner and Layne (2014). This procedure probabilistically matches data to a master reference file by Social Security Number, name, location, and date of birth. The PIK process is nearly comprehensive: in the 2013 ACS, about 93% of individuals were assigned a PIK, and nearly all 1040 records receive a PIK (Bond et al. 2013).

Using this information, we construct two samples: one focal sample of individuals that we use to analyze union formation, and a second sample of matched couples that we use to analyze assortative matching and partner income. Appendix Figure A1 illustrates the birth cohorts and age ranges we consider. We describe the construction of these samples below.

⁴ More generally, our work is related to U.S. studies that develop a connection between marriage market forces and population inequality (e.g. Western, Bloome and Percheski 2008; Schwartz 2010; Greenwood et al. 2014; Bloome 2017; Eika et al. 2019; Ciscato and Weber 2020; Gonalons-Pons et al. 2021; Binder 2021).

⁵ While tax units with sufficiently low incomes are not required to file taxes, low-income individuals still face a strong incentive to file to receive government benefits such as the Earned Income Tax Credit and Child Tax Credit (Ramnath and Tong 2017).

A. *Childhood Family Income and the Individual Sample*

To define person i 's economic background, we take the average annual Adjusted Gross Income (AGI) of the adults who claimed person i as a dependent when i was aged 10 to 18, omitting negative AGIs from this average.⁶ We call this concept “childhood family income” (CFI). This concept does not tie children to one unchanging set of caregivers, but rather allows parents to change according to who claims the child as a dependent. This reflects modern instability in many children’s living arrangements (Smock and Schwartz 2020). We require at least two potential data years of AGI observations before the child turns 18 to construct CFI. Given that we have access to dependent links on the 1994-1995 and 1998-onward tax forms, this means that the 1978 birth cohort is the earliest one we can analyze.

To construct our individual sample, we merge CFI information onto the 2011-2019 ACS files. Because a valid PIK is necessary for this merge, we restrict our analysis to ACS respondents who were assigned a PIK. We consider the 1979-1986 birth cohorts, as more recent cohorts were not old enough to be of median union-formation age. Given gender differences in age at union formation, we include men born between 1979 and 1983 (orange and gray cells shown in Figure A1) and women born between 1982 and 1986 (gray and green cells). Thus, we observe men at ages 31-35 and women at ages 28-32. Given this relatively young age range, we should not interpret our calculations as lifetime partnering rates or expected partner incomes. However, the racial-ethnic disparities we identify at these ages are strongly correlated with lifetime disparities. Moreover, this age range is when many individuals invest in higher education, pay down education debt, save for and purchase homes, and plan for or have children. Understanding union formation and family income dynamics during this age range is of clear importance.

Finally, we focus our analysis on U.S.-born ACS respondents. Non-native-born ACS respondents tend to have higher missing rates of PIK and childhood family income than do native-born respondents. Preliminary analyses suggested that this missingness was not random.⁷ Thus, we focus on a target population of U.S.-born individuals, for whom we have representative information on childhood economic circumstances and adulthood marriage market outcomes. This target population should be kept in mind especially when considering results for Hispanic and Asian, non-Hispanic individuals. However, it should not be consequential for our main inferences about disparities between White non-Hispanic and Black non-Hispanic individuals. Our sample size amounts to roughly 1.3 million individuals.

⁶ AGI includes wages, dividends, capital gains, business income, and retirement income. We omit negative AGI values from this average because these are often transitory negative shocks to high income households (e.g., large capital losses) and do not represent the permanent income of parents who claim children on their tax forms. This matches the specification of Chetty et al. (2014), who provide further information.

⁷ For example, we found a significantly different marriage rate between the full ACS sample and the ACS sample for which we could observe CFI. Moreover, this disparity remained when we reweighted the sample on observables to adjust for missing CFI, so it is more than just the result of observable sociodemographic differences. However, this problem disappeared when we imposed a US-born restriction.

B. *Defining Partners in the Couple Sample*

The ACS indicates how each person in a household is related to the household reference person. Thus, members of our sample who are the reference person, or the partner of the reference person, can easily be linked to their partners. This process is more challenging in multifamily or multigenerational households. For example, if a 28-year-old woman is living in her parents' home along with her partner, she would be listed as a child of the reference person and her partner would be listed as an "other nonrelative," but no information would exist about how the two individuals relate to each other.

Given this limitation, we supplement ACS relationships with filing status information from the IRS 1040s. For each person sampled in ACS year t , we merge on the PIK of the first spouse with whom that individual filed taxes jointly in years $\{t, t+1, \dots, t+5\}$.⁸ We link this person to their IRS spouse if neither they nor their IRS spouse is already linked to an ACS partner, both they and their IRS spouse are at least 15 years old according to their ACS response, and their IRS spouse resides in the person's ACS household. We classify couples as unmarried if either partner responds as unmarried to the individual marital status question that is asked of all ACS adult respondents. This procedure identifies additional marriages in which neither member is the ACS reference person. It also captures additional cohabitations for non-ACS reference persons that will become marriages within five years—consistent with our desire of capturing marriage-like relationships. For both methodological and substantive reasons, we limit our focus to different-sex couples. The ACS sample of same-sex couples is not large enough to support separate analyses of smaller racial-ethnic groups by family background, while dramatic differences in the social and legal context of same- and different-sex union formation suggest that separate analyses would be necessary.

Appendix Figure A1 shows the additional couples we identify with the IRS data. Approximately 48% of our individual sample reports being married, and of them, we can link 91% to their spouses using just the ACS. Bringing in the IRS 1040 data raises this fraction to 95%. Panel A shows that we identify 6% more married couples in the bottom quintile of the childhood family income distribution and about 3% more in the top quintile, although 10% of married individuals from the bottom quintile remain unlinked. Because the ACS does not have an individual cohabitation question, we cannot perform the same benchmarking exercise. However, Panel B shows that bringing in the IRS information raises the proportion of individuals participating in a non-marital cohabitation by a full percentage-point (or roughly 9%).

Our couple sample consists of all identified couples where one partner is a member of our focal individual sample, and the other partner belongs to a wider set of age ranges traced out in Figure A1. Our final sample consists of approximately 450,000 couples.

⁸ If a person filed taxes jointly with more than one spouse in the same tax year, we did not consider any of those relationships to be marriages for purposes of identifying IRS spouses. These cases may have arisen from filing errors (the legal requirement when filing income taxes jointly is to file with the person to whom one was legally married on the last day of the tax year) or from record linkage errors.

C. Racial-Ethnic Heterogeneity in our Samples

We focus our analysis on five mutually exclusive racial-ethnic groups: White non-Hispanic, Black non-Hispanic, Hispanic of any race, American Indian or Alaska Native non-Hispanic, and Asian non-Hispanic.⁹ We assign ACS respondents to racial-ethnic groups according to how they responded to race and ethnicity items on the ACS. Our estimates can be interpreted through two lenses: (1) how a person's own identity, or the identity prescribed to them by the household reference person, factors into their marriage market outcomes, or (2) how they might be racialized by prospective partners. We do not take a stand on these channels and maintain both are important mechanisms informing our results. In Section III, we more deeply examine marriage market disparities between White non-Hispanic and Black non-Hispanic women.

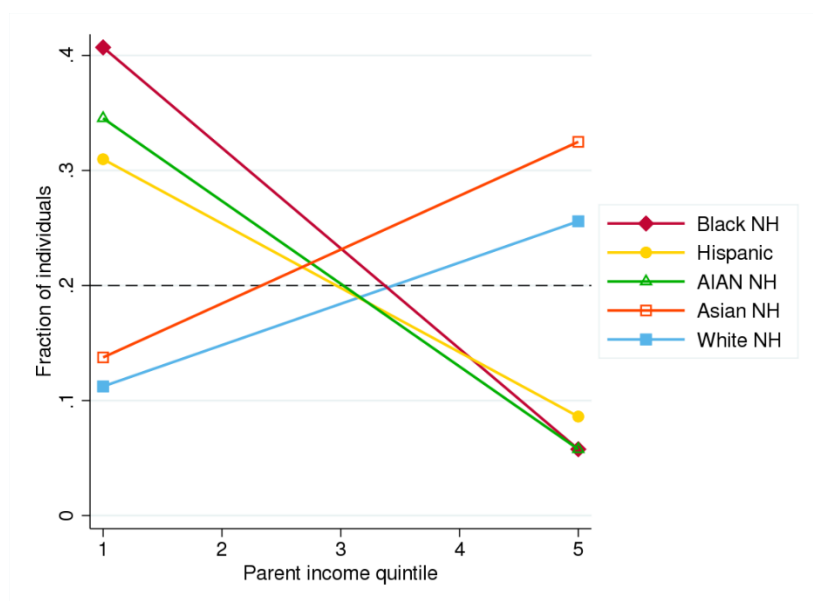


FIGURE 1. CFI BREAKDOWN BY RACIAL-ETHNIC GROUP

Note: See Section I.A for information on individual sample construction and measurement of childhood family income (CFI) rank. “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native.

Source: Individual sample described in Section I.A, which is generated by linking 2011-2019 American Community Survey to 1040 Forms from the Internal Revenue Service.

