The Role of Dating Markets in Shaping Maternal and Neonatal Health: Evidence from Sex Ratios at Birth

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Abstract

This paper provides the first causal evidence on how the strength of women's position in the dating market influences maternal and neonatal health outcomes. I proxy the strength of women's position by the availability of adult male partners. I introduce a novel instrument based on randomness in sex at birth to address the endogeneity of this variable. A stronger female position in the dating market leads to a reduction in out-of-wedlock births, lowers rates of chlamydia and hypertension in mothers, and decreases the incidence of low APGAR scores in newborns. Connecting this to racial health disparities, Black women's limited partner prospects contribute to 5-10% of the racial health gap. Eliminating racial disparities in incarceration would prevent 200-700 adverse outcomes annually among Black mothers.

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1 Introduction

In the US, maternal mortality rate among Black women is 2.5 times higher than among White women, and Black infants are twice as likely to die as White infants (CDC (2023a,b)). Black mothers also suffer from higher morbidity and worse birth outcomes. For instance, Black mothers are twice as likely to have hypertension as White mothers, and Black newborns are 75% more likely to have a low APGAR score[1] than White newborns[2].

While these health inequalities are persistent and have been well documented (Louis et al. (2015); MacDorman et al. (2021); Hill et al. (2022); Jang and Lee (2022)), their specific causes have proven difficult to pin down. Black women are exposed to many correlated factors that may negatively impact pregnancy outcomes. For example, they more frequently experience discrimination in healthcare (Aizer et al. (2004); Lillie-Blanton and Hoffman (2005); Almond et al. (2006); Buchmueller et al. (2016); Hoffman et al. (2016); Kuziemko et al. (2018); Eli et al. (2023); Alsan and Wanamaker (2018); Ly (2021)), suffer consequences of structural racism (Bailey et al. (2021); Lane et al. (2022)), and are more likely to be poor (Hoynes et al. (2011); Almond et al. (2011); Fryer et al. (2013); Elder et al. (2016); Carruthers and Wanamaker (2017)). Nonetheless, even accounting for differences in socioeconomic variables, racial health inequalities persist. Kennedy-Moulton et al. (2022) show that the disparity between Black and White infants occurs at all parental income levels.

An under-examined element among the factors contributing to these disparities is the influence of dating market dynamics. Achieving a better match and stronger female bargaining power in relationships is positively associated with improved health and welfare for both women and children. (Rao (1997); Adimora et al. (2002); Angrist (2002); Panda and Agarwal (2005); Cornwell and Cunningham (2008); Stevenson and Wolfers (2006); Li and Wu (2011); Armand et al. (2020)). Consequently, disparities in the strength of one's position in the dating market can influence matching quality and the distribution of power in relationships, ultimately driving differences in health outcomes. While one's competitive position in the dating market is not directly observable, the relative supply of male and female partners is key in shaping it (Becker (1973); Chiappori et al. (2002); Angrist (2002)). This aspect is particularly salient in the US context, where Black women face considerably unfavorable sex ratios in the dating markets[3]. More than 90% of relationships involve partners of the same race, and there are only 89 Black men for every 100 Black women, compared with

[1] APGAR score is given to a child 5 minutes after birth. It assesses a baby's skin color, heart rate, reflexes, muscle tone and breathing. It ranges from 0 to 10 and a score below 7 means the baby needs immediate medical attention.

[2] See figure III

[3] Sex ratio is defined as the ratio of men to women

102 White men for every 100 White women. However, isolating the impact of dating and bargaining power is challenging due to the highly endogenous nature of dating decisions. As a result, there remains a significant gap in understanding the causal effects of dating market dynamics on pregnancy outcomes and health disparities.

This paper aims to bridge this gap by providing the first causal evidence for the role of the dating market in generating health disparities. It has two principal objectives: (1) to investigate the causal link between the strength of women's position in the dating market and maternal and neonatal health in the US, and (2) to examine the extent to which racial disparities in the dating market contribute to health disparities.

The key contribution of this paper is a new identification strategy that addresses the challenge of endogeneity when exploring how dating market affects individual outcomes. My empirical strategy is based on the notion that the sex ratio affects partners' outside options and, subsequently, matching and bargaining power in the dating market (Becker (1973)). An obvious difficulty that has hampered past research on this topic is that the sex ratio itself may be endogenous. For instance, a high level of crime may lower the sex ratio by reallocating men to prisons and harm female health due to exposure to violence. I introduce a new instrument aimed to overcome such endogeneity. Specifically, I focus on heterosexual dating markets defined by the intersection of residence, race, and age groups[4] and I instrument local, adult sex ratios with the local sex ratios at the cohort's birth. Whether a newborn is a boy or a girl is close to 50% and plausibly random. My instrument leverages such randomness in the sex at birth and low spatial mobility. Particularly in smaller markets where the law of large numbers hasn't fully "kicked in", the chance of more male or female births tends to create significantly imbalanced sex ratios. I show that the local sex ratio at birth is a strong predictor of the local sex ratio of the cohort when it enters adulthood. I also address potential identification concerns by showing that the variation in the instrument and the subsequent results are not driven by sex-selective abortions, stopping rules, socioeconomic or environmental conditions around the time of birth, or selective migration. Furthermore, I provide suggestive evidence that the dating market is the key channel linking sex ratio and health, and I find no evidence that other potential channels might be at play. I then leverage this variation to measure how differences in the relative availability of potential male partners affect the maternal and neonatal health of 7 million births between 2011 and 2019 in the US. While I use this instrument in the context of health, it could be naturally extended to other outcomes affected by the matching and relationship bargaining power.

I find that a favorable female position in the dating market plays a vital role in determin-

[4] While some people prefer to date within own gender, across racial or age groups, I chose such definition for methodological reasons exposed in section 3.1.

ing maternal and neonatal health. Firstly, female health outcomes improve when there is more men on the market. Mothers facing a market at the 75th percentile of the proportion of men are 0.37 percentage points less likely to have chlamydia and 0.26 percentage points less likely to have hypertension than mothers in markets at the 25th percentile. These are substantial magnitudes relative to the mean: the average prevalence of these diseases is 1.8% and 2.2% respectively. Finally, infants born to mothers with high bargaining power are healthier. Moving a mother from a market at the 25th percentile to one at the 75th percentile decreases the chances that the newborn will have a low APGAR score by 0.2 percentage points (compared to a mean of 2.4%). While the signs on other outcomes such as birth weight, gestation, or assisted ventilation go in the expected direction, they remain below traditional statistical significance thresholds. Moreover, dating market dynamics appear to be key the channel driving these results. In markets where women are scarce, they achieve better marital outcomes. This observation supports prior findings that marriage market outcomes improve with a stronger position in the market, introducing a new source of exogenous variation to confirm these results. Increasing the proportion of men in the market from the 25th to the 75th percentile decreases the share of births with unknown fathers by 1.6 percentage points and out-of-wedlock births by 2.9 percentage points. These shifts in dating market dynamics are accompanied by changes in the composition of mothers, which may partially account for the observed health improvements. Stronger bargaining power may lead to different resolutions of disagreements between men and women regarding fertility choices, as documented in other settings (Ashraf et al. (2023)). In my study, women with stronger positions in the dating market have lower birth rates, despite higher partners' availability. Those who do decide to have a child tend to be healthier, more educated, and have more educated partners than mothers in less favorable markets. Importantly, one cannot be certain that the dating is the only channel through which the sex ratio impacts female and neonatal outcomes. My analysis identifies it as a key mechanism, with evidence on marriage market outcomes. Other channels might exist such as changes in violent behaviors or peer effects in education. While I cannot fully rule them out, I present suggestive evidence indicating that they are unlikely to drive the observed effects.

The magnitude of the effects can be contextualized within policies that alter the relative availability of male partners. I show that empirical variation in the sex composition, particularly across racial groups, is partly policy driven. In a decomposition exercise, I demonstrate that incarceration accounts for 40 to 50% of the sex ratio gap between Black and White dating markets, while violent deaths account for 2 to 7%. Therefore, policies that reduce disparities in incarceration rates among Black and White men[5] could have positive

[5]Section 4.2 reviews literature showing that the disparity in incarceration rates is partly shaped by

secondary effects on Black women and children. In line with these findings, Boen et al. (2023) discovered that state incarceration policies are related to birth outcomes, particularly among racial minorities. For instance, they show that a *truth in sentencing*[6] policy decreased incarceration and improved birth outcomes.

A counterfactual exercise provides insights into the order of magnitude of the effects of dating markets in the US. It demonstrates that the differences on the dating markets in the US could generate 5-11% of the racial gap in health outcomes between Black and White mothers. In a scenario where Black women face the same dating markets as White women the health disparities in chlamydia and hypertension among pregnant women would decline by 5% and 11% respectively, and the disparities in the low APGAR score by 8%. Improving the APGAR score would be particularly important because 11% of infants with low APGAR score die within a year of birth (compared to 0.2% of infants with normal score). Moreover, adults who have low APGAR score as children are significantly more likely to suffer from neurological disabilities and impaired cognitive functions (Ehrenstein et al. (2009)).

A policy modestly narrowing sex ratio disparities, akin to equalizing incarceration rates for non-violent offences between Black and White people, would still have important spillovers to the health of mothers and infants. It could prevent 200-700 adverse pregnancy outcomes per year among Black mothers through its effect on the dating market alone. While cautious about extrapolating the causal results to the population of non-violent inmates, I show theoretically that an increase in the supply of men, independent of their potential income, benefits all women. The model predicts that adding low-income men brings the most significant welfare increase to high-income women, as they enjoy the cumulative effect of better outside options across the income distribution.

The primary contribution of this paper is to provide the first causal evidence linking dating markets to pregnancy outcomes. The impact of matching and bargaining power on partners' outcomes is well-recognized in economics, beginning with Becker's insights (Becker (1973)). In his seminal work, Becker demonstrated how a scarcity of women in the dating market shifts relationship gains away from men and toward women. Grossbard-Shechtman (1984) extended this intuition to explore the sex ratio's effects on spouses' labor supply. The couple's decision-making framework has been extensively developed by Chiappori and coauthors (Chiappori (1988), Chiappori (1992), Bourguignon and Chiappori (1994), Browning and Chiappori (1998), Chiappori et al. (2002), Chiappori and Ekeland (2006)). Empirical studies have corroborated the importance of bargaining power for household outcomes

an interplay of biases and policies. It also discusses specific initiatives aimed at reducing disparities in incarceration.

[6] These policies require offenders to serve a significant part of their sentence.

(Blundell et al. (1993), Browning et al. (1994), Lundberg et al. (1997)). Researchers have shown that various measures of woman's empowerment within a household correlate with enhanced female health and safety (Li and Wu (2011); Armand et al. (2020); Rao (1997); Panda and Agarwal (2005); Stevenson and Wolfers (2006). Moreover, empowering a woman tends also to improve her children's well-being. Literature documented correlations between female bargaining power and the use of prenatal care (Beegle et al. (2001)), children morbidity and mortality (Thomas et al. (1999), Maitra (2004)) and spending on children (Thomas (1990); Lundberg et al. (1997); Calvi (2020)). Nonetheless, most of these studies do not identify causal relationships. My results add to this literature by demonstrating causally that stronger female position in the dating market positively affects health during pregnancy. Moreover, while previous studies identifying the link between relationship dynamics and welfare have been set in developing countries, this paper shows that leverage in dating also matters in the context of a high-income country where policy largely shapes the dating markets.

This study also adds to the literature linking the sex ratio in the dating markets to the distribution of bargaining power within relationships by proposing a new source of exogenous variation in sex ratios. Researchers used variation in the local, adult sex ratios to measure changes in the negotiating power of partners (Chiappori et al. (2002); Cornwell and Cunningham (2008); Adimora et al. (2002); Kang and Pongou (2020)). As the sex ratios might be driven by factors also affecting outcomes of interest, other studies relied on historical shocks to address such endogeneity (Angrist (2002); Lafortune (2013); Abramitzky et al. (2011); Brainerd (2016); Liu (2020); Alix-Garcia et al. (2022); Battistin et al. (2022)). One strength of my paper is to isolate the exogenous variation in the dating market dynamics through the use of a novel instrument for the local, contemporaneous sex composition in the dating market. My instrument can be used independently of time and location as long as the data on sex composition at birth is available. In the case of the US, it enables an investigation of the relationships and outcomes from recent administrative datasets.

My paper contributes to understanding racial differences in demographic structures, focusing on the lower sex ratios in Black communities, primarily driven by incarceration and early mortality (Pouget (2017)). Building on prior analyses, such as Hall (2000), I extend the decomposition of sex ratios to include factors such as incarceration, which proves to be the critical component, driving almost half of the gap between White and Black populations. Addressing biases within the criminal justice system could therefore play a significant role in reducing this imbalance.

Lastly, an important contribution of this paper is to provide evidence that the dating market might be a non-negligible source of racial health disparities. Removing Black women's disadvantage in the dating market could shrink the gap in adverse pregnancy outcomes between Black and White mothers by 5-10%. My findings also point to mass incarceration as a policy that might have unexpectedly widened racial health disparities in maternal and neonatal outcomes by reducing supply of potential male partners.

My research informs policymakers that empowering women in the dating market can improve maternal and neonatal health. Such insight is particularly relevant in the context of the US, where maternal and infant mortality are considerably higher than in comparable countries (Ventures (2021)). Five out of every 1000 live births in the US do not survive until their first birthday, a death rate that is 72% higher than in the European Union. Mothers and children belonging to racial minorities experience particularly elevated mortality rates (Petersen (2019)) and the disparities have been further amplified during the Covid-19 pandemic (Hoyert (2022)). Furthermore, disadvantages in health experienced early in life can persist into adulthood, harming the future social, educational and economic attainments of the child (Almond and Mazumder (2011); Barreca (2010); Currie (2009); Hoynes et al. (2016); Butikofer et al. (2016); Black et al. (2019)). Andrews and Logan (2010); East et al. (2017) and Giuntella et al. (2022) show that adverse health outcomes can persist even into the next generation, which may lead to the inter-generational transmission of inequalities. This literature thus highlights that policies enhancing health during pregnancy can have high returns for both mothers and children, and may be an important tool for reducing racial health disparities. Studies set in developing countries provide evidence that increasing female bargaining power improves children's health (Duflo (2003)), and educational attainment (Rangel (2006); Deininger et al. (2010); Björkman Nyqvist and Jayachandran (2017)). While empowerment can be achieved through various tools, the direct implication of my paper suggests focusing on eliminating racial disparities in the sex ratios, which are unintended consequences of such policies as mass incarceration.

The paper proceeds as follows. Section 2 presents the conceptual framework. Section 3 describes the data and the sample construction. In section 4, I perform the decomposition of racial differences in sex ratios. Sections 5 and 6 outline the empirical framework and results for the relationship between bargaining power and health outcomes. Section 7 shows the counterfactual scenarios. Conclusion closes the paper.

2 Conceptual Framework

The dating market tends to function according to economic principles. Men and women enjoy relationships and maximize utility by finding the best possible partner (Becker (1973)). However, the supply of potential mates constrains their options. Hence, changes in the supply affect the matching and the division of surplus in the equilibrium.