Figure 1 summarizes racial-ethnic heterogeneity in CFI distribution and sets the stage for our ensuing analyses. White non-Hispanic and Asian non-Hispanic individuals tend to be more affluent than average, with far less than 20 percent of these individuals originating from the bottom

⁹ These definitions are consistent with the guidance of the Office of Management and Budget (OMB) Statistical Policy Directive No. 15: Standards for Maintaining, Collecting, and Presenting Federal Data on Race and Ethnicity. We define each race group as that race alone and non-Hispanic. This implicitly creates a sixth group, which includes non-Hispanic respondents who identify as Native Hawaiian/Pacific Islander, “some other race”, or multiple racial categories. For simplicity, we do not report results for the latter two categories, and we do not analyze Native Hawaiian/Pacific Islander respondents separately due to sample size constraints.

quintile of the national CFI distribution and far more than 20 percent originating from the top quintile. The reverse is the case for Black non-Hispanic, American Indian or Alaska Native non-Hispanic, and Hispanic individuals. White non-Hispanic individuals are almost 4 times less likely to originate from the bottom quintile of the CFI distribution as Black non-Hispanic individuals, almost 4 times more likely to originate from the top quintile.

III. Describing Racial-Ethnic Inequality in Marriage Market Mobility

A. Extensive and Intensive Margins

We begin by using the individual sample to explore how an individual's propensity to participate in a romantic union (the *extensive margin*) varies with their race-ethnicity and CFI percentile. We construct an indicator that takes the value 1 if the individual responds as married to the individual marital status question or if we identify them as a member of a couple, and 0 otherwise.¹⁰ Figure 2 documents substantial variation in propensities to be partnered across racial-ethnic groups, and less variation across the CFI distribution within a group. Among women from the 60th percentile of the CFI distribution, roughly 70 percent of White, non-Hispanic women live with a partner, while only 58 percent of Hispanic women and 34 percent of Black non-Hispanic women do. That is, White non-Hispanic women are more than twice as likely to be partnered as Black non-Hispanic women with equivalent economic backgrounds.

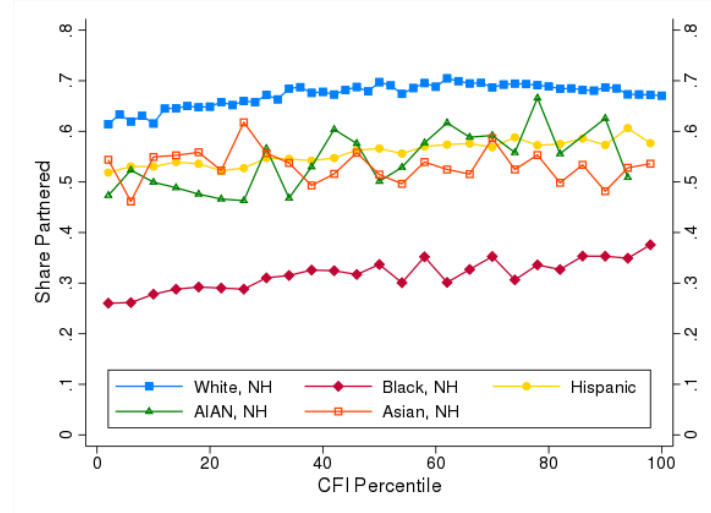


FIGURE 2. SHARE OF WOMEN PARTNERED BY CFI PERCENTILE AND RACE-ETHNICITY

Note: See Section I.A for information on individual sample construction and measurement of childhood family income (CFI) rank. “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native. Our partnered

¹⁰ Note that we do not impose any partner age restriction when measuring the extensive margin: we identify all couples we can with our ACS-IRS data linkage, without restricting on birth cohort or age, and then impose the age restriction (Figure A1) later when building the couple sample.

measure captures all marriages, all non-marital cohabitations involving the household head, and all non-marital cohabitations not involving the household head that will become marriages within the next 5 years. See Section I.B for further detail on measurement of couples.

Source: Individual sample described in Section I.A, which is generated by linking 2011-2019 American Community Survey to 1040 Forms from the Internal Revenue Service.

It is worth reacknowledging that the proportions presented in Figure 2 do not cover the universe of romantic unions (although we identify more unions than prior studies based on ACS data). Specifically, we cannot identify a subset of non-marital cohabitations that do not transition into marriages, nor can we identify any unions that span group quarters. This means that our statistics understate every group's propensity to partner, but especially those of low-CFI women and Black non-Hispanic women, who tend to partner with men at the highest risk of incarceration. Though these less-stable relationships are meaningful and worthy of study, we view excluding these unions in our context as appropriate for three reasons. First, as emphasized in the sociology literature (e.g. Smock and Schwartz 2020), cohabitations in the United States that do not transition into marriages tend to dissolve, and to exhibit less cooperation than other romantic unions. Our intent is to capture marriage-like unions that provide partners with economic stability beyond their own personal incomes, i.e. the subset of unions that are long-term, where partners cooperatively pool resources, and where joint financial investments can credibly be made. Second, individuals incarcerated in U.S. prisons tend to have extremely low earnings (American Civil Liberties Union 2022), and thus limited (if any) economic stability to offer to their partners. Third, incarceration of partnered men has been shown to dramatically increase the rate of partnership dissolution (e.g. Turney and Wildeman 2013; Turney 2015), suggesting we miss few stable unions with our current data collection.

Figure 3 uses the couple sample to illustrate how a woman's partner's economic background varies with her own background (the *intensive margin*). The figure shows upward-sloping plots of partner CFI rank against own CFI rank for all racial-ethnic groups. This indicates positive assortative matching on CFI, which we explore further in the next subsection. However, the marriage market returns to CFI depend considerably on racial-ethnic identity. For example, the 60th percentile White non-Hispanic woman, on average, partners with a man from the 60th percentile of the CFI distribution. However, an equivalent Hispanic woman partners with a man from the 53rd percentile, while an equivalent Black non-Hispanic woman partners with a man from the 42nd percentile. The White-Black gap in average partner rank also tends to rise throughout the CFI distribution (apart from the top few percentiles).

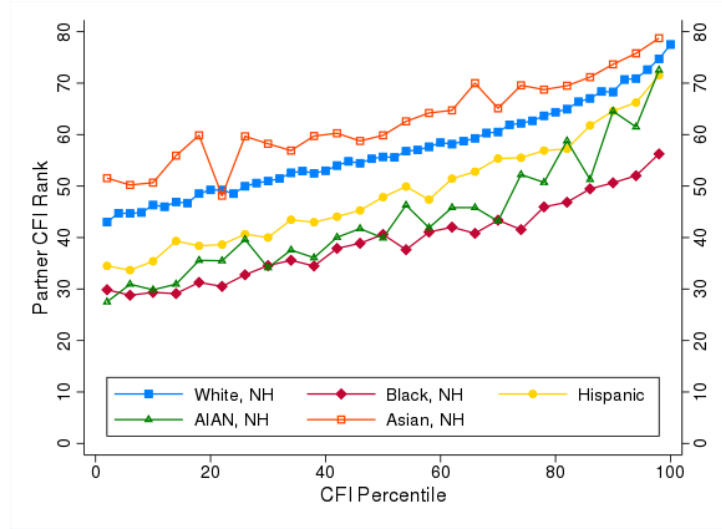


FIGURE 3. PARTNER CFI RANK AS A FUNCTION OF WOMEN’S OWN CFI RANK, BY RACE-ETHNICITY

Note: See Section I.A and I.B for information on couple sample construction and measurement of childhood family income (CFI) rank. “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native. Our sample of couples includes all marriages, all non-marital cohabitations involving the household head, and all non-marital cohabitations not involving the household head that will become marriages within the next 5 years. See Section I.B for further detail.

Source: Couple sample described in Section I.B, which is generated by linking 2011-2019 American Community Survey to 1040 Forms from the Internal Revenue Service.

B. Assortative Matching on CFI

These disparities in partner CFI rank relate to patterns of assortative matching on CFI, which we analyze in this subsection. We begin by computing a simple criterion $\sigma_{rp}(\tau)$ that measures, for partnered individuals that identify with racial-ethnic group r and belong to CFI percentile group p , the share of these individuals who partner with someone within τ percentiles of their own rank. Specifically, we classify White non-Hispanic individuals into 50 different percentile groups p , and other individuals into 25 different percentile groups.¹¹ For each partnered woman with exact CFI rank in this group, we assign an indicator $s_{white,p,i}(\tau) = 1$ if i ’s partner is within τ percentiles of her own exact percentile rank, and 0 otherwise. This yields

$$(1) \quad \sigma_{white,p}(\tau) = \frac{1}{N_{white,p}} \sum_{i \in p} s_{white,p,i}(\tau),$$

¹¹ That is, percentile group p consists of the $(2p-1)$ and $2p$ percentiles of the CFI distribution for White non-Hispanic individuals, and the $(4p-3)$ thru $(4p)$ percentiles for other groups.

where $N_{white,p}$ is the number of partnered White non-Hispanic women belonging to percentile group p . We present results based on $\tau = 8$, but they are similar for $\tau = 6$ or 10 as well.¹²

Figure 4 shows considerable variation in the simple criterion across the CFI distribution and for different racial-ethnic groups. CFI sorting is particularly strong at the bottom of the distribution for Black non-Hispanic and Hispanic women, and particularly strong at the top for White non-Hispanic and Asian non-Hispanic women. For example, among individuals from the 10th percentile of the CFI distribution, 40 percent of Black non-Hispanic women partner with someone within 8 percentiles of the 10th percentile, but only 17 percent of White non-Hispanic women do. At the 90th percentile, these numbers reverse: 36 percent of White non-Hispanic women partner within 8 percentiles of 90, but only 17 percent of Black non-Hispanic women do. Thus, a bottom-CFI Black non-Hispanic woman is less likely than a White non-Hispanic woman to “partner up” in the distribution. On the other hand, a top-CFI Black non-Hispanic woman is likelier than an equivalent White non-Hispanic woman to “partner down” in the distribution. This pattern indicates a mobility wedge, whereby social class structure reinforces itself through the marriage market across generations. We provide further evidence of this fact in the next subsection.

The simple criterion presented above, while informative, is not interpretable as a fundamental measure of assortative matching. To understand this point, observe that top-CFI White individuals have a high propensity to match with a top-CFI partner. This pattern could occur for two reasons: 1) because individuals match randomly on CFI but assortatively on race-ethnicity, and there is a plentiful stock of top-CFI White individuals; or 2) because individuals match assortatively on CFI apart from other factors, and top-CFI White individuals match more assortatively on CFI than do others. Accordingly, we refine Figure 4 by presenting two “formal” assortative matching criteria suggested by Chiappori et al. (2020). Each criterion controls for mechanism 1) and expresses assortativeness generated by mechanism 2). It is informative to explore how both mechanisms determine the mobility wedge.

We compute the first formal criterion by regressing an indicator for one partner i being within tolerance τ of a given CFI percentile on an indicator for whether their partner j is within that same tolerance. More explicitly, for a given racial-ethnic group r and CFI percentile p , we partition the sample into two categories $c_1 = \{i : P_i \in [p - \tau, p + \tau]\}$; $c_2 = \{i : P_i \notin [p - \tau, p + \tau]\}$. We estimate the following linear probability model separately for each racial-ethnic group and CFI percentile:

$$1\{j \in c_1\} = \alpha_{pr} + \beta_{pr} 1\{i \in c_1\} + \varepsilon_{ipr}$$

This yields the coefficient estimate:

$$(2) \quad \beta_{pr} = Pr(j \in c_1 \mid i \in c_1) - Pr(j \in c_1 \mid i \in c_2)$$

¹² We chose $\tau=6, 8$, or 10 rather than smaller numbers for statistical power and disclosure avoidance issues, particularly for non-White racial-ethnic groups.

which is the additional probability that a person is from a given CFI percentile group if their partner is also from that group, relative to if their partner is not from that group. This measure takes the simple criterion defined above and subtracts off the probability that a person from outside the CFI percentile group has of forming a union with someone from inside the CFI percentile group. Intuitively, the larger the given group, the larger this offsetting term will be when matching on CFI is random.

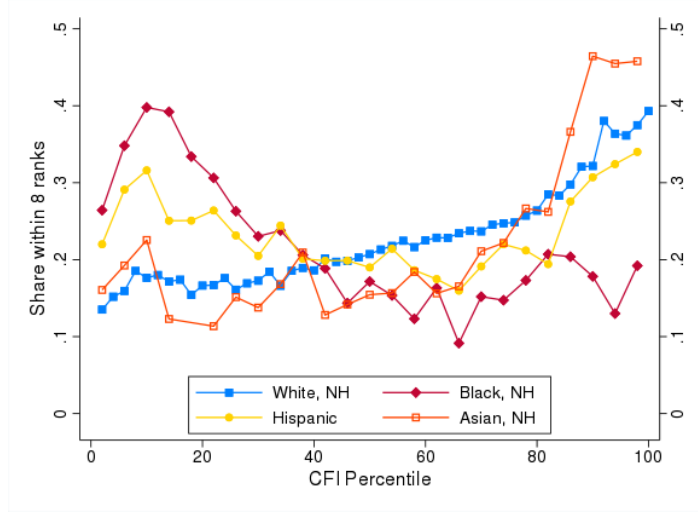


FIGURE 4. SIMPLE ASSORTATIVE MATCHING CRITERION, BY RACE-ETHNICITY AND CFI

Note: Simple criterion records the share of individuals whose partner has a CFI percentile rank within 8 percentiles of their own rank. See Section I for information on sample construction and measurement of childhood family income (CFI) rank. “NH” stands for non-Hispanic. Our sample of couples includes all marriages, all non-marital cohabitations involving the household head, and all non-marital cohabitations not involving the household head that will become marriages within the next 5 years. See Section I.B for further detail on measurement of couples. American Indian / Alaska Native group has been suppressed for disclosure avoidance purposes.

Source: Couple sample described in Section I.B, which is generated by linking 2011-2019 American Community Survey to 1040 Forms from the Internal Revenue Service.

The second formal criterion, from Eika et al. (2019), is defined as follows:

$$(3) \quad EMZ_{pr} = \sum_{n \in \{1,2\}} w_n \cdot \frac{Pr(i \in c_n, j \in c_n)}{Pr(i \in c_n) Pr(j \in c_n)}$$

Given a partitioning of the sample into two CFI percentile groups, this criterion computes the likelihood that two partners belong to the same group relative to what we would expect if matching on CFI group was random, and then sums the relative likelihoods across the two groups according to weights w . Chiappori et al. (2020) demonstrate that this measure is valid for any nonnegative choices of w that sum to 1. In fact, if we weight each likelihood ratio by the marginal probability that i belongs to the given category (i.e. $w_n = Pr(i \in c_n)$), then $EMZ_{pr} = 1 + \beta_{pr}$. So that our two criteria are not identical, we choose the more complex weighting scheme used by Eika et al. (2019): $w_n = Pr(i \in c_n, j \in c_n) / (Pr(i \in c_1, j \in c_1) + Pr(i \in c_2, j \in c_2))$.

Figure 5 plots each of the two criteria for women, across the CFI distribution and for different racial-ethnic groups. The plots look similar to the simple criterion plot presented in Figure 4. Both plots continue to show stronger assortative matching on CFI in the tails of the distribution as compared with the middle, with poorer social groups exhibiting the strongest assortative matching at the bottom and richer social groups exhibiting the strongest assortative matching at the top. The weighted EMZ criterion (Panel B), in particular, suggests that Black non-Hispanic and American Indian or Alaska Native non-Hispanic women exhibit much different assortative matching patterns in the tails of the distribution than do White non-Hispanic or Asian non-Hispanic women, in ways that reinforce initial group differences in economic status. Hispanic women, by comparison, exhibit sorting patterns in between these two extremes. These results suggest that the racial disparities in partner CFI rank shown in Figure 3 are driven not just by a tendency for same-race matching, but also by fundamentally different tendencies across racial-ethnic groups to match assortatively on CFI rank. In the next Section, we provide further evidence that the availability of same-race, same-rank partners shapes assortative matching patterns—widening mobility gaps beyond what would be predicted by a “neutral” tendency to match within race.

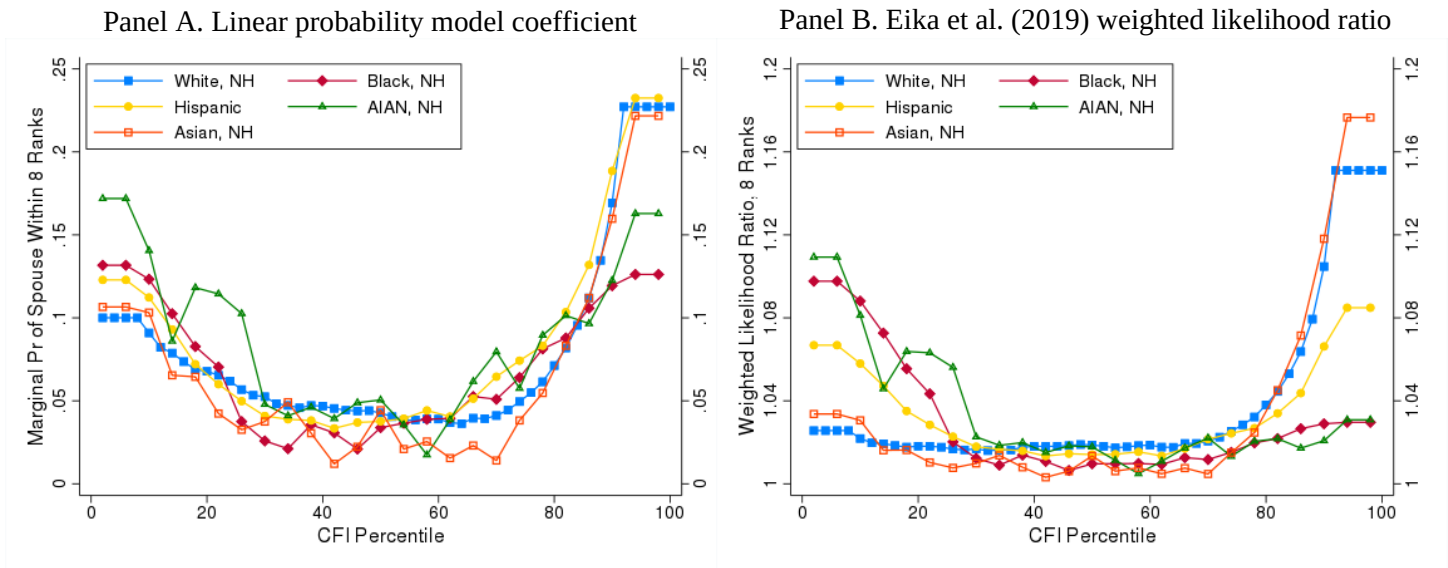


FIGURE 5. FORMAL ASSORTATIVE MATCHING CRITERIA,
BY WOMAN PARTNER'S RACE-ETHNICITY AND CFI

Note: See Equations (2) and (3) for descriptions of how each criterion is computed. See Section I for information on sample construction and measurement of childhood family income (CFI) rank. “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native. Our sample of couples includes all marriages, all non-marital cohabitations involving the household head, and all non-marital cohabitations not involving the household head that will become marriages within the next 5 years. See Section Data for further detail on measurement of partnerships. *Source:* Couple sample described in Section I.B, which is generated by linking 2011-2019 American Community Survey to 1040 Forms from the Internal Revenue Service.