Technically, the sex ratio may influence matching and the intra-household allocation of decision power in several ways. A mechanism that has been thoroughly investigated operates through equilibrium on the marriage market. In the appendix section C.12, I motivate such mechanism by solving a simple dating market model. Focusing on intuition, suppose that there is an increase in the supply of men relative to women on the dating market. Women are now more likely to find and sustain a partnership. Moreover, the competition among men to secure a female partner becomes stronger. Experimental evidence from speed dating and dating apps indeed shows that women become more selective when they face larger pool of potential mates (Fisman et al. (2006); Fong (2020)). Consequently, a woman ends up with a higher-quality partner. A priori, whether it increases or decreases the quality of an average match is an empirical question, because it can mean that previously single, low quality woman can now find (a low quality) partner. Nonetheless, such mechanism would require strong monogamy, which is also an endogenous outcome subject to bargaining. Moreover, in economic terms, men have to "pay a higher price" for a match. Practically, the price will consist of a shift in decision power within the household, from men to women. This shift, in turn, may have diverse translations: financial transfers, more leisure time, higher partner fidelity, fewer occurrences of domestic violence, or better healthcare. While such a marriage market equilibrium mechanism requires some minimum level of intertemporal commitment, it is by no means the sole justification for the importance of the sex ratio. To take just one example, suppose an opposite (and somewhat extreme) world in which no commitment is feasible so that spouses are constantly bargaining about their joint decisions. The threat points—particularly the situation of each spouse after a hypothetical divorce—play a vital role in determining the outcome. A favorable sex ratio strengthens women's bargaining position by making it easier to find a new partner post-divorce, as matching and bargaining power are unseparably linked; the ability to secure a desirable partner enhances a woman's bargaining position.

All in all, one can expect female and pregnancy health to improve as a consequence of the favorable changes in the dating market, and numerous studies tend to confirm this prediction. First, the positive effect may arise simply from gaining a partner. Two-adult households, particularly when compared to single mothers, can achieve higher income through specialization and resource pooling. Increased income is associated with improved neonatal health outcomes (Hoynes et al. (2015)), while women with lower incomes face higher risks of severe adverse pregnancy outcomes (Kennedy-Moulton et al. (2022)). Additionally, being unmarried or a single mother can negatively impact mental health (DeKlyen et al. (2006)). Marriage is also associated with a premium in improved pregnancy outcomes (Buckles and

Price, 2013). Second, securing a higher-quality partner—whether wealthier, healthier, or more educated—can enhance health outcomes. A higher-income spouse is linked to improved health for women (Skalická and Kunst, 2008). A healthier partner can also generate positive spillover effects, enhancing the health, employment, and income of their spouse (Fletcher, 2009; Jeon and Pohl, 2017; Du and Zaremba, 2024). Additionally, a partner's higher education is associated with better health, even after accounting for selection (Monden et al., 2003; Guo et al., 2020). Third, as women match with higher quality partners and gain bargaining power, they experience fewer occurrences of domestic violence and less stress (Rao (1997); Panda and Agarwal (2005); Banks (2011)). As stress and the risk of violence decline, women's health should ameliorate. Studies have found that stress and exposure to intimate partner violence is a risk factor for hypertension (Zhang et al. (2013), Mason et al. (2012)). Pregnant women are particularly vulnerable to these factors which cause adverse pregnancy outcomes (Currie (2013b), Currie et al. (2018), Aizer (2011)). Fourth, more bargaining power translates to better nutrition and subsequent improved health (Li and Wu (2011)). Fifth, sex ratio is also related to sexual health. As women explained during interviews in a qualitative study by Dauria et al. (2015), due to low supply of men, women tend to engage in shorter partnerships which are more often focused on sex and hence are higher risk. Quantitative research corroborates these claims by showing that scarcity of men is associated with more sexual partners, especially among men (Adimora et al. (2002), Cornwell and Cunningham (2008), Pouget et al. (2010)). This could explain why communities with high male incarceration, and hence low sex ratio, suffer from worse sexual health (Thomas et al. (2008), Johnson and Raphael (2009), Stoltey et al. (2015), Kang and Pongou (2020)). Preventing STIs during pregnancy is particularly valuable as such infections are associated with poor birth outcomes (Ryan et al. (1990); Elliott et al. (1990)).

Hence, various channels exist through which a favorable sex ratio leads to better maternal health. Note that one does not need women to have a specific preference for children's well-being, such as in Duflo (2003). As neonatal outcomes are a function of female health during pregnancy, it is enough to assume that a woman cares about her own health. This limited assumption also provides the basis for lack of symmetry: improvement in male health has no direct consequences on birth outcomes. Nonetheless, it is also plausible that mothers might care more about health of children. Under such scenario, men may be willing to dedicate more resources to ensure that female desire for healthy children is satisfied if women have more bargaining power. Therefore, I hypothesize that increasing the proportion of men on the dating market improves female health and, consequently, neonatal health.

3 Sample Construction and Data

3.1 Defining Dating Markets and Computing Sex Composition

I measure differences in bargaining power through deviations from a balanced sex composition in a woman's dating market. The explanatory variable of interest is the proportion of the dating market that is male (*proportion male* henceforth), and I compute it from the Census 2010 which provides the exact population count at the level of interest. While I use the proportion rather than the sex ratio, the two measures have a one-to-one relationship, and I am using the words sex ratio and sex composition interchangeably when describing the imbalance in the dating markets. Moreover, all the results are robust to using the sex ratio instead of the proportion male (see appendix section A.7).

I define dating markets as the intersection of age group, race, and county. In other words, I assume that individuals within the same 5-year age cohort, of the same race, and residing in the same county participate in a single dating market. Naturally, alternative conceptualizations of the dating market exist, encompassing broader geographic regions, different age brackets between genders, and diverse racial compositions. However, my approach does not aim to capture the entire market; rather, it focuses on a segment substantial enough to influence dating dynamics and bargaining power. Even partial shifts in the market can significantly alter market power. In the context of new parents within the natality data, 42% of couples fall within my definition of the market [7]. While this does not cover the entire population, I justify this choice based on its simplicity, the feasibility of constructing an instrument, and its capacity to capture a segment large enough to impact marriage outcomes, as demonstrated in the following sections. Furthermore, as shown in Appendix C.11, allowing for relationships that cross the boundaries of my definition would make my current estimates conservative. Additionally, my research focuses on individuals of heterosexual orientation; a substantial portion of the population may prefer same-gender partners, for whom the sex ratio would not serve as a relevant measure of bargaining power, making my current methodology inapplicable. Finally, I include married individuals in the dating pool, as they can either divorce or engage in extramarital affairs, thereby remaining potentially available partners and relevant to the bargaining dynamics.

My definition of the market also follows previous literature such as Chiappori et al. (2002), Charles and Luoh (2010), Cornwell and Cunningham (2008), and Johnson and Raphael (2009), except that I reduce the geographic scope of the markets to the county. Two reasons motivate this choice. Firstly, search patterns are usually local. People typically find partners

[7] Figures in the section demonstrate measures of shares of couples formed within the market by the market type.

through friends, at local events, or online (Rosenfeld et al. (2019)). Friendship networks tend to be local (Backstrom et al. (2010), Laniado et al. (2018)) and, according to a survey of online dating app users by Kirkham (2019), 2/3 of respondents set their search radius to 30 miles or less. Moreover, dating usually requires physical proximity at a high frequency. Unfortunately, no US dataset contains information on the county where spouses lived before marriage. However, evidence from another developed country, Poland, shows that 90% of spouses lived within 38 miles of each other before marriage (see figure A.1 in the appendix). Additionally, to assess the geographic scope of the market, I examine whether the marriage rate in a county is influenced by the sex composition (at birth) of the dating markets in neighboring counties. With a high level of confidence, I can rule out any significant effects of such cross-county spillovers (table A9). Secondly, I can accurately compute sex composition among non-incarcerated populations in a county by leveraging exact population count on the census-block level. While the procedure requires substantial computing power, it helps to overcome limitations of traditionally used ACS or Census samples, which provide information only on higher geographic level and contain substantial sampling variation[8].

Age is the second criterion that I use to define dating markets. People must be in the same age cohort to belong to one market. The cohorts are people aged 15-19, 20-24, 25-29, and 30-34 in 2010. These groups stem from the cells' definition in the Census Summary tables, but they reflect the age composition of partnerships relatively well. Figure A.2 in the appendix shows the father's and mother's age patterns in the natality data. Around 40%-50% of pregnant women in these age groups have a child with a man in the same age group.

The final criterium is racial homophily. I use four racial groups: White, Black, Asian, and Native Americans[9]. People tend to date within their own race for either availability or preference reasons. Evidence from a speed-dating experiment corroborates a racial preference among women (Fisman et al. (2008)). This pattern is clear in the natality data, especially for White and Black mothers (figure B.21 in the appendix). More than 90% of Black and White women have a child with a father of their race. These proportions are less dramatic for Asian and Native women, but most parents are still of the same race[10]. Interracial parents

[8]Note that having too large definition of the market makes the estimates conservative. Particularly, it adds irrelevant noise to the sex composition of the true market.

[9]Census only allows to distinguish between Hispanic and non-Hispanic White at this granularity level. Hence, the White group excludes Hispanics, while other groups may contain people of Hispanic origin. To remain consistent, I exclude White Hispanic mothers from the health data. Unfortunately, older natality data has not recorded Hispanic origin; hence, the instrument includes the Hispanic population

[10]The statistics concerning same-race partnerships primarily reflect market outcomes, rather than solely competitive opportunities. Nevertheless,constructing markets using weighted averages, where the weights are determined by the proportions of inter-racial and inter-age-group partnerships, does not alter the results. Therefore, I opt for a more straightforward approach, defining the markets as the intersection of these three

are slightly more frequent in smaller locations (figure A.7 in the appendix). Timewise, the share of interracial parents has been slowly increasing over the past 40 years, but it remains low (appendix figure A.4 in the appendix)[11]. I expect my measure of bargaining power to be less noisy in markets with fewer interracial relationships. Indeed the heterogeneity analysis (in the appendix figure: C.25) shows that the main results are stronger in more racially segregated locations.

It is important to acknowledge that, empirically, individuals tend to match on the educational attainment. However, the ability to establish a relationship with a highly-educated partner, which is closely associated with higher income, can depend on one's bargaining power. Consequently, education appears to be an endogenous variable, and thus, I do not use it to define the markets.

Given the definition of the dating market, I compute the sex composition as the number of non-institutionalized men from the county c, of race r and in the cohort a over the overall non-institutionalized population in the same c, r, a cell. I use census-block level data to identify and remove prisons and hence to circumvent the lack of incarceration data at the county/race/cohort level. [12].

The instrument calculates the sex composition at birth analogously, based on the natality data (1976-2006). The details of the instrument construction are relegated to the section 5.

3.2 Health Outcomes

I measure neonatal and health outcomes using 2011-2019 natality data. This data totals around 40 000 000 observations covering all births which occurred in the US in the period of interest. It contains information on mothers' and fathers' characteristics and mothers' and newborns' health outcomes. Examples of included variables are the mother's marital status, her education, whether she had any infections during pregnancy, the infant's birth weight, and whether the child needed medical assistance after the delivery. Notably, the restricted version of the data indicates race, year of birth, and the mother's county of residence. Based on these variables, I assign each woman to her dating market. A limiting assumption is that the sex composition in 2010 was relevant for mothers giving birth up to 2019. Nonetheless, the sex composition tends to be persistent (as shown later), and the instrument alleviates this issue by leveraging this persistence.

aforementioned factors.

[11] I do not find evidence that people enter into more interracial relationships when they face a tight market, although results are noisy.

[12] I identify *jails and prisons* by finding census blocks where more than 50% of the population is institutionalized. This threshold has been chosen as minimizing the overall classification error. It results in 20% of the institutionalized population being misclassified as free and 2% of the free population being misclassified as incarcerated. The instrument eliminates this measurement error.

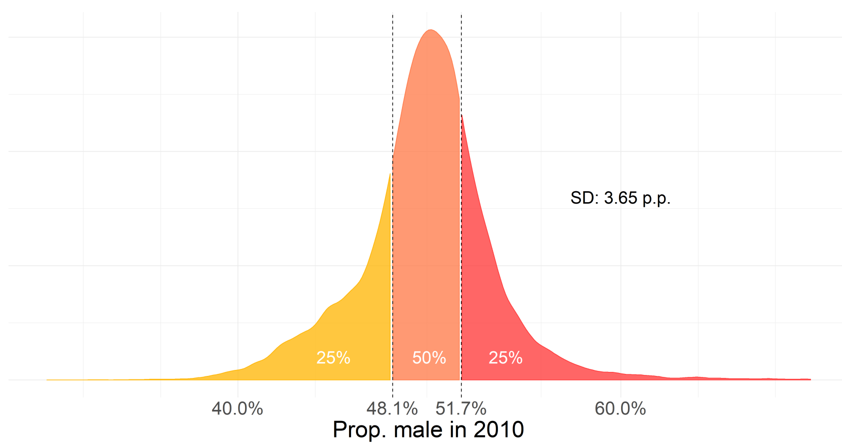
4 Descriptive Statistics: Sex Composition and Health Outcomes

Sex composition in the US dating markets varies substantially. Notably, there are significant racial discrepancies in the sex ratio, which are largely policy driven. Moreover, the racial health inequalities coincide with racial differences in the sex ratios.

4.1 Variation in the sex composition of the dating markets

American women face very different availability of men on their dating market depending on their age, race, and location. Consider the distribution of the markets according to their sex composition on the figure I. The proportion of males at the 25th percentile is 48.1%, which means that there are only 92 men per 100 women. In an entirely monogamous society, 8% of women would not find a partner. At the 75th percentile, men make up 51.7% of the market. Hence, there are around 108 men per 100 women. Not only each woman could potentially find a partner, but also some mates will remain available if she ever wants to switch partners.

Figure I: Density of Proportion Male in 2010

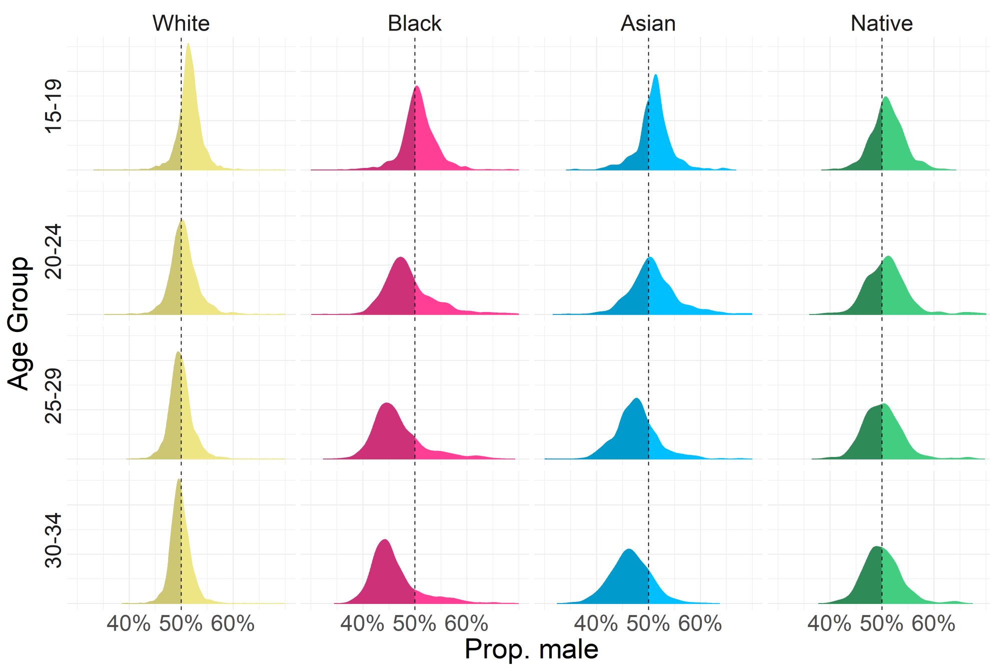


Notes: Figure shows the empirical distribution of the sex compositions. Each observation represents the proportion of men among agents on the dating market. The two vertical lines show the first and the third quartile. Standard deviation is noted on the side. Markets with fewer than 100 people are excluded.

Racial differences drive a considerable part of this variation. For example, a Black woman aged 30-34 may struggle to find a partner on a median dating market as men are scarce: they represent only 45% of the market (82 men per 100 women). On the other hand, White women of the same age face a median dating market that is perfectly balanced, with the proportion of males being 50%.