C. Implications for Inequality in Family Income Mobility

Motivated by these patterns, we combine extensive and intensive margins together into an *expected income from partner (EIFP)* statistic. For women identifying with racial-ethnic group r and belonging to CFI percentile p , we write

$$(4) \quad EIFP_{rp} = \underbrace{\Pr(\text{have partner} \mid r, p)}_{\text{extensive margin}} \cdot \underbrace{E[\text{partner income} \mid r, p]}_{\text{intensive margin}}.$$

This statistic is the product of the probability of living with a romantic partner and the average personal income of partners—measured in adulthood directly from the ACS—and can be considered a measure of the expected marriage market returns for an individual of type rp .

Figure 6 graphs women’s *EIFP* by race-ethnicity and CFI percentile. Conditional on the latter, White non-Hispanic and Asian non-Hispanic women tend to have the highest *EIFP*, while American Indian or Alaska Native non-Hispanic and Black non-Hispanic women have the lowest. At the 10th CFI percentile, the gap in *EIFP* between White non-Hispanic women and Hispanic women is roughly \$5,000; the *EIFP* gap between White non-Hispanic and Black non-Hispanic women is a full \$16,000. (Income is expressed in 2015 U.S. dollars.) Except for the top few percentiles, these gaps tend to rise throughout the CFI distribution. For example, at the 90th percentile, the *EIFP* gap between White non-Hispanic and Hispanic women is roughly \$10,000, and the gap between White non-Hispanic and Black non-Hispanic women is roughly \$30,000. The White-Black gaps are large relative to the roughly \$9,000 gap in individual earned income between the average White non-Hispanic woman and the average Black non-Hispanic woman aged 25-44, observed in 2019 ACS data.

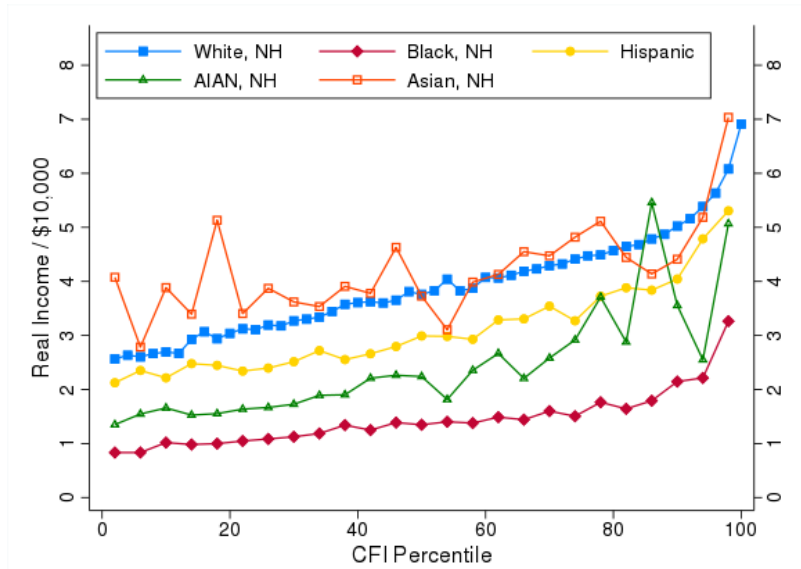


FIGURE 6. WOMEN’S EXPECTED INCOME FROM PARTNER (*EIFP*),
BY RACE-ETHNICITY AND CFI PERCENTILE

Note: See Equation (4) for a description of how the *EIFP* statistic is computed. Income is expressed in ten thousands of 2015 U.S. dollars. See Section I for information on sample construction and measurement of childhood family income (CFI) rank. “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native. Our sample of couples includes all marriages, all non-marital cohabitations involving the household head, and all non-marital cohabitations not involving the household head that will become marriages within the next 5 years. See Section I.B for further detail on measurement of couples.

Source: 2011-2019 American Community Survey linked to 1040 Forms from the Internal Revenue Service.

Table 1 maps these differences in CFI-conditional partner income into differences in intergenerational family income mobility. For each woman in our ACS sample, we assign their adulthood family income (AFI) as the sum of their own annual personal income and their partner’s (set to zero if we do not identify that individual as partnered). We then compute four different mobility statistics that map the distribution of CFI into the distribution of AFI:

- i) the share moving into the 2nd-5th quintiles of AFI, conditional on starting in the bottom quintile of CFI,
- ii) the share moving to the top quintile conditional on starting at the bottom,
- iii) the share remaining in the top quintile conditional on starting there, and
- iv) the share moving to the bottom quintile conditional on starting at the top.

Panel A of Table 1 records mobility statistics observed in our sample. Consistent with prior work, we find sizable cross-group differences in intergenerational mobility. While 73 percent of White non-Hispanic women starting in the bottom quintile of CFI end up in the 2nd-5th quintiles of AFI, only 57 percent of Black non-Hispanic women do. In addition, while 11 percent of White non-Hispanic women starting in the bottom quintile of CFI end up in the top quintile of AFI, only 3 percent of Black non-Hispanic women do. Similarly large gaps exist for the share remaining in the top quintile (39 percent for White non-Hispanic women and 16 percent for Black non-Hispanic women) and the share moving down to Q1 of AFI from Q5 of CFI (8 percent for White non-Hispanic women versus 20 percent for Black non-Hispanic women).

Panel B presents the same mobility statistics, computed on a counterfactual distribution in which the personal income of each woman from CFI percentile p is replaced with the personal income of a randomly-selected White non-Hispanic woman who is also from CFI percentile p .¹³ Consistent with estimates of modest differences in women’s personal income across racial-ethnic groups (e.g. Bayard et al. 1999, Chetty et al. 2020), we find that this counterfactual exerts modest impacts on intergenerational mobility. Compared with the actual data, a slightly larger share of Black non-Hispanic women who start in the top quintile stay there (18 percent versus 16 percent), and a slightly smaller share drop down to the bottom quintile (17 percent versus 20 percent). The same pattern holds for Hispanic women. One exception is that American Indian or Alaska Native non-Hispanic women experience a noteworthy increase in upward mobility and decrease in downward mobility.

Finally, Panel C presents a counterfactual distribution in which women’s *partner* incomes are manipulated in the same manner as their personal incomes were in Panel B. In contrast to Panel

¹³ To minimize the impact of sampling error, particularly for the American Indian / Alaska Native group, we use a bootstrap procedure in which we randomly simulate 100 different counterfactual distributions, compute mobility statistics for each counterfactual distribution, and then report the average of each group of 100 statistics.

B, this simulation brings the mobility of Black non-Hispanic and Hispanic women much closer to that of White non-Hispanic women. In this counterfactual scenario, Black non-Hispanic and Hispanic women experience slightly higher rates of moving out of the bottom quintile than do White non-Hispanic women, and they experience only slightly lower rates of moving from the bottom to the top or remaining at the top. Comparing White non-Hispanic and Black non-Hispanic women in Panels A and C, we calculate that replacing observed partner income distributions with those of White non-Hispanic women eliminates 83.6% of the observed disparity in the probability of moving from the bottom to the top quintile, and 89.9% of the observed disparity in the probability of remaining in the top quintile. One note of caution is in order here, which is that the simulation does not consider the possible endogeneity of women’s personal incomes with respect to their partners’ incomes (i.e., negative income elasticities of labor supply). However, research suggests that these elasticities have become quite small (McClelland and Mok 2012), and the women’s incomes are increasingly correlated with their partners’ (Gonalons-Pons et al. 2021). The results overall indicate that marriage market dynamics are a key force behind current racial-ethnic disparities in women’s intergenerational mobility.¹⁴

TABLE 1—INTERGENERATIONAL MOBILITY OF WOMEN’S FAMILY INCOMES

Mobility statistic	White, NH	Black, NH	Hispanic	AIAN, NH
<i>Panel A. Observed Data</i>				
Pr(move out of Q1)	0.73	0.57	0.72	0.54
Pr(move from Q1 to Q5)	0.11	0.03	0.08	0.03
Pr(remain in Q5)	0.39	0.16	0.29	0.22
Pr(move from Q5 to Q1)	0.08	0.20	0.13	0.17
<i>Panel B. Counterfactual: All Groups have White Women's Personal Income</i>				
Pr(move out of Q1)	0.73	0.56	0.69	0.63
Pr(move from Q1 to Q5)	0.11	0.03	0.07	0.05
Pr(remain in Q5)	0.39	0.18	0.33	0.27
Pr(move from Q5 to Q1)	0.08	0.17	0.11	0.12
<i>Panel C. Counterfactual: All Groups Have White Women's Partner Income</i>				
Pr(move out of Q1)	0.67	0.72	0.74	0.66
Pr(move from Q1 to Q5)	0.09	0.08	0.09	0.06
Pr(remain in Q5)	0.37	0.34	0.35	0.30
Pr(move from Q5 to Q1)	0.11	0.10	0.11	0.13

Note: “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native. “Q” refers to quintile. This table maps the distribution of CFI into the distribution of adult family income (AFI), which is the sum of an

¹⁴ Appendix Table A1 presents similar counterfactual simulations in which all groups are assigned Black non-Hispanic women’s personal or partner income distributions (rather than White non-Hispanic women’s). The results are qualitatively similar: changing personal income distributions exerts small effects on racial-ethnic disparities in intergenerational mobility, while changing partner income distributions eliminates the majority of White-Black and White-Hispanic mobility gaps.

individual's personal income and their partner's income (set to zero if no partner present). For example, "Pr(move out Q1)" is the conditional probability that a women from the bottom CFI quintile is not in the bottom quintile of AFI. Panel A is the observed data. Panel BI) replaces observed personal (partner) income for each woman from CFI percentile p with the personal (partner) income of a randomly-selected White non-Hispanic woman also from percentile p . This process is repeated 100 times; the reported mobility statistics are averaged across these 100 counterfactual distributions.

Source: 2011-2019 American Community Survey linked to 1040 Forms from the Internal Revenue Service.

IV. Proximate Determinants of the Mobility Gap: Evidence from Local Marriage Market Regressions

The previous section described a mobility wedge in the marriage market, whereby a White non-Hispanic individual from a given CFI percentile obtains a much higher *EIFP* than does an equivalent Black non-Hispanic individual. These partner income disparities almost completely determine Black-White differences in intergenerational family income distribution. In this section, we present novel analyses that shed light on the forces driving this mobility wedge.

Our approach exploits variation in channels of socioeconomic stratification across local marriage markets to estimate the effects of these channels on *EIFP*, separately for White non-Hispanic women and for Black non-Hispanic women. We use the estimated race-specific coefficients to examine how differential exposure to marriage market resources (e.g., group differences in CFI), as well as common exposure to socioeconomic stratification (e.g., overall inequality in CFI) shape disparities in marriage market outcomes. We focus on White non-Hispanic and Black non-Hispanic women only in this section for two reasons. First, sample size issues limit the reliable computation of local-area marriage market outcomes for most groups of color. Second, the history of anti-Black discrimination in many local jurisdictions generates plausible variation that can be applied to the study of Black-White disparities.

A. Regression Methodology and Interpretation

We define a local marriage market as a core-based statistical area (CBSA)—a grouping of one or more counties that share an urban center and are economically linked through commuting patterns.¹⁵ We assign each woman to a local marriage market according to their *birth* CBSA, defined using the county of birth recorded in the Census Bureau's version of the Social Security Administration Numident file. We choose birth CBSA rather than adulthood CBSA for two reasons: (1) to avoid concerns about selective migration in adulthood that might arise due to marriage market characteristics, and (2) because childhood circumstances comprise the intergenerational processes we seek to measure. This choice of geography can be thought of as an instrument for adulthood marriage market conditions, or as eliciting direct effects of childhood exposure on adulthood marriage market outcomes.

¹⁵ This concept is smaller than a commuting zone, allowing for more detailed analysis than is possible with public-use microdata.

Formally, we regress the average marriage market outcome observed among women of racial-ethnic group r born in CBSA c —denoted as Y_{cr} —on a set of explanatory variables of interest ($\mathbf{M}_{cr}$) and other control variables ($\mathbf{X}_{cr}$):

$$(5) \quad Y_{cr} = \alpha_r + \rho_r' \mathbf{M}_{cr} + \delta_r' \mathbf{X}_{cr} + \varepsilon_{cr}.$$

We estimate this regression separately for White non-Hispanic women and for Black non-Hispanic women, thus allowing the ρ coefficients of interest to vary by race. We consider the following three outcomes: assortative matching on CFI, *EIFP*, and intermarriage. To measure CFI assortativeness, we estimate a linear probability model of a male partner’s membership in the top quintile on the woman partner’s own membership in that quintile, just as in equation (2). We call the resulting linear probability model coefficient “Q5 sorting”. *EIFP* is computed as in equation (4), except at the CBSA-by-race-ethnicity level rather than the race-ethnicity-by-percentile level. Finally, we compute the share of Black non-Hispanic partnered women who have White non-Hispanic partners at the CBSA level. This allows us to assess intermarriage as a potential channel through which socioeconomic forces generate *EIFP* gaps between White non-Hispanic and Black non-Hispanic women. To improve precision of our estimates, we require at least 20 individual- or couple-level observations within a given CBSA-by-race cell. We also weight each cell by the sum of the ACS person weights contained within it.

For each birth-CBSA-by-racial-ethnic group, we construct several explanatory variables of interest:

- First, we consider the *share of individuals with top-quintile CFI*.¹⁶ This allows us to control for initial economic status in *EIFP* regressions to isolate mobility gaps, and also to examine whether different groups of women are rewarded similarly for similar childhood economic statuses.
- Second, we define *sex ratios* for people living in housing units (i.e., adjusted to exclude individuals in group quarters such as prisons) to examine the impact of sex imbalances arising from differential mortality or incarceration on marriage patterns.
- Third, we examine the impact of overall inequality on race-specific marriage market outcomes by defining a *CFI inequality* measure. This measure is the natural log of the mean CFI among those from the top quintile, minus the natural log of the mean CFI among those from the bottom four quintiles. This measure effectively describes how many times richer the typical top-quintile person is relative to the typical non-top-quintile person in the CBSA.¹⁷
- Fourth, we examine the impact of residential *racial segregation* by computing a standard dissimilarity index (Jahn, et al. 1947). This measure ranges from 0 to 1 and describes the percentage of people that would need to move to a different tract within

¹⁶ Results were similar when we instead defined this measure as the share of individuals with bottom-quintile CFI.

¹⁷ We found similar results when we used the bottom quintile, rather than the top quintile, to partition groups for constructing our log inequality measure.

a CBSA to equalize the racial composition across all tracts within the CBSA.¹⁸ To increase precision, we construct this index with the full universe of IRS 1040 records that match our birth cohort restrictions, rather than the ACS.¹⁹

Our control variables include region fixed effects and the natural log of the CBSA population. Fixed effects absorb time-invariant regional marriage market characteristics, such as differences in norms surrounding marriage. Controlling for population allows us to abstract from market dynamics driven by scale. We also control for residential income segregation by computing the same dissimilarity index, except for top-quintile-CFI versus not-top-quintile CFI individuals, instead of according to racial-ethnic categories.

Despite these control variables, one might note that because birth location is not plausibly random, it is difficult to assign a causal interpretation to our estimated relationships between M_{cr} and marriage market outcomes. While we do not dispute this, we contend that the main issue our design faces is not one of econometric bias, but rather one of economic interpretation. For example, suppose that Black non-Hispanic individuals born into more-segregated cities have characteristics (unobserved to the econometrician) that are less rewarded in the marriage market than do Black non-Hispanic individuals born into less-segregated cities. We interpret this extra disadvantage not as a confounding exogenous variable, but rather as a variable endogenous to the forces that produce a segregated society. Put differently, cross-CBSA inference does not inform us about the short-run effects of a marginal reduction in segregation. However, such an inference is potentially informative about the long-run effects of a large-scale desegregation of American society, allowing for endogenously determined characteristics to adjust in equilibrium. We view our inferences as akin to those of Chetty et al. (2014) and following work, who interpreted correlations between intergenerational mobility and area-level socioeconomic features.

B. Results

The first two columns of Table 2 present cross-CBSA regression results for Q5 assortative matching. Looking at the first row, we find support for the hypothesis that the availability of same-race, same-rank partners conditions assortative matching. Specifically, we find that a 10 percent increase in the share of Black non-Hispanic individuals from the top quintile increases the Q5 sorting coefficient by .0038, and the effect is statistically significant at the 5 percent level. To provide a sense of magnitude, the standard deviation across CBSAs in the log Q5 share of Black non-Hispanic individuals is roughly 0.6. Thus, a one-standard-deviation increase in Black non-Hispanic CFI raises the Q5 sorting coefficient by .023, or roughly 20 percent of the average Q5

¹⁸ Formally, the dissimilarity index for CBSA c is defined as $D_c = \frac{1}{2} \sum_{t=1}^N \left| \frac{a_t}{A_c} - \frac{b_t}{B_c} \right|$, where a_t is the population count of group Type A in tract t and A_c is the population count of group type A in the CBSA and defined analogously for group type B.

¹⁹ We use address information on the tax records to assign CBSA and tract identifiers. To generate accurate population counts for each racial-ethnic group, we match the tax records to the Census Best Race and Ethnicity file, an internal data product that harmonizes survey and administrative data sources to define single, time-invariant race and ethnicity values for each individual who was assigned a PIK.

sorting coefficient of 0.11.²⁰ We find qualitatively similar results for White women, although of slightly smaller magnitudes. Looking at the third row of the table, we also find statistically significant effects of prevailing CFI inequality in the CBSA on Q5 sorting. However, the effects point in *opposite* directions: a 10 percent increase in inequality *raises* the White Q5 sorting coefficient by .0058, but *lowers* the Black non-Hispanic Q5 sorting coefficient by .0185. This finding suggests that greater inequality results in a more-differentiated pool of elite White individuals, while at the same time lowering the access of relatively well-off Black non-Hispanic individuals to these elite segments of the market.²¹

The third and fourth columns of the table report results for *EIFP* (measured on a log scale for ease of interpretation), our main outcome of interest. We find that both White non-Hispanic women and Black non-Hispanic women benefit from higher sex ratios and CFI distributions in the local marriage market. These effects are in line with standard matching theories: if women are scarcer relative to men of their own race or are in a marriage market with a larger share of own-race, high-income men, they are likelier to find a desirable partner. However, Black non-Hispanic women benefit less from these marriage market features. A 10 percent increase in the share of own-race individuals with top-quintile CFI raises White non-Hispanic women's *EIFP* by 1.8 log points, but raises Black non-Hispanic women's *EIFP* by only 0.6 log points. This indicates that the White-Black gap in *EIFP* is particularly large among individuals who originate from the top quintile of the CFI distribution.