Figure II details the distribution of the sex composition in the dating markets. It shows the densities of the proportion of males in the market within each race and cohort. The vertical dashed lines represent 50% and correspond to a balanced sex composition. Shaded areas to the left of these lines are proportional to the number of markets with more women than men. Several observations follow from the graph. Firstly, men tend to dominate the markets in the younger cohorts. This is because male births are more likely. However, this trend reverses with age because men have lower survival rates. Secondly, White and Native populations have relatively symmetrical distributions. There are equally many markets with too few men and too few women. The variance is the lowest for White people, meaning their dating markets are the most often balanced. Thirdly, there is a substantial imbalance in the sex composition among Black and Asian populations. Both groups have a sizable number of markets where men are scarce. The problem is the most severe for Black people aged 25-34, where most of the dating markets are largely dominated by women. These striking racial disparities invite the question of what are their main drivers.

Figure II: Density of Proportion Male in 2010 by Race and Cohort



Notes: Figure shows the empirical distribution of the sex composition. Each observation represents the proportion of men among agents on the dating market. The dashed line represents the balanced sex composition of 50%. Markets with fewer than 100 people are excluded.

4.2 Explaining racial differences in sex composition

I quantify various factors' contribution to the racial disparities in the sex ratio by analyzing how the disparity would change if there were no racial differences in the factor's value. To achieve this, I construct a simple descriptive model in which the number of available mates is a function of parameters such as incarceration rates, mortality rates, and immigration rates. Using this model, I calculate the difference in the proportion of men between the actual situation and a hypothetical scenario where the chosen parameter matches that of White people, who serve as the reference group for disparity. This difference reveals the impact of the specific factor in question. I present here the main insights of this analysis, while the details of the methodology, data, assumptions, and the all results can be found in the appendix section A.2.

For Black people, the most critical driver by far is incarceration. Incarceration rates for Black males are considerably higher than for White males. Note that 10% of Black men aged 30-34 are in prisons, while the equivalent number for White men is 2%. Results shows that if Black people faced the same incarceration rates as White people, the difference in the sex compositions would shrink by 45% (see plot A.9 in the appendix). Moreover, a substantial part of missing Black men is in prison for non-violent offenses. Even equalizing the incarceration rates just for non-violent crimes would decrease the racial gap in sex ratios by a quarter (see figure A.10 in the appendix). Interviews in Banks (2012) share insights of Black women who experienced adverse effects of lack of potential partners. Quantitative studies have shown that women living in communities more exposed to male incarceration start working earlier (Mechoulan (2011)), work more and are less likely to marry (Charles and Luoh (2010), Liu (2020)). These effects are in line with implications of lower bargaining power of women induced by the scarcity of men (O'Flaherty (2015)). An additional factor worth mentioning is mortality due to violence. If Black people died due to violent causes at the same rate as White people, the difference in sex compositions would be about 5% smaller. Migration is the most important factor driving the scarcity of men among Asians living in the US. It entirely explains the observed empirical gap. In fact, if the sex composition of Asian migrants mirrored that of White migrants, the gap would reverse, and 52% of Asians in the US would be male. The difference in the sex ratios between Native Americans and White Americans equals only 0.15%. While some factors contribute more to the gap, I will not discuss them in detail, given the negligible difference in size.

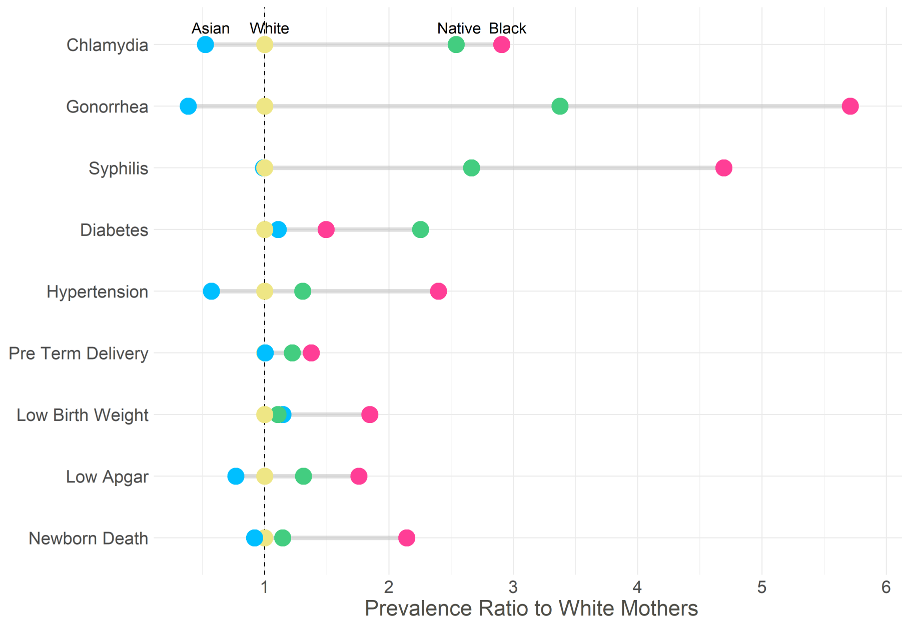
Differences in the migration patterns for Asian people and the disparities in the incarceration rates for Black people largely explain the observed deviations in the sex compositions. While policies related to, for instance, incarceration may influence outcomes through various channels beyond just affecting the sex ratio, the goal of this paper is to isolate the pure effect of changes in the dating market dynamics on outcomes. By doing so, it aims to contribute to the discussion on policies by measuring the separate portion of their impact that may arise specifically through their influence on the dating market. While migrants' decisions are voluntary, the gap between Black and White sex composition partly results from an interplay between biases and policies. Black people are more likely to be stopped and searched (Gelman et al. (2007); Mastracci (2018)), arrested (Kochel et al. (2011); Mitchell and Caudy (2015)), prosecuted and held in pre-trial detention (Spohn (2009); VERA (2012); Arnold et al. (2018)), charged and sentenced more harshly (Rehavi and Starr (2014); Sutton (2013)) compared to similar White people in the same situations. Consequently, the association of policies and bias in the criminal justice system sent a disproportionate number of Black men behind bars. Section A.2 examines the causes of the disproportionate incarceration of Black men and explores criminal justice initiatives that could mitigate incarceration disparities without adversely affecting public safety. Implementing these policies would not only narrow the gap in sex ratios but also positively impact the marriage market prospects for Black women and, as argued in this paper, improve the health of Black infants. Indeed, racial differences in sex composition are closely associated with disparities in health outcomes.

4.3 Large racial disparities in maternal and neonatal health

Pregnancy outcomes of Black mothers are considerably worse than outcomes of White mothers. Figure III illustrates this pattern using 2011-2019 natality data. It sets the prevalence of an outcome among White mothers as a benchmark. Next, it shows how much larger is the prevalence among another racial group when compared to White mothers. Asian women have similar health outcomes as White women. Asian mothers are considerably more likely to be highly educated (see figure A.12 in the appendix) and education is strongly correlated with health outcomes (figures A.13, A.14). Such advantage likely compensates other drawbacks that may hamper health in this racial group. Native and Black women had a higher prevalence of negative outcomes for each measure, with much higher severity among Black mothers. Compared to White women, Black women are at 3 times higher risk of having chlamydia, 5.7 times higher risk of Gonorrhea, and 4.8 times higher risk of having Syphilis during pregnancy. Moreover, they are more likely than White women to have hypertension and Diabetes pre-pregnancy. Black infants are more often delivered too early, with low birth weight, and more frequently have too low APGAR scores. Finally, Black infants are twice as likely to die shortly after birth. Importantly, these inequalities cannot be explained by differences in socio-economic measures such as education: they persist at each education level, as the figure A.14 in the appendix shows. I also show that disparities in deaths cannot be explained by differential marital rates (figures A.5 and A.6 in the appendix).

The health gap between White and Black mothers has been attributed to various sources. Structural racism is an important factor explaining this phenomenon (Bailey et al. (2021)). Past policies affected housing and socioeconomics situation of Black people (Williams and Collins (2001)) and their access to healthcare (Alsan and Wanamaker (2018), Hoffman et al.

Figure III: Racial Disparities in Pregnancy Outcomes



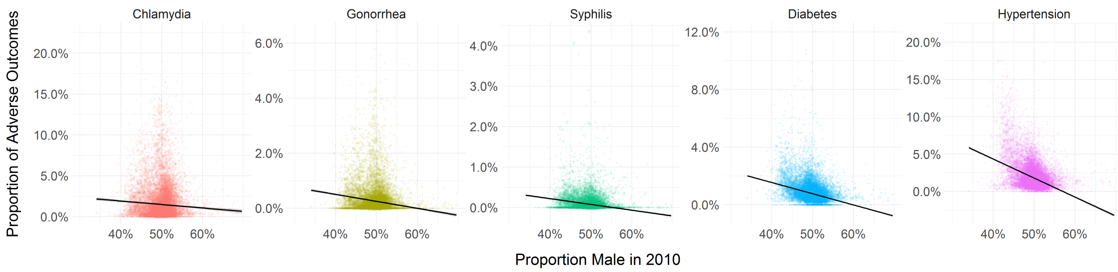
Notes: The light dots on the dashed line correspond to the baseline of the White mothers. Other dots represent the ratio of the average prevalence of a morbidity among a racial group to the average prevalence among White mothers.

(2016), Ly (2021)). As the consequences of racist policies are persistent, they co-determine the population's current health. For instance, black people are still more likely to live in neighborhoods exposed to pollution (Lane et al. (2022)), which damages infant health (Currie et al. (2009); Currie (2013a)). In addition, Black people are insured at lower rates (Buchmueller et al. (2016), Lillie-Blanton and Hoffman (2005)).

This paper argues that the disadvantage that Black women have on the dating market contributes to the overall inequalities in maternal and neonatal health. Black women face dating markets with substantially fewer available men than White women. In addition, the sex composition of the market is correlated with pregnancy outcomes. As illustrated in figure IV, scarcity of men on the dating market is associated with more frequent adverse effects among pregnant women.

The black line in figure IV represents an estimated linear relationship between the market's sex composition and adverse outcome's prevalence among women on that market. It is negative for each outcome, meaning that women and infants are less healthy when men are scarce. This correlation invites a more rigorous analysis which follows in the next sections.

Figure IV: Relationship between Sex Composition and Health Outcomes



(a) Maternal Outcomes

(b) Infant Outcomes

Notes: Each dot on the scatter plot corresponds to a dating market. Y axis shows the average prevalence of an adverse outcome among pregnant women belonging to a market. X axis shows the proportion of the market which is male. The lines correspond to an OLS fitted to the scatterplot weighted by the number of women.

5 Relationship Between Health and Sex Composition: Empirical Framework

The empirical framework relies on comparing women in markets with an abundant supply of men to women in markets with relatively few men. Under a strong assumption that markets' sex ratios are exogenous (conditional on covariates), one could retrieve the treatment effect by estimating the following regression 1:

$$y_{i,crb} = \beta PM_{crf(b)} + \gamma X_i + \lambda_{c,y-b} + \delta_{r,y-b} + \alpha_{r,2010-b} + \epsilon_i \tag{1}$$

The left-hand side variable is an outcome $y_{i,crb}$ of a mother i who resides in a county c, is of race r, and was born in year b. The main independent variable of interest is $PM_{crf(b)}$, which measures the proportion of men in the mother's dating market identified by county c, race r, and the cohort $f(b)$, which is a function of her year of birth b.

The number of observations allows to include a large set of controls and fixed effects that could potentially alleviate the issue of the endogeneity. The variable X_i controls for the cohort size in 2010. I also include *County-Age at birth* fixed effects $\lambda_{c,y-b}$ [13], *Race-Age at birth* fixed effects $\delta_{r,y-b}$ [14] and *Race-Single Age* fixed effects $\alpha_{r,2010-b}$. These variables aim to capture the variation that may produce a spurious correlation between the proportion of males and health outcomes. County economic characteristics may impact both migration of young people and health outcomes; hence I control for the county fixed effects and allow them to be age specific. Furthermore, there exist substantial racial differences in sex composition and health which may be caused due to third factors. To ensure that my results are not driven by these cross-racial differences, I include interactions between race and age, as well as race and cohort, to flexibly account for these variations. Controlling for single years of age helps to reduce the variance of the residuals as pregnancy outcomes vary considerably and non-linearly with age. Mother's age at birth does not appear to be moved by market imbalance as documented in the table A13. Results are qualitatively unchanged when excluding mother's age from controls. Hence, I effectively compare women of the same race giving birth at the same age, while accounting for cohort-specific and county-specific factors. The remaining standard deviation in the proportion male after accounting for all the fixed effects and covariates is 2 percentage points. While other maternal and paternal characteristics, such as parents' education, are available in the data set, controlling for them in the regression could lead to a bias, as they might be affected by the treatment (sex ratio), and hence they are bad controls (Angrist and Pischke (2009)).

The parameter β captures the treatment effect if the variable $PM_{crf(b)}$ is uncorrelated to residuals when conditioning on controls. This assumption presumes that within race-age and county-age variation in sex composition is not related to other factors that could determine health outcomes. Nonetheless, even accounting for a rich set of covariate, there could be omitted variables affecting both the sex ratio and outcomes. As an example, consider areas with a high level of criminal activity. One may expect that such markets would experience a scarcity of men who are in prison. Simultaneously, women exposed to violence experience worse pregnancy outcomes (Currie et al. (2018)). Such bias would lead to overestimation of β. Alternatively, consider a correlation between industry structure and poverty. Industries attracting male workers, such as mining, may be located in impoverished areas with poor health and high mortality (Hendryx and Ahern (2009); Cortes-Ramirez et al. (2018)), which would bias β downwards. These factors could produce a correlation between sex composition and health outcomes even without bargaining power.

Hence, to isolate the exogenous variation in sex composition, I leverage randomness in the sex ratio at birth. The instrument for PM_{cra} is the proportion of male births or race r

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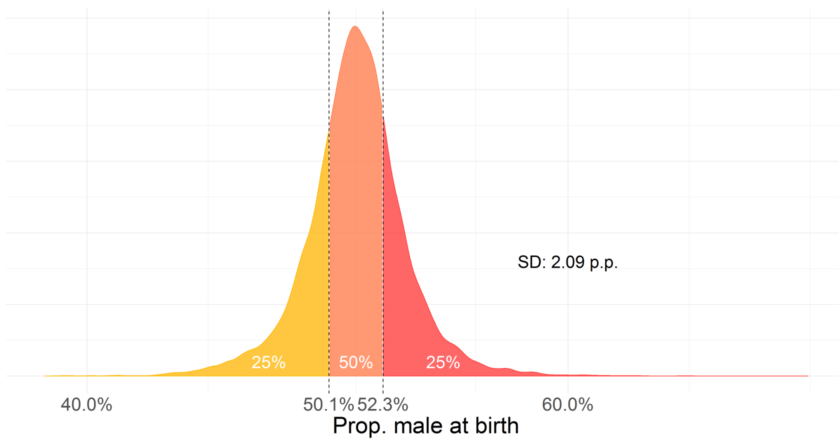
[13] y represents the year of child's birth, hence $y - b$ is mother's age at birth of the child.
[14] Single age cohort is represented by mother's age in 2010: $2010 - y$

in county c in years when the cohort a was born. Denote it as PMB_{cra}.

For example, consider the dating market of White people residing in the Maricopa County, Arizona, who are 25-29 years old in 2010. The instrument for this observation is the proportion male among White newborns in Maricopa County, Arizona, born between April 1980 and April 1985. I calculate the proportions using the restricted version of the Vital Statistics Natality microdata for 1975-2005. This dataset permits to calculate number of boys and girls born in each county, race, and month-year. Figure V shows the distribution of the instrument together with its standard deviation and the first, and the third quartile. Figure A.15 in the appendix shows the distribution of the sex composition at birth by race and cohort.

Figure V: Density of Proportion Male at Birth



Notes: Figure shows the empirical distribution of the sex composition at birth. Each observation represents the proportion of male births among all births in the market. The two vertical lines show the first and the third quartile. Standard deviation is noted on the side. Markets with fewer than 200 and more than 5000 births are excluded. Each market has the same weight.