Moving from race-specific factors to prevailing stratification variables (rows 1-2 to rows 3-4 of Table 2), we find that a 10 percent increase in overall CFI inequality exerts little effect on White non-Hispanic women's *EIFP* (insignificant increase of 0.3 log points), but substantially lowers Black non-Hispanic women's *EIFP* (significant decrease of 3.1 log points). Similarly, racial-ethnic segregation harms both groups, but especially Black non-Hispanic women: a 10 percentage-point increase in the dissimilarity index reduces White non-Hispanic women's *EIFP* by 1.3 log points, but Black non-Hispanic women's *EIFP* by 3.9 log points. Racial-ethnic disparities in *EIFP* appear to originate not just from disparities in race-specific demographic factors, but also from common exposure to an unequal and segmented society.

The final column of the table reports results for intermarriage: the CBSA-level probability that a Black non-Hispanic woman partners with a White non-Hispanic man (conditional on her having a partner at all). The results suggest that intermarriage is a mediating channel for the *EIFP* disparities noted above. For example, we find that a 10 percent increase in the share of Black non-Hispanic women with top-quintile CFI increases intermarriage by a statistically significant 0.12 percentage points. Recalling that the standard deviation of this variable is 0.6, a one-standard-deviation increase in the CFI distribution raises intermarriage by 0.72 percentage points. This

²⁰ The standard deviation in the Q5 sorting coefficient is 0.149, so another way to think about this is that a one-standard-deviation increase in Black non-Hispanic CFI is associated with an increase in Q5 sorting of $.0228/0.149=0.153$ standard deviations.

²¹ Our results for White non-Hispanic women, and preliminary analyses in which we pooled racial-ethnic groups together, support the positive relationship between inequality and assortative matching first noted by Fernandez et al. (2005). The differing patterns for Black non-Hispanic women, however, add nuance to these findings.

effect size may not seem large, but it is roughly 12 percent of the mean intermarriage probability in our CBSA sample, which is only 6.1 percent. We find that inequality constrains intermarriage: a 10 percent increase in CFI inequality reduces intermarriage by 0.51 percentage points. (A one-standard-deviation increase in inequality reduces intermarriage by 0.82 percentage points, which amounts to 14 percent of the sample mean.) In addition, racial-ethnic segregation strongly deters intermarriage: a 10-percentage-point increase in the dissimilarity index reduces intermarriage by 1.4 percentage points. (A one-standard-deviation increase in segregation reduces intermarriage by 36 percent of the sample mean.)

TABLE 2—THE EFFECTS OF SOCIOECONOMIC STRATIFICATION ON WHITE NON-HISPANIC AND BLACK NON-HISPANIC WOMEN’S MARRIAGE MARKET OUTCOMES

	Q5 Sorting		ln(<i>EIFP</i>)		Pr(w/ White partner Black, partnered)
	White	Black	White	Black	
Log share in Q5	0.022* (.012)	0.038* (.020)	0.179*** (.014)	0.064** (.030)	0.012** (.005)
Log adj sex ratio	0.033 (.027)	-.054 (.080)	0.167*** (.035)	0.046 (.091)	-.028* (.017)
Log Q5 inequality	0.058*** (.021)	-.185** (.082)	0.029 (.036)	-.307** (.121)	-.051** (.021)
Racial segregation	-.054* (.032)	0.031 (.176)	-.128*** (.048)	-.393* (.206)	-.141*** (.050)
CFI segregation	0.073 (.058)	0.265 (.301)	-.049 (.077)	-.110 (0.349)	0.029 (.063)
Market size	x	x	x	x	x
Region	x	x	x	x	x
R ²	0.088	0.061	0.358	0.292	0.400
N	850	150	850	150	150

Note: Table presents Ordinary Least Squares regression estimates. “Q” refers to quintile; “adj” stands for “adjusted”. Each observation is a CBSA-by-race-ethnicity cell, where individuals are classified according to their birth CBSAs. See Section III.A for information about the construction of explanatory and outcome variables. Additional control variables include “market size”—i.e., the natural log of the total person-weighted CBSA sample size—and indicators for each Census region. Each observation is weighted by its underlying person-weighted sample size. Robust standard errors appear below coefficient estimates in parentheses. Standard statistical significance legend used. *N*s are rounded for disclosure avoidance purposes.

Source: 2011-2019 American Community Survey linked to 1040 Forms from the Internal Revenue Service.

C. Forecasting the Effects of a Large-Scale Reduction in Socioeconomic Stratification

How does the organization of American society shape White-Black gaps in family income? To put the above results in perspective, we consider a counterfactual experiment in which we i) eliminate our observable measures of demographic disadvantage; and ii) reduce stratification, by lowering U.S. income inequality to Scandinavian levels and eliminating racial-ethnic segregation. We compute *EIFP* gaps in the observed data and in this counterfactual scenario.

First, consider Panel A of Table 3, which reports the average covariate and outcome levels in the observed data. Both White non-Hispanic and Black non-Hispanic women face high average levels of CFI inequality. The average log Q5 inequality measure is roughly 1.4, indicating that average CFI level of individuals from the top quintile is $\exp(1.4) \cong 4.1$ times as large as the average CFI level of individuals from the 1st-4th quintiles. There is also a large gap in CFI levels between White non-Hispanic and Black non-Hispanic individuals: in the typical CBSA, roughly 25 percent of White non-Hispanic individuals originate from the top quintile, whereas only 5 percent of Black non-Hispanic individuals do. Both groups are exposed to highly segregated environments: the average CBSA has a racial-ethnic dissimilarity index of roughly 0.5 in the White non-Hispanic sample and 0.6 in the Black non-Hispanic sample. Finally, the average CBSA contains 0.97 non-institutionalized White non-Hispanic men per White non-Hispanic woman, but only 0.77 non-institutionalized Black non-Hispanic men per Black non-Hispanic woman.

Panel B of the table records covariate levels and outcomes in the counterfactual world.²² We find that the counterfactual experiment closes over half of the 137-log-point *EIFP* gap between White non-Hispanic and Black non-Hispanic women in the average CBSA. That is, the average White non-Hispanic woman goes from having roughly 3.9 times as much partner income as the average Black non-Hispanic woman (in the data) to roughly 1.9 times as much partner income (in the counterfactual world). In level terms, the average partner income gap shrinks from around \$30,000 to around \$15,000. Moreover, the intermarriage rate more than triples, from around 6 percent in the data to around 19 percent in the counterfactual world. Although substantial partner income gaps remain, and the share of Black non-Hispanic women partnering with White non-Hispanic men remains small, the results suggest that a large-scale reduction of inequality and segregation in America would have substantial spillover effects in the marriage market

Two remarks are in order. First, although White non-Hispanic women have a substantial advantage over Black non-Hispanic women in childhood family income, equalizing the CFI distribution across racial-ethnic groups explains only a modest share of our findings. Specifically, reducing the Q5 of share of White non-Hispanic women to that of Black non-Hispanic women reduces the log *EIFP* gap from 1.37 to 1.09. The additional counterfactual reduction from 1.09 to 0.66, reported in the table, occurs conditional on CFI distribution. That is, the counterfactual experiment reduces the observed disparity in upward intergenerational mobility of family income by $(1.09-0.66)/1.09=40$ percent.²³ Second, it is important to emphasize that our estimates only consider CBSA-level disadvantages that are identified by birth location. To the extent that our birth-city-level measures are imperfect proxies for the full extent of Black non-Hispanic disadvantage in marriage markets—due to hyperlocal patterns of disadvantage not reflected in our

²² The 0.77 value for log Q5 inequality is determined by the following calibration. Under the assumption that family income is distributed lognormally, which is a reasonable approximation to U.S. data, then a 0.77 value for log Q5 inequality is consistent with a Gini coefficient of around 0.26, which is slightly below the Gini for Sweden according to recent OECD data. The reduction in log Q5 inequality from around 1.4 to 0.77 means that the average Q5 family goes from being around 4.1 times as rich as the average Q1-Q4 family to being around 2.2 times as rich.

²³ We get similar results when we increase the Black non-Hispanic share in Q5 to equal the White non-Hispanic share: the log *EIFP* gap falls from 1.37 to 1.27, and the full counterfactual experiment reduces the gap to 0.79. Thus, the simulation reduces the mobility wedge by $(1.27-0.79)/1.27=38$ percent.

broader measures (Chetty et al. 2020), or adulthood experiences of disadvantage orthogonal to birth disadvantage—our estimates understate the effects of socioeconomic stratification on racial-ethnic differences in intergenerational family income mobility.