The primary motivation behind this instrument relies on three assertions. First, the instrument is relevant because a substantial amount of people live close to their childhood homes. The demographic structure of the generation tends to be locally persistent and, consequently, the sex composition at birth helps to predict the proportion of men in the future. Second, the exogeneity plausibly holds because sex at birth is predominantly random. Hence, it is exogenous to the pregnancy outcomes 20-30 years later when women in this cohort become of childbearing age. Third, the dating market likely serves as the key channel through which the sex ratio at birth influences health outcomes.

5.1 Relevance

The first assertion can be corroborated using *Opportunity Insights* data. Chetty et al. (2018), using various administrative sources, followed the cohort born between 1978 and 1983 until their adulthood. While there is no direct answer to how many people still live in their childhood county, data provides information on the share of adults who live in the same commuting zone (CZ) and the same census tract (CT). CZ is larger than a county and CT is smaller than a county, so they provide upper and lower bounds on the share of adults living in their childhood county. Figure A.16 in the appendix is based on this idea. It shows that between 20% and 60% percent of adults still live in their childhood county and that these numbers are relatively stable across genders and races. Consequently, none of the gender-race groups should specifically drive the first stage. Additionally, a paper by Sprung-Keyser et al. (2022) shows that 60% of individuals aged 26 live within 10 miles of where they lived at the age of 16, and 80% live within 100km. Hence, one may expect a non-negligible amount of persistence in the sex composition of local cohorts.

5.2 Exogeneity

Although exogeneity cannot be directly verified, I enhance the credibility of this assumption through a series of simulations and empirical tests.

It can be shown that the empirical distribution of sex composition at birth is almost identical to the one that would arise if the sex at birth was a random Bernoulli trial. In appendix section A.3, I use simulations to demonstrate the similarity of the distributions. The instrument practically leverages the sampling variation in the mean probability that a birth is male. A well-known property of sampling variation is that it decreases in the sample size. In particular, assuming that each birth is an iid bernouilli trial with probability of male birth p, the standard deviation of sex composition in a county of size n is $\sqrt{\frac{p(1-p)}{n}}$. In appendix section A.4 I show that the observed variation in the sex composition for a given cohort size is almost exactly as it would be predicted by this formula. Moreover, consistently with the above formula, I demonstrate that the relationship between the log(Variance) on log(Cohort size) is linear with the slope -1. Hence, the behavior of the empirical variance is consistent with the sampling variation of bernouilli variable, and hence randomness at birth.

Figure VI illustrates this pattern empirically. The sex composition is nearly balanced in all the largest markets[15]. However, significant variation in the proportion of male births is observed in smaller markets. This variation can be attributed to chance, where some cohorts happen to have more male or female births. Since these cohorts are small, they remain

[15] The sex ratio at birth slightly skews toward men

unbalanced.Ashlagi et al. (2017) demonstrate theoretically that even small imbalances can significantly influence matching markets. The variation becomes negligible only in cohorts with more than 5000 births, representing less than 20% of the markets. Hence, I exclude them from the main analysis. In the robustness sections A.9 and A.8 in the appendix, I show that choosing a different threshold does not affect the results. Note that I also exclude cohorts below 200 births as they tend to produce extreme values of sex ratio and have few subsequent deliveries.

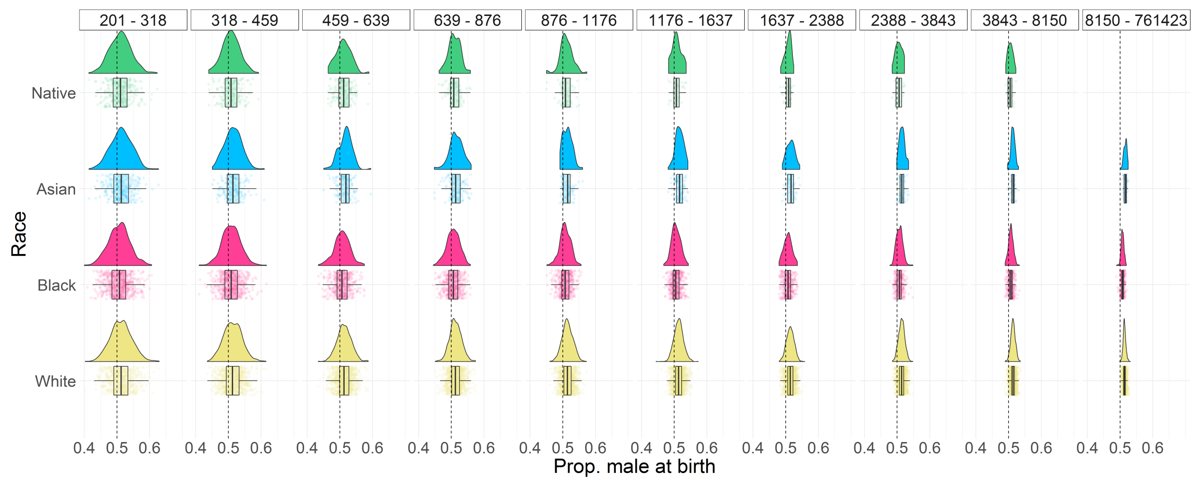


Figure VI: Density of Proportion Male at Birth by Cohort Size

Notes: Figure shows the empirical distribution of the sex composition at birth. Distributions are divided by the deciles of the size of the cohort.

The sample restricted in this way covers around 27% of all Americans in these cohorts and 33% of births during the study period. For illustration purposes, some counties with the smallest cohorts are Polk County, Florida, for its Asian population, and Cheyenne County in Kansas, for White people. Conversely, some counties with the largest cohorts are Middlesex County, New Jersey, for its Asian population, and Escambia County, Florida, for Black people. Hence the sample can include markets in large urban counties with populations in the millions, and as shown in Appendix section B.1, the urban markets play a significant role in driving the results. It is worth noting that focusing on small markets may have implications for the estimated treatment effect, a topic I address when discussing the first stage.

I further provide a series of robustness checks to show that sex ratio at birth is not affected by a range of potential confounders. Some argue that sex composition at birth can be determined by socioeconomic factors, which can also impact health outcomes in the next generations. A particular concern stems from Trivers-Willard hypothesis stating that good conditions tend to favor male offspring, which found some evidence in societies with son-preference (Lee and Orsini (2017, 2018)). However, I conduct detailed examination in the appendix section C to show that, in my sample, the sex ratio at birth is not predicted by the mother's education, age, relationship status or local economic conditions during pregnancy. In the same section, I also provide evidence that pollution is not influencing the sex ratio at birth.

Moreover, a sex selective abortion could endanger this identification strategy if son preference also impacts maternal health in the next generation. While existent, sex selective abortion in the US is of small magnitude. Abrevaya (2009) finds evidence of sex selective abortion only among Chinese and Indian mothers in the US. He computes that around 2000 Chinese and Indian female births were missing in the US between 1992 and 2004, which correspond to 0.04% of Asian births. If the same rate of missingness held for my period of interest, it would change the sex composition in the Asian category by only 0.09 percentage points, which correspond to 3% of a standard deviation. Moreover, the potential effect of sex selective abortion would likely go against my hypothesis. Girls suffer worse health outcomes in communities with son preference, both in their native countries (Ganatra and Hirve (1994); Borooah (2004); Bharadwaj and Lakdawala (2013); Barcellos et al. (2014)) and in the US (Almond and Cheng (2020); Blau et al. (2020)). Consequently, one would expect worse female and maternal health in areas with a higher proportion of men induced by sex selective abortion. Overall, due to small magnitude and likely opposite effect, sex selective abortion is unlikely to drive my results. Similarly, as documented in subsection C.3, stopping rules are unlikely to have influenced the sex composition at birth in the U.S. during the period of interest. While parity might be associated with the sex ratio at birth (Almond and Edlund, 2008), it is unlikely to account for the observed variation. For parity to act as a confounder, it would need to vary non-randomly across markets, such that some markets have significantly higher or lower average parity, conditional on cohort, race, county, and their interactions. Additionally, to explain the observed variation in the sex ratio at birth, the standard deviation of county-level parity would need to be implausibly large—on the order of 33—given that increasing parity by one decreases the probability of a male birth by only 0.06% (table A10).

5.3 Exclusion Restriction

While the main results in Section 6 demonstrate that the dating market is likely the primary channel through which the effect operates, there may be concerns that the sex ratio at birth could also influence other factors that subsequently impact health outcomes. In this subsection, I aim to address these concerns by showing that key factors such as education, crime, migration, divorce, and social networks are not significantly influenced by the sex composition at birth.

One potential concern is that gender peer effects might influence outcomes in locations with unbalanced sex ratios. For example, Hoxby (2002) uses variation in the gender composition of school cohorts to show that both girls' and boys' performance improves when there are more females in the classroom. Consistent with this, related research underscores the beneficial impact of a higher proportion of female peers on academic outcomes (Lavy and Schlosser, 2011; Sacerdote, 2011; Lu and Anderson, 2015). Nonetheless, I believe this concern does not pose a significant challenge to the identification strategy for the following reasons.

First, the aforementioned advantages do not appear to persist into more favorable long-term labor market outcomes, as observed by Anelli and Peri (2019). Second, the direction of the documented peer effects consistently opposes the pathway hypothesized in this paper, both across studies and life stages, where a higher share of men improves female outcomes through a stronger dating market position. Therefore, my findings cannot be attributed to pre-existing peer effects within the educational context. Third, I conduct an additional robustness check using Opportunity Insights data, which allows me to rule out with high confidence any significant impact of sex composition at birth on educational attainment (Table A19).

Using the same Opportunity Insights data, I also examine the potential impact on crime. I find that being part of an unbalanced cohort does not affect the probability of incarceration, which alleviates concerns that a heightened sex ratio could exacerbate antisocial behaviors. While Edlund et al. (2008) indicates that markets with a surplus of males often experience higher crime rates in China, this observation contradicts my hypothesis and findings, which demonstrate that a higher proportion of men improves outcomes for females.

Another concern might be related to migration. An unfavorable sex ratio at birth could prompt individuals to relocate to areas with a more favorable dating market. If this migration is not selective, it poses no issue beyond potentially weakening the first stage. However, if it is selective, it could influence the results and might even be considered an effect of the dating market. In the dedicated subsection B.3, using census migration data, I show that women indeed tend to migrate out of areas with an unfavorable sex ratio and into those with a more favorable one. However, additional findings suggest that this migration is not selective, at least in terms of income measures

Previous research (Dahl and Moretti, 2008) has documented that having daughters may be associated with higher rates of family dissolution, which in turn could impact child development. To assess whether this might be a channel for the observed effect, I examine whether divorce rates are more prevalent in areas with a higher proportion of female births.

The regression analysis presented in Section C.6 shows no evidence that a higher share of female births is associated with increased divorce probability in the likely parent generation.

Growing up in an unbalanced cohort could also influence the development of soft skills. Although these skills are challenging to measure directly, they may manifest in social behaviors, such as the structure of social networks or participation in pro-social activities. Using data from Opportunity Insights, I demonstrate in Section C.5 that the sex composition at birth, with high confidence, does not have any significant impact on these measures of social behavior.

While I have addressed several potential alternative channels, it is important to acknowledge that there may be other unobserved factors at play that are difficult to assess. This is a limitation of the current analysis. Nonetheless, the subsequent results provide strong support that a crucial channel is the scarcity of partners and the associated changes in dating and marriage dynamics, which appear to be driving the observed effects.

5.4 Specification and Outcomes

If the above mentioned assumptions hold, the instrument eliminates problems present in the OLS estimation. Firstly, it isolates the variation in the sex composition unrelated to endogenous factors such as migration, economic conditions, or crime. Hence, it is a better proxy for women's bargaining power in the dating market. Moreover, it focuses on changes in bargaining power while holding factors affecting household specialization fixed. Consequently, it addresses a different mechanism than the one analysed by Autor et al. (2019), who investigate the gendered impact of economic shocks on household outcomes. Secondly, it guards against measurement error. As the sex ratio at birth is a persistent predictor of the sex composition in the future, it reduces the worry that 2010 measurement is no longer relevant for births in later years. In particular, it indicates that markets with high proportion male at birth will have relatively high proportion male for the next 15-35 years.

I proceed with the IV framework by estimating the following equations:

$$\hat{PM}_{i,crf(b)} = \zeta PMB_{i,crf(b)} + \theta X_i + \kappa_{c,y-b} + \pi_{r,y-b} + \tau_{r,2010-b} \tag{2}$$

$$y_{i,crb} = \beta \hat{PM}_{crf(b)} + \gamma X_i + \lambda_{c,y-b} + \delta_{r,y-b} + \alpha_{r,2010-b} + \epsilon_i \tag{3}$$

The estimation proceeds as the usual TSLS. That is, it first predicts the value of the proportion male in 2010 given the proportion male at birth and the covariates (equation 2). The first stage hence isolates the variation in 2010 sex composition, which is only due to randomness in sex at birth. Next, I use the predicted values in the second stage (equation

3) to estimate the treatment effect β.

I analyze three sets of outcomes. The first set of outcomes pertains to maternal health. It is measured by whether the mother is diagnosed with chlamydia, gonorrhea, or syphilis during pregnancy and whether she had diabetes or hypertension pre-pregnancy. The choice of these variables is motivated by previous studies on this topic. For instance, Cornwell and Cunningham (2008) shows that the scarcity of men on the dating market allows them to sustain multiple partnerships due to higher bargaining power. Consequently, we would expect that a low proportion of men produces denser sexual networks, resulting in a higher likelihood of sexually transmitted infections among women. In addition, Li and Wu (2011) provides evidence that resource allocation more favorable to women can affect their health through changes in nutrition, which is an essential factor in the risk of diabetes (CDC (2022)). It is also plausible that empowered women match with more educated and better earning partners. Consequently, they can afford higher quality food, reducing risk of obesity associated with diabetes. Finally, diabetes could lead to pregnancy complications, and women with bargaining power may be more likely to refuse pursuing pregnancy if it is a health risk. Furthermore, mothers in markets with a high proportion of men may be at a lower risk of hypertension, given that women with bargaining power are less likely to experience domestic violence, which implies a lower stress level (Rao (1997), Panda and Agarwal (2005)). Finally, note that an association of maternal health with proportion male could be alternatively explained by a differential selection into motherhood, where healthier women pursue pregnancy when they have bargaining power.

The second set of outcomes contains variables relevant to neonatal health. In particular, I examine whether birth was pre-term (gestation < 37 weeks), weather brithweight was low (weight < 2500g), whether the APGAR score is below 7, whether the newborn was put on assisted ventilation, and whether it was alive at the time of writing the birth certificate. In the markets with a high proportion male, I would expect longer gestation, higher birth weight, lower incidence of low APGAR score and assisted ventilation, and a higher likelihood of survival.

The final set of outcomes focuses on a likely key channel: marriage market dynamics. If the proportion of males is a valid distribution factor and affects bargaining power, it should act not only on the health outcomes but also on the variables related to matching. Hence, the dependent variables include a dummy for whether the father is known [16], whether mother is married and the difference in mother's and father's education years. I expect that higher proportion male on the market decreases the likelihood of an unknown father's birth and

[16] Following Spencer (2022), I assume that father is unknown if the birth certificate does not contain information about his age

increases the likelihood that the mother is married. Moreover, the effect on the difference in years of education should be negative as the father's relative education improves because women can achieve a higher quality partner. Movement in these outcomes would not only corroborate that the sex ratio affects bargaining power, consistent with other findings in the literature (Angrist (2002); Abramitzky et al. (2011)), but also provide evidence that improvements in health are linked to dynamics within the dating market.

6 Relationship Between Health and Sex Composition: Results

The instrumental variable framework provides evidence that a higher proportion of men on the dating market improves female marital prospects, maternal health, and neonatal outcomes. The validity of the IV inference depends largely on the strength of the relationship between the sex composition at birth and the proportion male in 2010. Table I reports estimation results of the first-stage equation 2.

Table I: First Stage

Dependent Variable:	Prop. male 2010
Model:	(1)
Prop. male at birth	0.2329
	(0.0236)
Fit statistics	
Within R^2	0.065
Wald Kleibergen-Paap (IV only)	97.3
Dependent variable mean	0.496
Observations	7,138,182

Notes: The regression contains controls for cohort size in 2010 and at birth, County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male at birth* correspond to β in equation 2. Each observation represents a single birth. Standard errors are clustered at the County-Race level.

It shows that the sex ratio at birth is strongly correlated with the proportion of men in 2010. The coefficient is positive and highly significant. Hence, I conclude that the instrument is relevant. However, the magnitude is substantially lower than one, which can partially be explained by incarceration and migration patterns balancing highly uneven sex ratios. A detailed discussion on migratory response to the sex ratio and its implications for the validity of the instruments is in appendix section B.3.

While the first stage estimation is sufficiently strong overall, understanding who this instrument affects—and thus which population the effect arises from—requires considering a broader empirical strategy. The primary interest lies in the impact of dating market imbalances and bargaining power on health outcomes. Therefore, it is important to consider whose markets and bargaining power are most affected by this instrument, focusing on three key aspects: sample inclusion, the strength of the first stage, and the heterogeneous relevance of markets measured in this way.

Regarding sample inclusion, the only criterion used is birth cohort size. Given that the impact of imbalance and bargaining power might vary with cohort size, it is important to note that the estimated effect is local to the population of compliers in small markets. Despite the label, "small markets" encompass a wide range of demographics, from isolated counties to urban minority segments, as well as cohorts emerging during demographic downturns. Focusing on smaller markets involves a trade-off. While I gain variation in sex composition, individuals in smaller markets may be more inclined to seek partners outside their county, race, or age group. This suggests that the bounding exercise in Appendix section C.11 would apply with a higher $\alpha_{c,c'}$, making the estimates conservative compared to changing the full market. Additionally, it is worth noting that the instrument's variation is driven by the U.S.-born population, as foreign-born migrants are not in the US natality data.

Understanding for whom the instrument is strongest is also a key consideration to grasp where the effect is coming from. The instrument tends to be more potent in less geographically mobile cohorts. Evidence presented in Appendix Table A2 indicates that the first-stage relationship is more pronounced for younger cohorts, who have had less time to experience displacement. Similarly, the first stage is stronger for Native and Black Americans, who are less mobile compared to White or Asian populations (A3). Furthermore, the first stage is larger in urban markets (A4), which also exhibit stronger results. When considering the size of the county where the market is located, the first stage appears stronger in small and mid-sized counties and weaker in the largest counties (A.19).

The impact of the instrument is also closely tied to the importance of the market segment defined by my criteria within the population. Analyzing the percentage of couples that meet this definition, it appears that the relevance is most pronounced for cohorts over 19 in 2010 (A.2), who already represent the majority of births. This market definition is also more pertinent for White and Black populations, who are more inclined to seek partners within their race (B.21), and for mid-sized markets where racially homogeneous relationships are more prevalent (A.7). Furthermore, as demonstrated through the model (C.13), market imbalances influence the bargaining power of everyone, including those already in relationships and at high end of the market, as they experience the most significant changes in their outside options.

These considerations will shape how I interpret and apply the coefficients when predicting the effects of changes in the sex ratio. In Section 7, I focus on the impact of these changes on health outcomes within the Black population, where the instrument is likely more effective. This is due to a lower likelihood of exclusion from the sample compared to Whites, as Black dating markets tend to be smaller. Additionally, the first stage is stronger for this race group , and 91% of Black births occur in urban markets. The relevance of my market definition is also amplified by higher rates of racially homogeneous partnerships within this group.

I perform a formal test for weak instrument using Kleinbergen-Paap (KP) Wald statistic (Kleibergen and Paap (2006)). Since I assume within cluster correlation of residuals, a test based on the traditional non-robust F statistic would not be valid (Olea and Pflueger (2013)). Kleinbergen-Paap statistic is robust to non-homoeskedastic errors and it is equivalent to the efficient F-statistic from Olea and Pflueger (2013) in case of a single instrument (Andrews et al. (2019)). The KP Wald statistic is 97.3, so the instrument is not weak. In the further analysis, I use the KP Wald statistic in conjunction with tF critical values developed by Lee et al. (2021) to perform valid t-ratio inference for the IV coefficients. This is necessary as a standard t-ratio tests tend to over-reject the null hypothesis in the IV setting.

To further corroborate the instrument's validity, I show that it is related only to the future sex composition in its own cohort but not other cohorts in the same county and race. Hence, it is highly unlikely that this relationship could be explained by omitted factors related to county of residence. Figure VII illustrates this placebo exercise. It shows the relationship between prop. male at birth PMB_{cra} on the x-axis and proportion male in 2010 PM_{crs} on y-axis. Proportions are residualized with respect to race. The diagonal panels represent the first stage where the sex composition at birth correlates with the future sex composition in the same cohort, that is a=s. The off-diagonal panels are placebos that plot sex composition at birth in one cohort against the future sex composition of another cohort from the same county and of the same race, that is $a \neq s$. The linear relationships are represented visually and through the estimated coefficients. All diagonal relationships, as expected, are positive and highly significant. The correlation is stronger in young cohorts with less time to get incarcerated or engage in migration. The off-diagonal placebo relationships are close to null. Most p-values are above traditional thresholds, and the magnitudes are low. Thus, the relationship between the instrument and the endogenous variable is likely to stem from persistence in cohorts' demographics rather than from other nuisance factors. This placebo increases the confidence in the instrument; hence I proceed with the second stage estimation. The results of the IV estimation are in Panel B of table II, while the OLS results are in panel A.

Set of results regarding *Maternal Health Outcomes* in table II provides evidence that the scarcity of women on the dating market ameliorates health during pregnancy. While in

Table II: IV and OLS Results

Panel A: OLS RESULTS

Maternal Health Outcomes Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*	*Adverse Maternal Health Index*
Prop. male 2010	-0.0189	-0.0072	-0.0022	-0.0067	-0.0326	-0.137
	(0.0033)	(0.0012)	(0.0007)	(0.0015)	(0.0045)	(0.019)
Dependent variable mean	0.015	0.003	0.0008	0.008	0.019	0
Observations	23,224,271	23,224,271	23,224,271	23,257,824	23,257,824	23,224,271

Infant Health Outcomes Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*	*Adverse Neonatal Health Index*
Prop. male 2010	-0.0472	-0.0486	-0.0085	-0.0092	-0.0022	-0.093
	(0.0053)	(0.0046)	(0.0021)	(0.0054)	(0.0007)	(0.011)
Dependent variable mean	0.113	0.082	0.021	0.041	0.003	0
Observations	24,467,061	24,461,432	24,385,422	23,246,802	23,266,090	23,142,465

Marriage Market Outcomes Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*
Prop. male 2010	-0.1912	0.3055	-0.6211
	(0.0208)	(0.0329)	(0.0788)
Dependent variable mean	0.113	0.650	0.306
Observations	23,299,377	23,818,474	20,174,436

Panel B: IV RESULTS

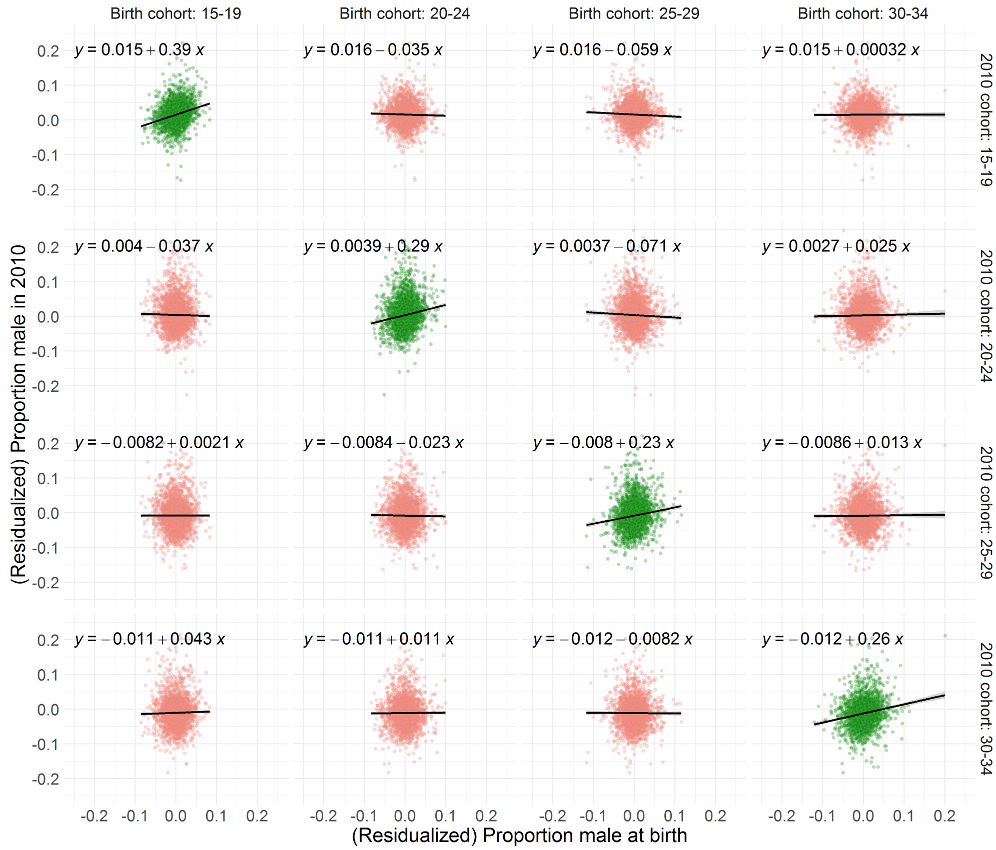
Maternal Health Outcomes Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*	*Adverse Maternal Health Index*
Prop. male 2010	-0.0676	-0.0042	-0.0019	-0.0317	-0.0955	-0.3268
	(0.0266)	(0.0093)	(0.0049)	(0.0169)	(0.0322)	(0.1105)
Dependent variable mean	0.019	0.003	0.0008	0.010	0.022	0
Observations	7,138,182	7,138,182	7,138,182	7,151,592	7,151,592	7,138,182
Sig. at 5% (Lee et al. 2022)	Yes	No	No	No	Yes	Yes
Wald KP (1st stage)	97.3	97.3	97.3	96.6	96.6	97.3

Infant Health Outcomes Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*	*Adverse Neonatal Health Index*
Prop. male 2010	-0.0798	-0.0644	-0.0512	-0.0681	-0.0013	-0.271
	(0.0545)	(0.0461)	(0.0251)	(0.0413)	(0.0084)	(0.1105)
Dependent variable mean	0.121	0.087	0.024	0.046	0.003	0
Observations	7,540,450	7,539,221	7,515,076	7,149,031	7,155,905	7,116,816
Sig. at 5% (Lee et al. 2022)	No	No	Yes	No	No	Yes
Wald KP (1st stage)	97.2	97.5	97.0	96.5	96.0	95.8

Marriage Market Outcomes Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*
Prop. male 2010	-0.4025	0.7563	0.0300
	(0.1311)	(0.1840)	(0.5214)
Dependent variable mean	0.127	0.621	0.360
Observations	7,166,343	7,478,536	6,105,173
Sig. at 5% (Lee et al. 2022)	Yes	Yes	No
Wald KP (1st stage)	96.1	98.0	79.7

Notes: Negative *Diff. in Edu.* means that the father is more educated than the mother. In the Panel B, the proportion of men in 2010 is instrumented with proportion of men at birth of the cohort. Each regression contains controls for cohort size in 2010 and at birth (Panel B only), County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample of markets between 200-5000 people. Standard errors clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented together with an information whether the coefficient is significant at 5% according to tF statistic (Lee et al. 2022).

Figure VII: First Stage Placebo



Notes: Figure shows linear relationships between proportion male at birth and proportion male in 2010. The values are residualized with respect to the race. The diagonal panels represent the correlation between the prop. male at birth PMB_{cra} and the prop. male in 2010 PM_{cra} for the same cohort (and market). The off-diagonal panels plot a placebo relationship between sex composition at birth of one cohort PMB_{cra} and prop. male in 2010 of a different cohorts but of the same race and county. The estimated coefficients are provided on each graph.

the OLS results (Panel A) all coefficients are statistically significant and go in the expected direction, only two IV coefficients (Panel B) are statistically significant, although they all have the expected signs (OLS results for the same sample as IV are virtually identical to the larger OLS sample and presented in the table A5). Increasing share of men on the market results in fewer mothers having chlamydia and hypertension. The magnitudes are three times as large as the OLS estimates, which suggests that a simple OLS largely underestimates the impact of the bargaining on health. IV results imply that moving from the 25th to 75th percentile of the proportion male decreases the share of mothers with chlamydia by 0.26 percentage points (compared to the mean of 1.9%) and hypertension by 0.37 percentage points (mean of 2.2%). To avoid the issues related to multiple-hypothesis testing, and to gain statistical power, I aggregate the main outcomes to an index. I follow Hoynes et al. (2016) by taking a simple average of z-scores of all the outcomes. The lower the index, the fewer adverse health events. The coefficient on the index is negative and strongly significant. Regarding the magnitude, closing the gap in sex compositions between Black and White people would reduce the gap in the index by 6%.

Furthermore, an increase in men's share of the dating market results in healthier newborns. OLS results show small, but statistically significant correlation between all the outcomes and the proportion of men on the market (Panel A, *Infant Health Outcomes* in table II). IV results demonstrate that increasing the supply of men on the market relative to women causally lowers the percentage of infants with a low APGAR score (Panel B, *Infant Health Outcomes* in table II). For example, children born to mothers in the 75th percentile of prop. male are 0.2 percentage points less likely to have an APGAR score below seven compared to children of mothers at the 25th percentile. This is a sizeable difference given that only 2.43% of infants have APGAR lower than 7. To give additional context, expansion of EITC reduced share of children with low APGAR score by 0.185 percentage points Hoynes et al. (2015). While other coefficients are of the hypothesized sign, they are not statistically significant at the traditional thresholds[17]. The negative and significant coefficient on the index indicates that increasing the number of men on the market would reduce the adverse birth outcomes. These effects are slightly stronger for the male newborns (see appendix figure C.24), but the gender differences are not statistically significant. Furthermore, the effects are also amplified for older mothers (figure C.26). This heterogeneity could be due to longer exposure to the imbalanced markets, but also to higher vulnerability to pregnancy-related problems.

Further analysis suggests that the dating market is a key channel mediating these outcomes (Panel B, Table II), as the imbalance in the market significantly shifts women's positions within the relationship dynamics. Women are considerably less likely to give birth to an unknown father and more likely to be married during delivery. The magnitudes are twice as large as in the case of the OLS estimate (Panel A, table II). Changing the proportion of men from the 25th percentile (0.4836) to the 75th percentile (0.5225) decreases the chance of birth without a father by 1.6 percentage points, and it increases the share of married mothers by 2.9 percentage points. Both coefficients are significant according to tF standard errors. The coefficient on the difference in education is small and not statistically significant, contrary to the OLS result. Importantly, the positive effect on female marriage extends to the general female population and is not limited to the subset giving birth. As documented in the appendix (Section B.2), women in more favorable dating markets are more likely to be married, with this effect already evident at age 24 and persisting as they

[17] While fewer women can lead to a lower crowding of maternity wards, this is unlikely to drive the results because most of the relevant outcomes (such as hypertension or marital outcomes) are determined before delivery or even pregnancy

age. Overall, the higher proportion of men on the market has a favorable causal impact on the mother's situation in the marriage market. The results regarding marital outcomes are overall consistent with empirical literature (Angrist (2002); Charles and Luoh (2010); Abramitzky et al. (2011); Brainerd (2016)) showing that the scarcity of women improves their marital prospects and decreases the rate of out-of-wedlock births.

The above findings demonstrate that women's position in the dating market improves. I discuss three potential mechanisms linking this improved market position to health outcomes.