TABLE 3—AVERAGE CBSA-LEVEL COVARIATES AND OUTCOMES
FOR WHITE NON-HISPANIC AND BLACK NON-HISPANIC WOMEN

	<i>Panel A. Observed Data</i>			<i>Panel B. Counterfactual</i>		
	White	Black	Gap	White	Black	Gap
<i>Covariates</i>						
Log Q5 inequality	1.37	1.48	-0.11	0.77	0.77	0.00
Log share in Q5	-1.40	-2.94	1.54	-2.94	-2.94	0.00
Share in Q5	0.25	0.05	0.19	0.05	0.05	0.00
CFI segregation index	0.37	0.41	-0.04	0.37	0.41	-0.04
Racial segregation index	0.48	0.63	-0.15	0.00	0.00	0.00
Log adjusted sex ratio	-0.03	-0.26	0.23	-0.26	-0.26	0.00
Adjusted sex ratio	0.97	0.77	0.20	0.77	0.77	0.00
<i>Outcomes</i>						
Log <i>EIFP</i>	10.61	9.24	1.37	10.37	9.71	0.66
<i>EIFP</i>	40830	10530	30300	31890	16480	15410
Intermarriage		0.06			0.19	

Note: Table presents CBSA-level averages of marriage market covariates and outcomes in the observed data and in the counterfactual scenario. See Section III.A for further information on the construction of the CBSA sample and the lists covariates. Each CBSA observation is weighted by its underlying person-weighted sample size. *EIFP* stands for expected income from partner: see equation (2) for further information on its construction. Intermarriage is probability that a Black non-Hispanic woman partners with a White non-Hispanic man, conditional on having a partner at all.

Source: 2011-2019 American Community Survey linked to 1040 Forms from the Internal Revenue Service.

V. Discussion

We have built a novel dataset, by linking American Community Survey responses with parental tax records, to generate a variety of new findings regarding the intergenerational transmission of family income. We have focused our analyses on a comparison between White non-Hispanic and Black non-Hispanic women and have shown the following, conditional on childhood family income (CFI). First, White non-Hispanic women have roughly double the propensity to live with a romantic partner as do Black non-Hispanic women. Second, White non-Hispanic women partner with much higher-CFI individuals on average than do Black non-Hispanic women. Third, top-CFI White women are much likelier to match assortatively on CFI than top-CFI Black women, while the reverse holds for bottom-CFI individuals. Fourth, these margins converge to produce a wide mobility wedge, where Black non-Hispanic women can expect 60 percent less partner income from participating in the marriage market as can equivalent White non-Hispanic women. This expected partner income disparity accounts for almost the entire

observed gap in family income mobility across generations. Finally, these disparities appear to be driven by prevailing income inequality and racial-ethnic segregation in local marriage markets.

While it is straightforward to generate our findings from a simple matching framework, the framework suggests a nuanced policy implication: a tradeoff between increasing within-race mobility in the marriage market and decreasing the racial mobility gap. To illustrate these points, consider an environment in which individuals are characterized by either of two social identities (White or Black) and either of two economic statuses (Poor or Rich), where White individuals are Richer on average than Black individuals. Let q_R denote the share of race group R that is Rich: thus, $q_B < q_W$. We abstract from sex-ratio considerations by assuming that both sides of the matching market have identical sizes and distributions of each characteristic. We consider a matching process in which everyone is assigned to one of two submarkets according to a randomly distributed same-race preference, or friction that impedes cross-race interactions. Denote the two submarkets as π and ρ . We capture segmentation with the parameter σ , which describes the share of Black (White) individuals assigned to submarket π (ρ). Thus,

$$(6) \quad q_\pi = \sigma q_B + (1 - \sigma)q_W; \quad q_\rho = \sigma q_W + (1 - \sigma)q_B.$$

With $\sigma > 1/2$, we have $q_\pi < q_\rho$ and the majority of Black (White) individuals participating in the poorer (richer) submarket. After submarket assignment, submarkets clear according to a frictionless matching process where economic status is the sole matching characteristic (a la Becker 1973).

Table 4 specifies the equilibrium of this matching market by race group. For each race group, the allocation is determined by three parameters: q_R ; β_R , which is the linear probability model assortative matching index discussed earlier; and r_R , which is the share of race group R 's partners that are Rich. The segmentation process dictates the following identities

$$(7) \quad \beta_B = \sigma \beta_\pi + (1 - \sigma)\beta_\rho; \quad \beta_W = \sigma \beta_\rho + (1 - \sigma)\beta_\pi$$

$$(8) \quad \begin{aligned} r_B &= \sigma \left((1 - \beta_\pi)q_\pi + \beta_\pi q_B \right) + (1 - \sigma) \left((1 - \beta_\rho)q_\rho + \beta_\rho q_B \right); \\ r_W &= \sigma \left((1 - \beta_\rho)q_\rho + \beta_\rho q_W \right) + (1 - \sigma) \left((1 - \beta_\pi)q_\pi + \beta_\pi q_W \right) \end{aligned}$$

where β_s describes economic assortativeness in submarket s . Market-clearing constraints imply that the four matching probabilities in each box are between 0 and 1, and sum to 1. These determine the endogenous object $r_R^* = r_R - q_R \beta_R$, which is the share of Poor partners from group R that match with a Rich partner.

To see how a race-neutral intervention to increase mobility could increase the racial mobility gap, first imagine that matching is perfectly assortative with respect to economic status in each submarket. This occurs when $\beta_R = 1$ and $r_R^* = 0$. In the resulting market equilibrium, there is no mobility gap because there is no mobility for anyone: each Poor (Rich) individual is matched to another Poor (Rich) individual, regardless of race. Now consider an intervention that makes

matching random with respect to economic status. This occurs when $\beta_R = 0$ and $r_R^* = r_R$. In this new equilibrium, a mobility gap emerges: all Black (White) individuals have an r_B (r_W) probability of matching with a Rich partner, yielding a mobility gap of $r_W - r_B$.

TABLE 4—MATCHING PATTERNS BY RACE, IN TERMS OF MARGINAL CFI DISTRIBUTION AND LINEAR PROBABILITY MODEL ASSORTATIVE MATCHING PARAMETER (β)

		Partners of Black individuals		
		Poor	Rich	Total
Black individuals	Poor	$(1-q_B)(1-r_B^*)$	$(1-q_B)r_B^*$	$1-q_B$
	Rich	$q_B(1-r_B^* - \beta_B)$	$q_B(r_B^* + \beta_B)$	q_B
	Total	$1-(r_B^* + q_B\beta_B)$	$r_B^* + q_B\beta_B$	
		Partners of White individuals		
		Poor	Rich	Total
White individuals	Poor	$(1-q_W)(1-r_W^*)$	$(1-q_W)r_W^*$	$1-q_W$
	Rich	$q_W(1-r_W^* - \beta_W)$	$q_W(r_W^* + \beta_W)$	q_W
	Total	$1-(r_W^* + q_W\beta_W)$	$r_W^* + q_W\beta_W$	

Note: Equation (2) defines the linear probability model assortative matching parameter, which is β_R for race group R . The parameter q_R is the share of individuals of race group R that are Rich. The endogenous object $r_R^* = r_R - q_R\beta_R$, where r_R is the share of race group R 's partners that are Rich. See text for discussion.

Our empirical results also showed that assortative matching on CFI is differentially strong for the Richest White individuals (relative to the Richest Black individuals) and the Poorest Black individuals (relative to the Poorest White individuals). The model illustrates how these differential sorting patterns widen mobility gaps beyond the “race-neutral sorting” case discussed above. For expository purposes, suppose that $\sigma = 1$, such that the marriage market is perfectly segmented on race. Suppose further that matching is random with respect to CFI in the Black submarket, but perfectly assortative on CFI in the White submarket. It follows that Rich Black individuals have an r_B probability of matching with a Rich partner, while Rich White individuals have a probability of 1. This yields a mobility gap of $1 - r_B$, which is larger than the $r_W - r_B$ gap found in the race-neutral sorting benchmark case. It is easy to show that this result holds for any $\sigma > 1/2$.²⁴

²⁴ In the general case of imperfect segmentation, when matching is random in the poorer submarket and perfectly assortative in the richer submarket, Rich Black individuals have a $\sigma q_\pi + 1 - \sigma$ probability of matching with a Rich individual, while Rich White individuals have a $\sigma + (1 - \sigma)q_\pi$ probability. In the benchmark scenario of random matching in both submarkets, Rich Black individuals have a $\sigma q_\pi + (1 - \sigma)q_\rho$ probability of matching with a Rich individual, while Rich White individuals have a $\sigma q_\rho + (1 - \sigma)q_\pi$ probability. Given $\sigma > 1/2$ and Equation (6), a racial mobility gap for Rich individuals exists in both cases, but is smaller in the benchmark case.

These tradeoffs between increasing mobility in a race-neutral sense and reducing the racial mobility gap arise because, in racially segmented marriage markets, mobility increases the extent to which an individual's marriage market outcomes rise and fall with the average economic status of their racial-ethnic group. American public schooling is a relevant example. Public schooling increases the mixing of individuals across economic lines, promoting economic mobility. However, the severe extent of racial-ethnic segregation in the public school system implies that preferential egalitarianism toward the majority racial-ethnic group may widen racial-ethnic mobility gaps in ways that spill over to the marriage market. In a similar vein, improving low-income students' access to affluent, White private schools might reduce assortative matching of Rich White individuals and thus lower the racial mobility gap at the top of the CFI distribution. However, so long as these low-income students are themselves predominantly White, this will occur at the expense of a racial mobility gap at the bottom of the CFI distribution. Policies that engage youths with a more economically diverse set of peers and experiences without addressing racial segmentation might improve one metric of inequality at the expense of another.