First, having a partner and being married may have a direct positive effect on health. For instance, Currie and Moretti (2003) suggest that marriage can lead to better pregnancy health. In contrast, single motherhood may reduce household resources and increase the likelihood of poverty, both of which are linked to poorer health outcomes.

Second, women may achieve a more favorable allocation of household resources within a couple, leading to improved health. This could manifest in increased spending on healthcare, nutrition or the ability to enforce partner fidelity. My empirical analysis suggests that the health improvements are not solely the result of enhanced healthcare utilization around childbirth. For instance, as shown in Appendix Table A11, a more favorable market position does not significantly impact prenatal care usage. Instead, the improvements seem to arise because women in stronger market positions are already healthier when they become pregnant, with lower rates of diabetes, hypertension (Table II), and overweight (Table A13). Thus, better dating market may benefit women throughout their lives, contributing to better health when it comes time to give birth.

Third, better position in the dating market may influence the selection into motherhood. For example, women may be more empowered to insist on contraceptive use if they are not willing to have children. My results could then arise if women who want to pursue pregnancy are healthier. In Appendix Section A.11, I explore the relationship between sex composition and the decision to become a mother. I find that when women are in short supply, birth rates decline, primarily driven by a decrease among unmarried women. This decline is consistent with increased female bargaining power, as women generally prefer fewer children than men (Figure A.8). This shift in fertility is associated with positive selection into motherhood, where mothers tend to be healthier and more educated, with more educated partners (Table A13). Notably, the age of the mother at birth is not linked to dating market imbalances. Overall, the quality of couples deciding to have children does not diminish as the supply of men increases. Instead, a stronger female position in the market tends to reduce fertility, leading to the selection of healthier mothers, which potentially averts births of less healthy children.

These specific channels open interesting areas for further research, however, regardless of which channel is at play, enhancing women's position in the dating market has the potential to significantly improve health outcomes.

In the appendix, section B, I extend my framework to unveil additional insights stemming from changes in the dating market sex composition. Firstly, I highlight that the predominant impact of these changes occurs, consistently with stronger first stage, within urban markets, mitigating concerns related to the applicability of my findings to larger urban centers. Secondly, my analysis indicates that the effects of bargaining are more pronounced among racial minorities, potentially amplifying the consequences of increased male supply in these markets.

7 Counterfactual scenarios

Implementing a policy addressing the dating market disadvantage faced by Black women can help narrow the gap in health outcomes between them and White women. In this section, I use my causal estimates and simulations to quantify what share of the racial gap in health outcomes could be attributed to the racial disparity in the dating markets. I focus on Black mothers because Section 6 documents that this group exhibits strong compliance with respect to the instrument, and Section 4.2 shows that their sex ratio is largely driven by policy factors . Consequently, a policy could reverse the difference in sex compositions and potentially reduce the health disparities. While the counterfactual scenarios do not have a direct causal interpretation, they provide an order of magnitude of the effects of dating markets on health on the national scale.

I consider three counterfactual scenarios: eliminating the entire racial gap in the sex compositions, eliminating the gap stemming from the racial differences in the incarceration rates for non-violent offenses, and reducing incarceration rates to New York level. My focus is on the outcomes significantly affected by the proportion of men in the dating market: whether the mother is married, whether she has chlamydia or hypertension, whether the newborn had a low APGAR score, and health indices.

The first scenario asks how racial health inequalities would change if one completely removes Black women's disadvantage in the dating markets. To implement it, I create a counterfactual sex composition for Black women: Black women face the same proportion male as White women in the same county and age group. Next, I use my estimates to predict the counterfactual health outcomes and the racial disparities.

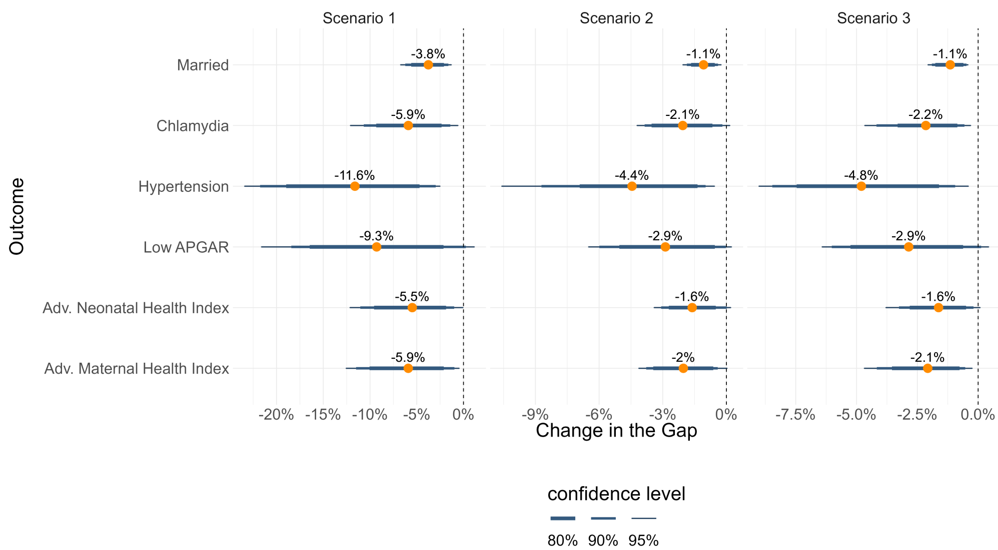
The second scenario focuses on a particular policy driving the sex ratios: incarceration rates for non-violent crimes. The counterfactual assumes that Black men and women are incarcerated for non-violent offenses at the same rate as their White counterparts in the same county and age group. The consequence of such policy would be releasing many Black men (and relatively few Black women) back to their communities. It is important to acknowledge that treatment effect for incarcerated population may differ from my estimates. As my instrument relies on randomness in sex at birth, it changes the sex ratio without affecting the general distribution of partners' quality. This is not necessarily the case for releasing inmates. Focusing on non-violent offenders aims to mitigate this concern by looking at individuals closer in characteristics to the general population. Moreover, releasing prison population, could also have separate effects on crime (Bhuller et al. (2018)). Nonetheless, as Lofstrom and Raphael (2016) note, at high level of incarceration, reducing prison population has relatively modest effect on crime. The advantage of my estimates is that they isolate the impact of changes in the dating market, independent of other related effects, allowing me to measure the portion of the policy impact that is solely attributable to the dating market dynamics.

One may still be concerned that incarcerated individuals have lower potential income, and therefore are not an attractive partner for the majority of women. Nonetheless, a dating market model implies that adding even low income individuals to the dating pool improves outcomes for all women. In the appendix section C.13, I adapt the model from section C.12 to accommodate a variety of assumption on the potential income of the individuals fueling the dating pool. While the detailed results are in the section C.13, the two important implications are the magnitude of female welfare gains depends relatively little on the quality of men added to the pool and that highest income women always benefit the most. These results are similar to findings by Chiappori and Oreffice (2008) who show that introducing more efficient birth control increases the welfare of all women, even those who do not use them. The intuition behind these findings is that low-income women, who were previously single, can now find a partner. As these women have now higher utility, outside option for all subsequent women improves. Hence, they obtain more favorable resource allocation in their partnerships.

As the model implies that female welfare gains do not change considerably with the quality of men added to the pool, I proceed with using my IV estimates in this counterfactual scenario. The details of the procedure of assigning incarcerated individuals to the county where they committed the offense are in the appendix section C.9. Next, I recalculate the sex composition, including newly released individuals, and use the model to predict the outcomes and racial disparities. While the measures outlined address several concerns, caution is still advised in interpreting these counterfactuals causally. Instead, their purpose is to establish a benchmark for understanding the magnitude of the potential impact of narrowing the sex ratio gap to an extent comparable to that arising from racial disparities in incarceration rates.

The third scenario reduces incarceration rates to the level of New York State. State of New York passed a set of reforms targeting non-violent offenders which plausibly led to a large decline in its prison population (Raphael and Stoll (2014)). Between 1999 and 2012 the incarceration declined by about 26% (Raphael and Stoll (2014)). Assuming that the reforms contributed to this decline, I check what would be health impact if all states implemented such reforms and decreased their incarceration rates to the level of New York. Hence, I set the county incarceration rate in each age-group and race to its equivalent for the New York State. If prior incarceration rate was lower than in NY, I keep the prior rate.

Figure VIII: Simulations: Reduction in Racial Health Inequality



Notes: Plot shows the reduction in the racial gap in health outcomes under the counterfactual scenarios. In "scenario 1" the proportion male that Black women are facing is set to be the same as for White women. In "scenario 2" I equated incarceration rates for non-violent offenses. "Scenario 3" corresponds to censoring the top incarceration at the value of New York incarceration rates. The horizontal lines show the confidence bands derived from the bootstrap. Orange point and the label above it are the mean reduction across all iterations.

The simulations rely on bootstrapping the estimation and comparisons sample, with details of the procedure in the appendix section C.10. The simulations show that Black mothers' disadvantage in the dating market can produce a significant share of racial health disparities. Figure VIII illustrates the results. Equating the sex composition of Black and White women reduces the gap in the number of births to non-married women by 3.5%. Moreover, the gap in the prevalence of chlamydia and hypertension among pregnant women shrinks by respectively 5.4% and 10.5%. The racial disparity in the newborns who need medical assistance (low APGAR score) diminishes by 9.2%. Finally, the gap in adverse health indices declines as well: by -5.5% for neonatal and by -5.9% for maternal health.

Equating the incarceration rates for non-violent offenses also reduces the gap in health outcomes, although to a smaller extent. It reduces the gap in out-of-wedlock births by 1.1%, the gap in chlamydia and hypertension by 2.2% and 4.2% respectively, and the gap in Low APGAR by 2.8%. The disparity in the neonatal health index decreases by 1.6% and in the maternal health index by 2%.

As a result of the last counterfactual scenario, both Black and White sex compositions would change. Nonetheless, the increase in the proportion of available Black males would be stronger given higher initial imprisonment. Reducing the incarceration rates to New York level would reduce health gap in marriage rate by 1.2%, gap in chlamydia by 2.1%, gap in hypertension by 4.5%, gap in the low APGAR score by 2.9%. and gap in adverse neonatal and maternal health indices by 1.6% and 2.1% respectively.

One could also ask whether a higher rate of inter-racial relationships could diminish the gap in the health outcomes. Bringing Black sex composition to the balanced level would require around 650 000 additional men. Since there is a surplus of White men, one could shift White men to Black women. This would require 2.2% of White men to enter relationships with Black women, and conversely 10.8% of Black women to consider White men [18]. While such transfer would decrease bargaining power of White women (decreasing their sex composition from 0.505 to 0.499), their loss would still be lower than the benefit to Black women.

I conclude that a substantial part of the racial health inequalities between Black and White women could stem from a worse situation in dating markets for Black women.

8 Conclusion

In this study, I investigate how a woman's position in the dating market influences pregnancy outcomes, using the sex composition of the dating market as a proxy for market power. My empirical framework identifies the causal effect by leveraging a novel instrument: the cohort's sex composition at birth. The findings indicate that increased male availability enhances maternal and neonatal health, evidenced by reduced instances of out-of-wedlock births, maternal hypertension, chlamydia, and low APGAR scores in newborns.

The observed health improvements stem from two primary mechanisms: enhanced partner quality and resource allocation for women with greater bargaining power, and a positive selection into fertility, where women opting for delivery in advantageous dating markets tend to be more educated and healthier. Nonetheless, the study cannot precisely disentangle the

[18] In the natality data, 1.3% of white men have children with Black women and 8.8% of Black women have children with White men

individual contributions of these mechanisms, presenting a limitation and a direction for future research.

The findings of this study suggest that policies empowering women can improve maternal and neonatal health and help reduce racial health disparities. Women's power in relationships can be influenced by gender-contingent transfers (Duflo (2003)) or laws governing divorce and asset division (Chiappori et al. (2002); Voena (2015)). My results demonstrate that policy can also shape women's position in relationships by altering the sex composition of the dating market. Mass incarceration policies have led to a scarcity of men, particularly in Black communities. Consequently, reducing racial disparities in incarceration through criminal justice reform would not only benefit Black men but also might have positive spillover effects on Black women and their children.

Finally, my findings highlight the impact of the dating market within the first 24 hours of a child's life. It is reasonable to expect that these effects continue and accumulates throughout the child's life. Understanding the effects' persistence could help address the inter-generational transmission of health inequalities by improving outcomes for the most vulnerable populations.

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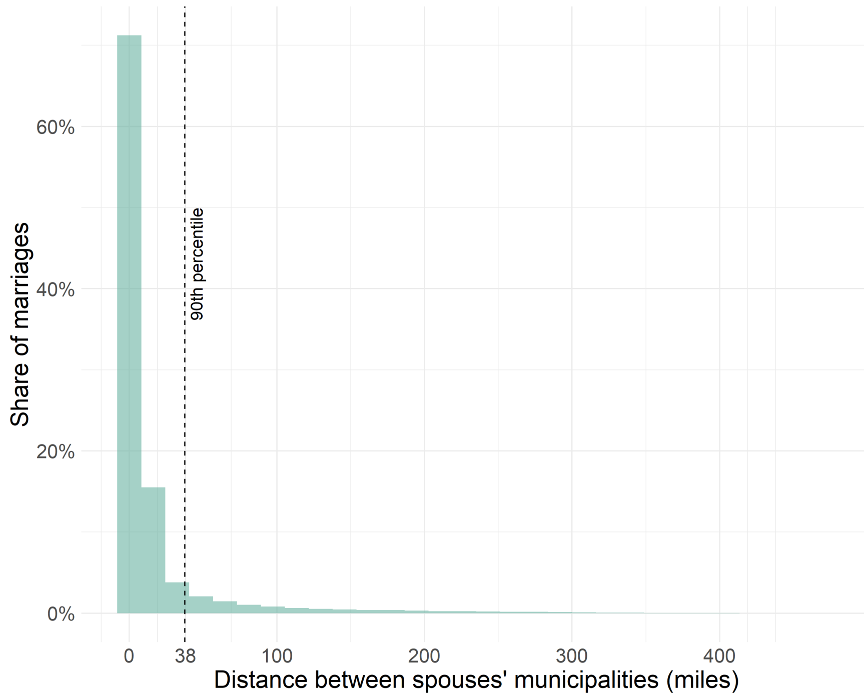
A Appendix: For Online Publication

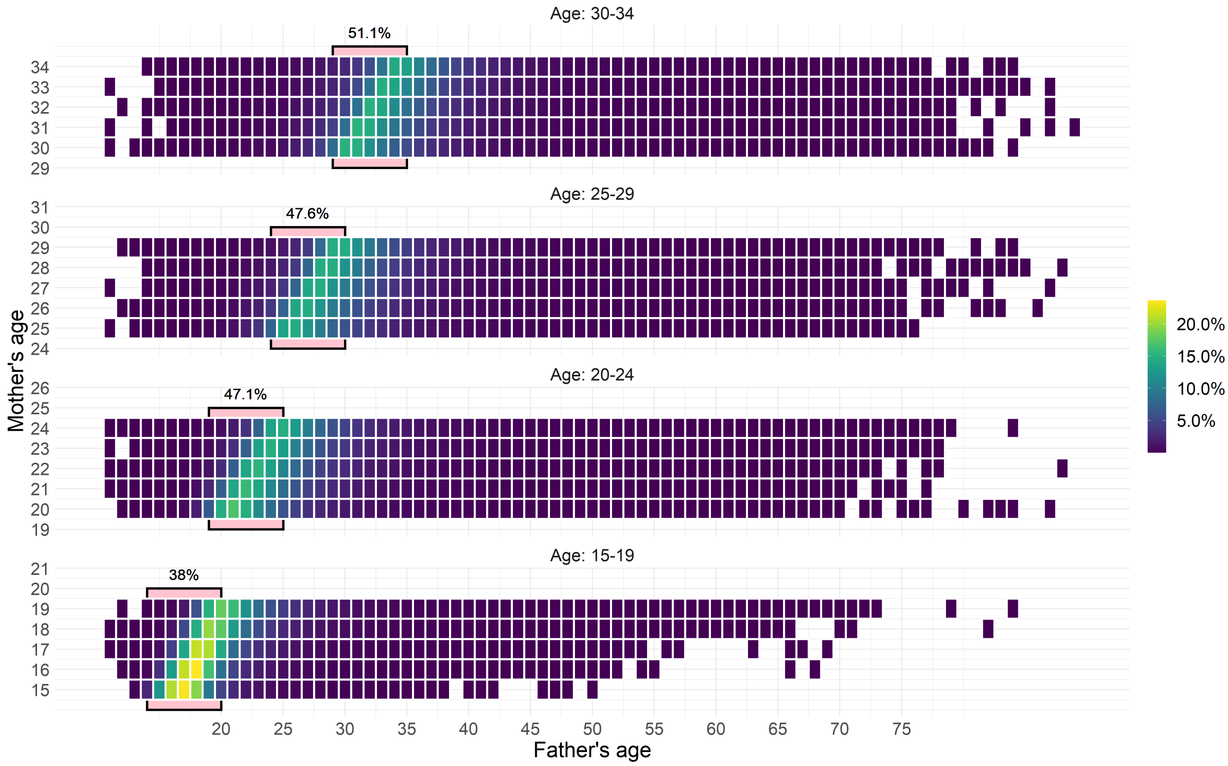
A.1 Additional Figures

Figure A.1: Histogram of Distances Between the Spouses



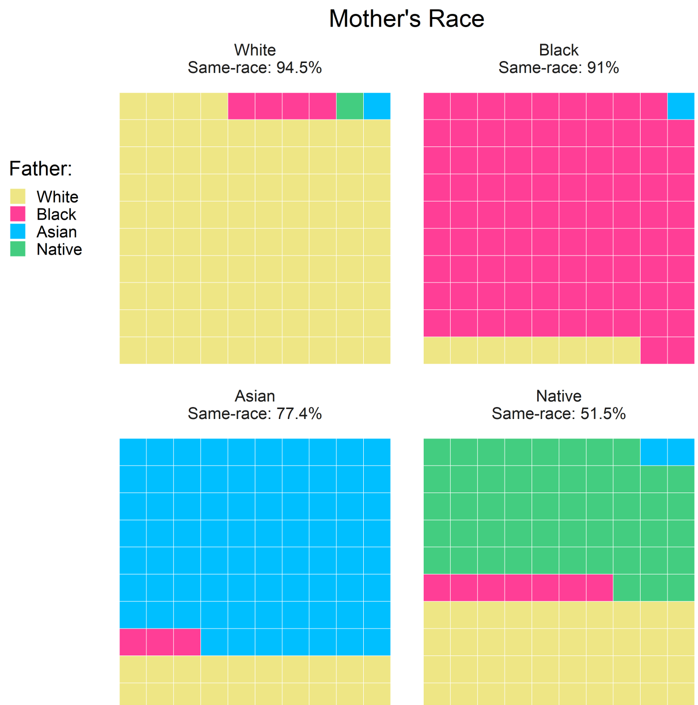
Notes: Figure plots histogram of distances between spouses residence municipalities before marriage. Source: Polish Marriage Certificates 2017-2019

Figure A.2: Age Composition of Parents



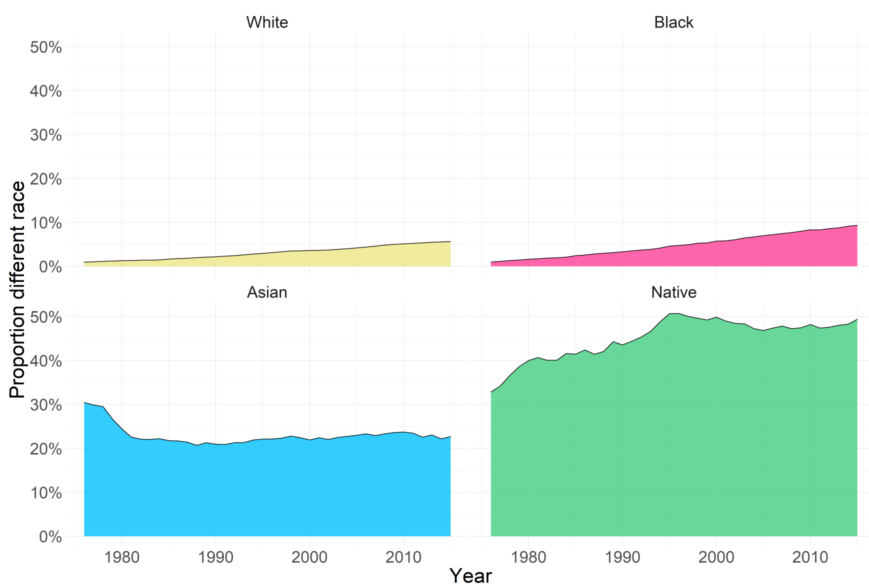
Notes: Each small box represents a couple with a father's age a_f and mother's age a_m. The color corresponds to the share of all mothers of age a_m who had a baby with a father of age a_f. Light colors on the diagonal indicate that most of women have children with men of their age. The larger boxes represent 5-years age group as in the definition of the dating markets. The number above the box represents the share of mothers in age group c who had baby with a father in the same age group. Source: Natality data 2011-2019

Figure A.3: Racial Composition of Parents



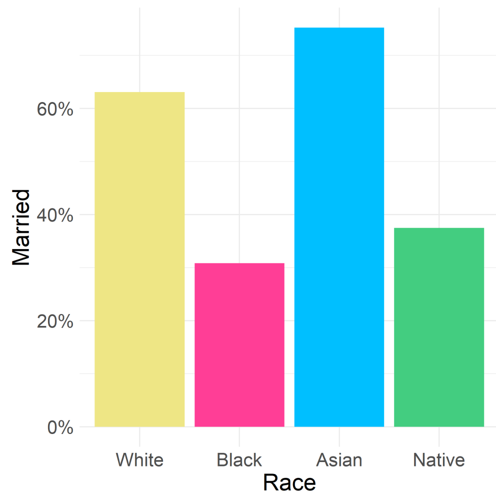
Notes: Plots show racial composition of fathers given mother's race. In each subplot, the number of colored boxes is proportional to the fathers of a given race. Source: Natality data 2011-2019

Figure A.4: Interracial Births



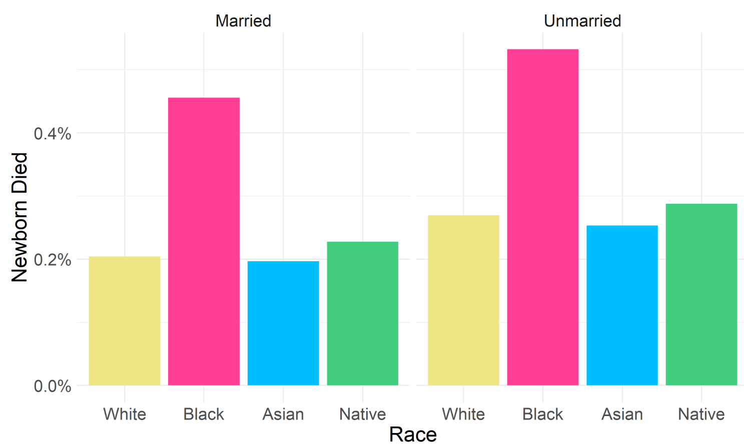
Notes: Each line represents the share of pregnancies such that the father is of a different race than the mother, conditional on mother's race Source: Natality data 1976-2016

Figure A.5: Marital Rates by Race



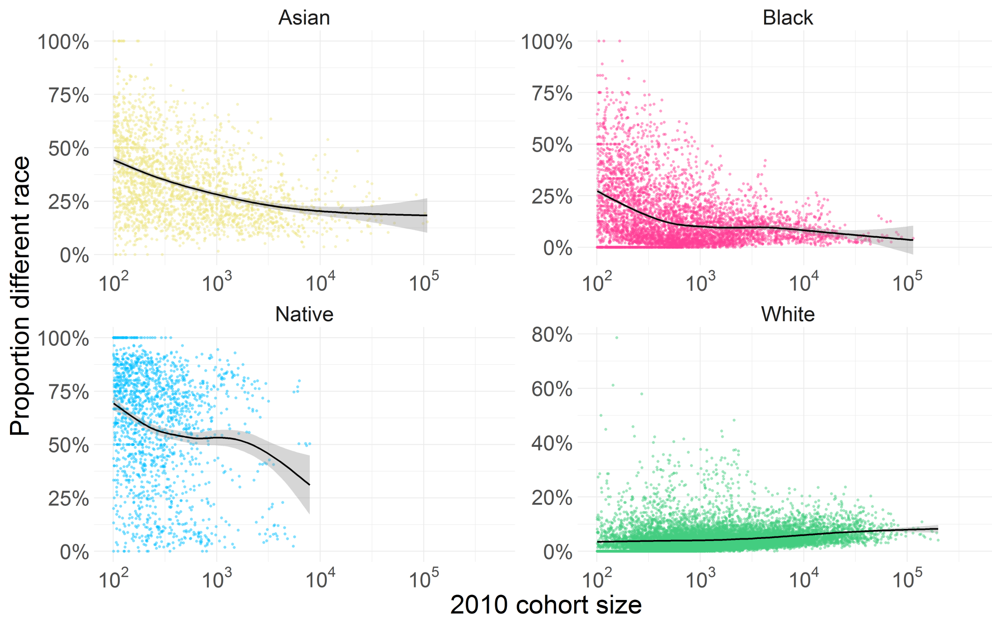
Notes: Each bar represents the share of married mothers by racial group. Source: Natality data 2011-2019

Figure A.6: Neonatal Deaths by Race and Marital Status



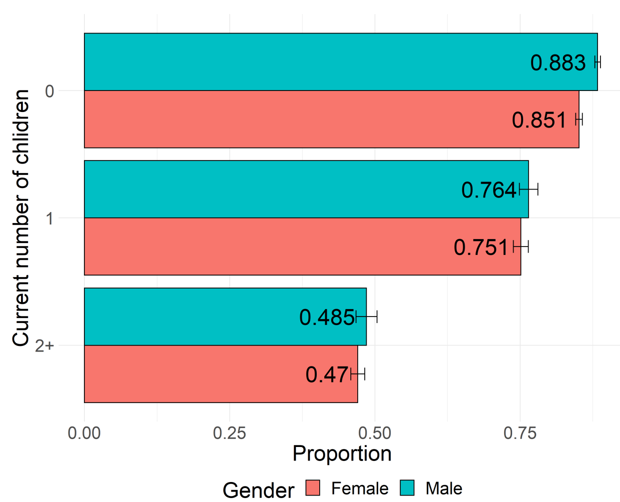
Notes: Each bar represents the share of newborns who died within one year of birth by racial group and marital status of the mother. Source: Natality data 2011-2019

Figure A.7: Interracial Births and Size of the Market



Notes: Each panel plots the size of the dating market (in 2010) vs the share of inter-racial relationships. Each dot represents a dating market. Curves correspond to a polynomial that has been fitted to the data.

Figure A.8: Do You Want to Have Another Child?



Notes: Figure shows proportion of respondents who want to have an additional child. The proportions are further stratified by the number of children already born to the respondent (*current number of children*). Source: National Survey of Family Growth 2011-2019.

A.2 Details on the decomposition of racial differences in the sex composition

Below I present the derivations for the case of the racial differences at the national level. The method may be easily further desegregated and I also present the results desegregated by race and cohort (figure A.11). Hall (2000) inspired this decomposition with his analyses of the changes in the sex ratio for Black people in the second half of the 20th century.

Starting with intuition, consider the incarceration as an example of a parameter inducing differences between Black and White sex compositions. The number of Black men and women available on the dating markets is the number of all Black men and women multiplied by the complement of gender-specific incarceration rates for Black people [19]. To measure the impact of incarceration, I replace the incarceration rates for Black people with the rates for White people while keeping all other factors constant. Then, I calculate what the proportion of men among Black people would be if they experienced the same incarceration rates as White people. Finally, I compare the actual difference in sex compositions between Black and White people to the computed counterfactual difference. This comparison tells us the contribution of incarceration to the difference in sex compositions.

Formally, let N_{rs} be the number of people of race r and sex s. This number can be decomposed in the part born in the US (B_{rs}) and foreign born (IM_{rs}).

$$N_{rs} = \underbrace{B_{rs}}_{\text{US Born}} + \underbrace{IM_{rs}}_{\text{Foreign Born}}$$

I model the number born domestically of race r and sex s who are at the dating market in 2010 in the following way. First, I multiply a hypothetical base population by the share born in the US $(1 - w_r)$ where w_r is share of the population of race r born abroad. This product represents all the domestic births in this race. Next, I multiply it by the race specific probability pb_{rs} that the birth is of sex s. Hence, I obtain the number of all domestic births of sex s and race r. In the following step, I multiply it by the survival rate, which is one minus the mortality rate among race r and sex s $(1 - m_{rs})$. Mortality can be further desegregated by the cause. Thus, I obtain the number of people in race r and of sex s who are still alive in 2010. Finally, I multiply it by the probability that they are not incarcerated $(1 - i_{rs})$ where i_{rs} is the race and sex specific incarceration rate. Note that the incarceration can be also further desegregated by the offence.

$$B_{rs} = \underbrace{BP_r}_{\substack{\text{Base}\\\text{Population}}} \underbrace{(1 - w_r)}_{\substack{\text{Proportion}\\\text{local born}}} \underbrace{pb_{rs}}_{\substack{\text{Probability that}\\\text{birth is of sex } s}} (1 - \underbrace{m_{rs}}_{\substack{\text{Mortality}\\\text{rate}}})(1 - \underbrace{i_{rs}}_{\substack{\text{Incarceration}\\\text{rate}}})$$

The term for the foreign born population is analogous with two modifications. The product $BP_r * w_r$ represents the baseline immigrant population of race r arriving to the US before 2010. This is multiplied by pi_{rs} which is the proportion of sex s among immigrants

[19] i.e. $N_{bm}(1 - i_{bm})$ where N_{bm} is the number of all Black men and i_{bm} is gender and race specific incarceration rate

of race r. Hence, the number Im_{rs} corresponds to all foreign born people of race r and sex s who are still alive and free in 2010.

$$Im_{rs} = \underbrace{BP_r}_{\text{Base Population}} \underbrace{w_r}_{\text{Proportion foreign born}} \underbrace{pi_{rs}}_{\text{Probability that immigrant is of sex } s} (1 - \underbrace{m_{rs}}_{\text{Mortality rate}})(1 - \underbrace{i_{rs}}_{\text{Incarceration rate}})$$

Parameters N_{rs},w_r, pi_{rs}, pb_{rs}, m_{rs}, and i_{rs} were computed from administrative data sources such as census and vital statistics. The details of the parameters computation and additional assumption are below.

In the next step, I calculate the value of the residual X_r which represents all unaccounted factors affecting sex composition. It is fitted through equating the empirical sex composition Pm_r to the predicted sex composition $\frac{N_{rm}}{N_{rm}+N_{rf}}$ multiplied by X_r:

$$Pm_r = \frac{N_{rm}}{N_{rm} + N_{rf}} * X_r \tag{4}$$

Note that $= \frac{N_{rm}}{N_{rm}+N_{rf}} * X_r$ is a function of parameters. I can use it to predict counterfactual sex composition that would arise under different values of the parameters. In particular, I substitute male and female values of the parameters in race r with their respective values among White males and females in the same age group. Hence, I obtain the counterfactual sex composition that would arise if there was no racial difference in that parameter. As an example, the procedure to calculate the impact of incarceration on the racial difference in the sex composition between Black and White people follows these steps. First, replace the incarceration rates for Black men and women by respective incarceration rates for White men and women. Second, compute the *counterfactual* proportion male for Black people with the new value of the incarceration rate according to equation 4, while keeping other parameters and X_r fixed. Third, Compute the *counterfactual* difference in sex compositions . Fifth, the difference between the *counterfactual* and the empirical difference is the contribution of the relevant factor.