Our CBSA-level regressions revealed that racial disparities in marriage market outcomes are amplified in communities with greater segregation (which our model would interpret as an increase in the segmentation parameter σ). These patterns reflect the legacy of devaluation and discrimination against Black people in the United States, and one might hope they fade with time. As the social and economic positions of Black and White Americans converge, preferences for same-race unions and search frictions that impede cross-race partnering may naturally weaken. But as stratification economists have argued (Darity, 2022; Chelwa, Hamilton, and Stewart, 2022), the persistence and magnitude of racial-ethnic disparities in market outcomes may reflect ongoing efforts of dominant groups to shape markets to their advantage. Applied to marriage markets, this alternative view suggests that the conditions of union formation are a tool that affluent groups can use to consolidate resources and to maintain their dominant economic position. If this account is correct, then it suggests the importance of policy interventions that treat seriously the exclusionary tendencies of elite White non-Hispanic populations.

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Appendix Figures and Tables

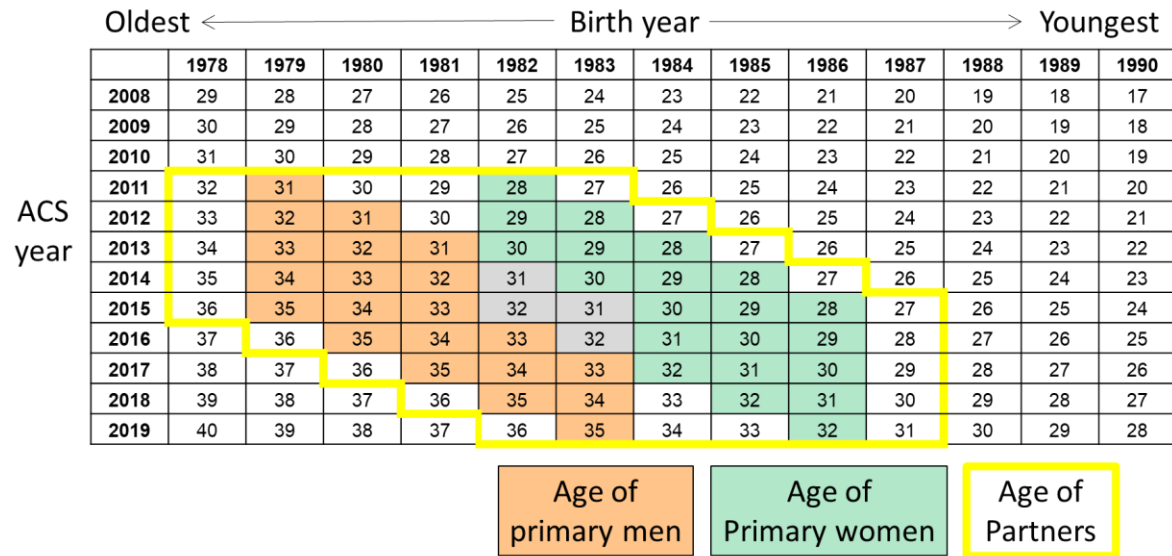


FIGURE A1. SAMPLE CONSTRUCTION AND AGE RESTRICTIONS

Note: Columns indicate year of birth and rows are the years respondents are observed in the ACS. Our individual sample contains men born between 1979 and 1983 and women who were born between 1982 and 1986 (highlighted in orange, gray, and green). Our couple sample consists of all identified partnerships in which one partner is a member of the individual sample and the other has an age-birth cohort combination that falls inside the yellow box.

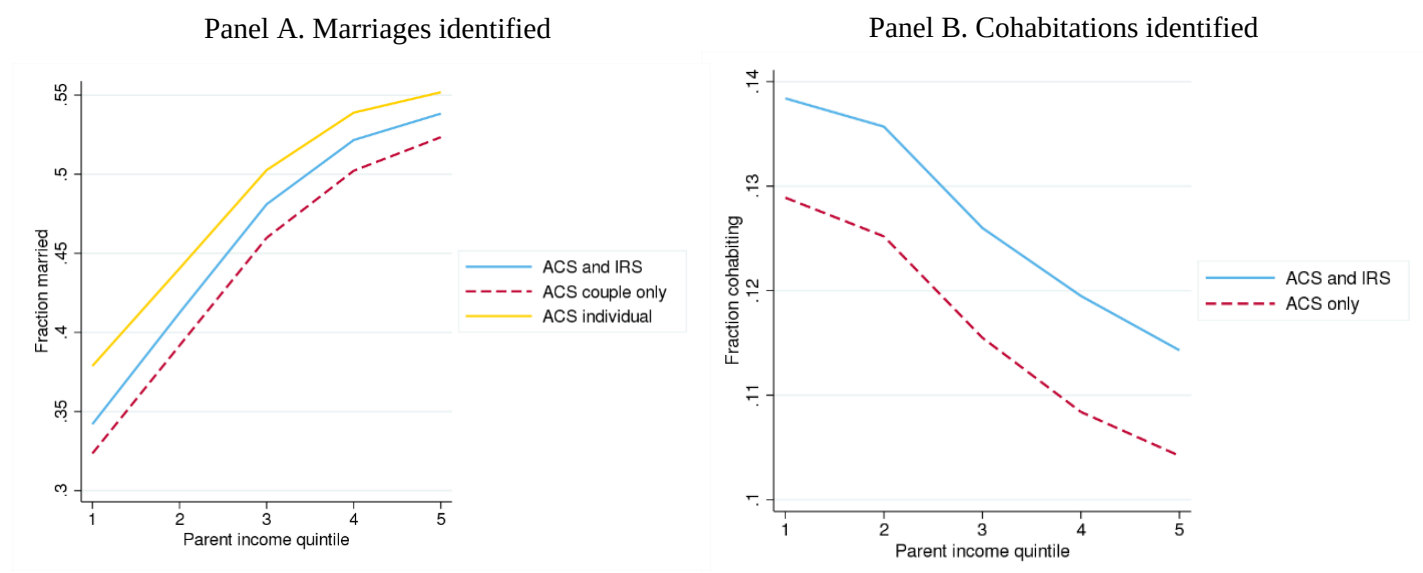


FIGURE A2. ADDITIONAL SPOUSES AND PARTNERS GAINED FROM TAX DATA

Note: This figure plots the fraction of individuals in each quintile of childhood family income by different relationship categorizations. In Panel A, we show the fraction of ACS respondents who report being married (yellow, solid), the fraction of ACS respondents who we can link to a spouse using the ACS (red, dashed), and the fraction of ACS respondents who we can link to their spouse using the ACS and filing status in the IRS 1040s. Panel B shows the fraction of individuals whose unmarried partners can be identified using the ACS (red, dashed) and the fraction of individuals whose unmarried partners can be identified using the ACS or by IRS 1040 filing status.

Source: Individual sample described in Section I.A, which is generated by linking 2011-2019 American Community Survey to 1040 Forms from the Internal Revenue Service.

TABLE A1—INTERGENERATIONAL MOBILITY OF WOMEN’S FAMILY INCOMES

Mobility statistic	White, NH	Black, NH	Hispanic	AIAN, NH	Asian, NH
<i>Panel A. Observed Data</i>					
Pr(move out of Q1)	0.73	0.57	0.72	0.54	0.83
Pr(move from Q1 to Q5)	0.11	0.03	0.08	0.03	0.27
Pr(remain in Q5)	0.39	0.16	0.29	0.22	0.44
Pr(move from Q5 to Q1)	0.08	0.20	0.13	0.17	0.10
<i>Panel B. Counterfactual: All Groups have Black Women's Personal Income</i>					
Pr(move out of Q1)	0.83	0.70	0.79	0.75	0.80
Pr(move from Q1 to Q5)	0.19	0.08	0.15	0.10	0.26
Pr(remain in Q5)	0.53	0.27	0.45	0.42	0.45
Pr(move from Q5 to Q1)	0.06	0.14	0.08	0.08	0.09
<i>Panel C. Counterfactual: All Groups Have Black Women's Partner Income</i>					
Pr(move out of Q1)	0.73	0.78	0.78	0.67	0.86
Pr(move from Q1 to Q5)	0.13	0.13	0.13	0.08	0.34
Pr(remain in Q5)	0.42	0.37	0.38	0.32	0.56
Pr(move from Q5 to Q1)	0.11	0.11	0.11	0.15	0.09

Note: “NH” stands for non-Hispanic; “AIAN” stands for American Indian or Alaskan Native. “Q” refers to quintile. This table maps the distribution of CFI into the distribution of adult family income (AFI), which is the sum of an individual’s personal income and their partner’s income (set to zero if no partner present). For example, “Pr(move out Q1)” is the conditional probability that a women from the bottom CFI quintile is not in the bottom quintile of AFI. Panel A is the observed data. Panel B (C) replaces observed personal (partner) income for each woman from CFI percentile p with the personal (partner) income of a randomly-selected White non-Hispanic woman also from percentile p . This process is repeated 100 times; the reported mobility statistics are averaged across these 100 counterfactual distributions.

Source: 2011-2019 American Community Survey linked to 1040 Forms from the Internal Revenue Service.