Parameters computations

Incarceration rate i_{rs} is calculated from census 2010 as the ratio of the population age 15-34 of race r and sex s located on census blocks with prisons to the total population age 15-34 of race r and sex s. The offense specific incarceration rates correspond to i_{rs} multiplied by the share of prisoners of race r and sex s being sentenced for a given offense. Such shares are collected from BJS CSAT online tool [20].

[20] https://csat.bjs.ojp.gov/advanced-query

Mortality rate m_{rs} is calculated from vital statistics mortality. To construct it, I first count all deaths to people of race r and sex s born between 1976 and 1996. I count all deaths starting with they first year of life until their age in 2009. Hence, data are collected from mortality files starting with the year when the oldest person in the cohort was born and ending in 2009. I further count the number of deaths for each of three causes (natural, violent, external as defined in ICD9 and ICD10). Next, I obtain the mortality rate by dividing the number of deaths by the number of people alive in 2010 plus the number of death.

The probability that the birth in race r was of sex s is calculated from the natality data 1976-1996 as the ratio of all births of race r and sex s to all births of race r.

Share of population of race r which is foreign born is calculated from the census 2010 microdata as the share of respondents of race r who were born in a foreign country

Probability that an immigrant of race r is of sex s is calculated from the census 2010 microdata as the share of all foreign born respondents of race r who are of sex s

Additional assumptions

Several simplifying assumptions need to hold, mostly due to data limitations. Firstly, death rates and incarceration rates are the same for local born and immigrant population. I also can't distinguish between US born and foreign born in mortality datasets. Secondly, Hispanics are included for all races. I can only distinguish Hispanics in mortality dataset starting in 1989 while my first cohort was born in 1976. Hispanics do change a lot, especially when it comes to migration. Thirdly, proportion foreign born/US born is from 2010 data, hence in reality it already accounts for mortality while I assume it does not. Same applies for the proportion of male among immigrants, however I correct for that using mortality data. Fourthly, I do not change relative shares of US born/foreign born population. Fifthly, I am not considering the interactions (i.e. changing more than 1 parameter at a time).

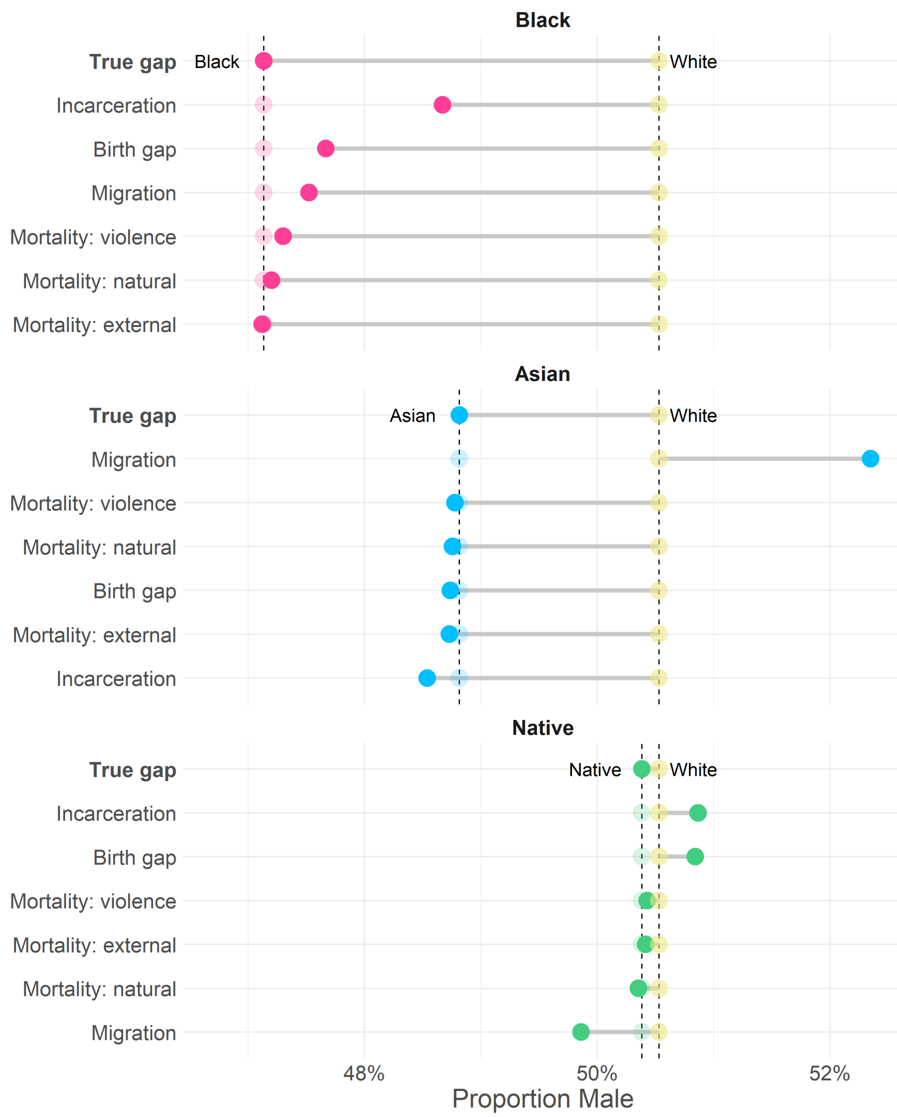
Main results

Figure A.9 demonstrates the primary factors driving the racial differences in sex composition. The x axis represents the proportion of men under each scenario, and y axis shows the parameters, ordered by their importance for each race. The first row in each panel illustrates the actual values of the sex compositions.

For Black people, the most critical driver by far is incarceration explaining 45% of the gap. Secondly, a non-negligible gap in the proportion of male births between White and Black people contributes about 15% to the overall difference in sex compositions. Propensity of male births is lower among Black people across the world. Finally, differential in violent deaths contribute about 5% to the gap. Migration is the most important factor driving the scarcity of men among Asians. The difference between Native Americans and White Americans are mostly negligible.

The desegregation by cohort shows that these gaps mostly arise above the age 20 for Black people and above the age 26 for Asian people.

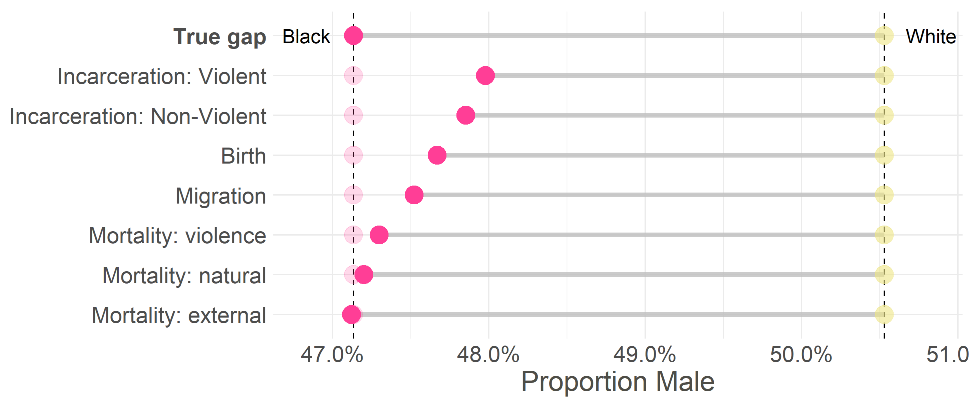
Figure A.9: Counterfactual Gaps in the Sex Composition



Notes: Each line on the figure shows the counterfactual gap (for the cohort 15-34 in 2010) that would arise if rates for a given factor were equlized to the value of White people. The dashed lines and the semi-transparent dots represent the true sex compositions.

Differences in sex ratios between Black and White people are policy sensitive. They come from biases interacting with legislation which prescribe harsher sentences for habitual offenders or particular drugs. An example in case was 100:1 sentencing disparity between crack cocaine, used disproportionately by Black people, and powder cocaine, consumed by White people[21]. Other types of ostensibly race neutral policies, such as a reform of technical violations of probation, can also have disproportionate impact on minorities (Rose (2021)). Consequently, the association of policies and bias in the criminal justice system sent a disproportionate number of Black men behind bars. Policies eliminating over-reliance on incarceration and the bias in the criminal justice system could reduce incarceration disparities. Hence, decision-makers have an influence over the gap in the sex compositions. For instance, Raphael and Stoll (2014) suggest that abandoning mandatory minimum sentencing for repeated offenders and reducing *truth in sentencing* laws which mandate that inmates serve minimum proportion of their sentences could reduce incarceration without harming public safety. Similarly, Sentencing (2008) and Ghandnoosh (2015) indicate that racial incarceration disparities could be decreased by expanding available bail and sentencing options, encouraging diversity in legal profession, diverting drug offenders to treatment, introducing gradual sanctions for probation violations, mandating racial impact analysis of legislation, and requiring training to overcome implicit racial bias.

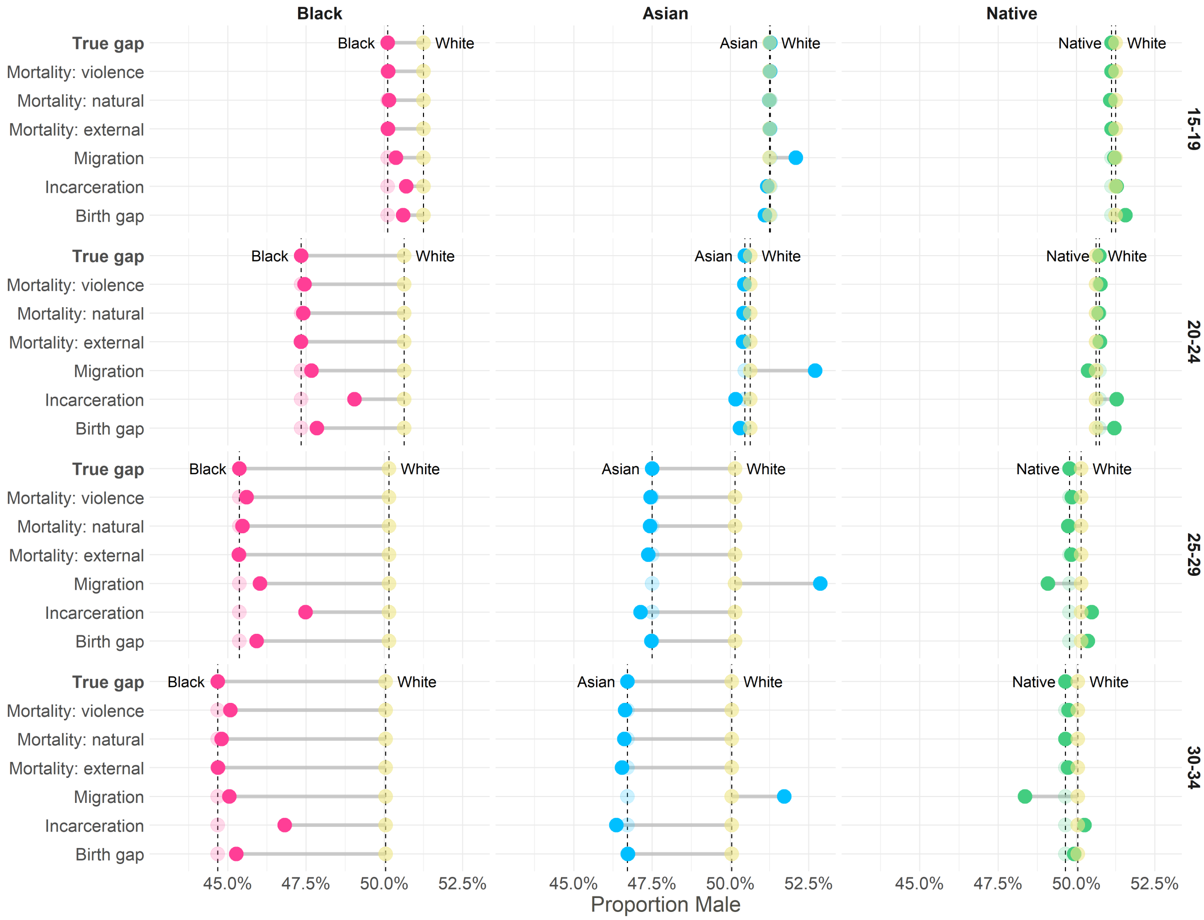
Figure A.10: Counterfactual Gaps in the Sex Composition



Notes: Each line on the figure shows the counterfactual gap (for the cohort 15-34 in 2010) that would arise if rates for a given factor were equalized to the value of White people. The dashed lines and the semi-transparent dots represent the true sex compositions.

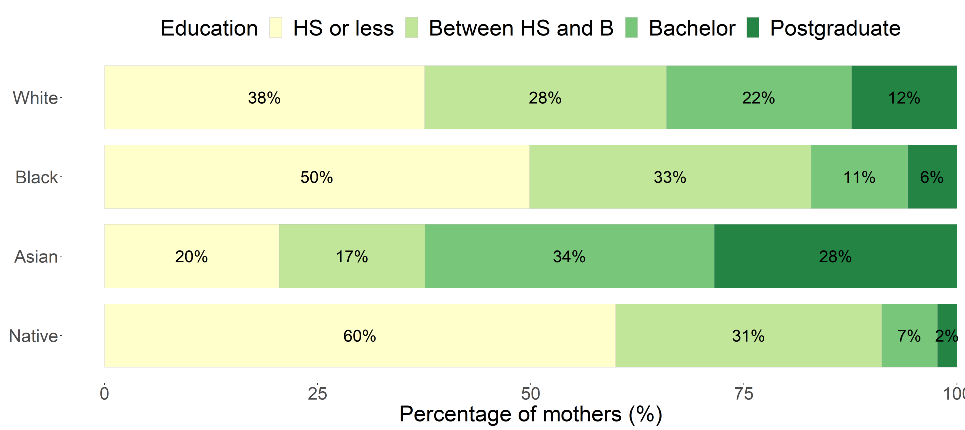
[21]Reduced to 18:1 by The Fair Sentencing Act of 2010

Figure A.11: Counterfactual Gaps in the Sex Composition: by Cohort



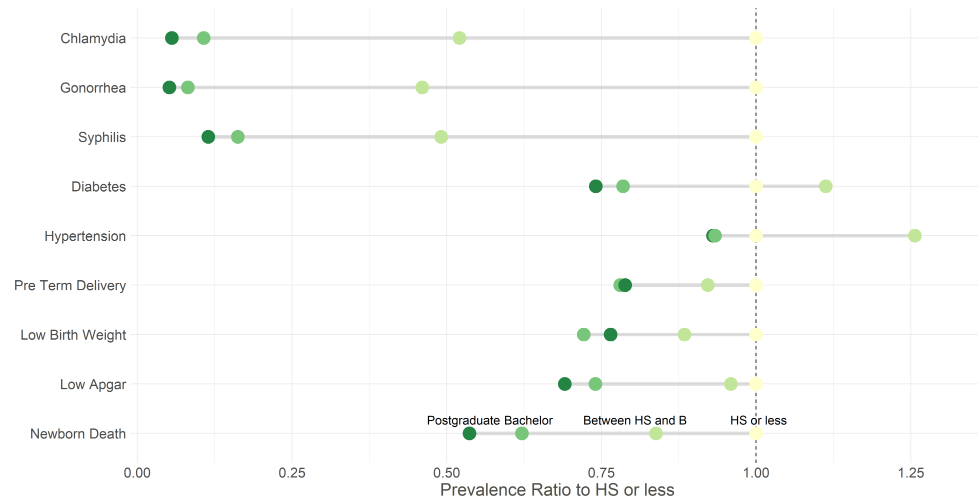
Notes: Each line on the figure shows the counterfactual gap (for the cohort 15-34 in 2010) that would arise if rates for a given factor were equalized to the value of White people. The dashed lines and the semi-transparent dots represent the true sex compositions.

Figure A.12: Education of Mothers by Race



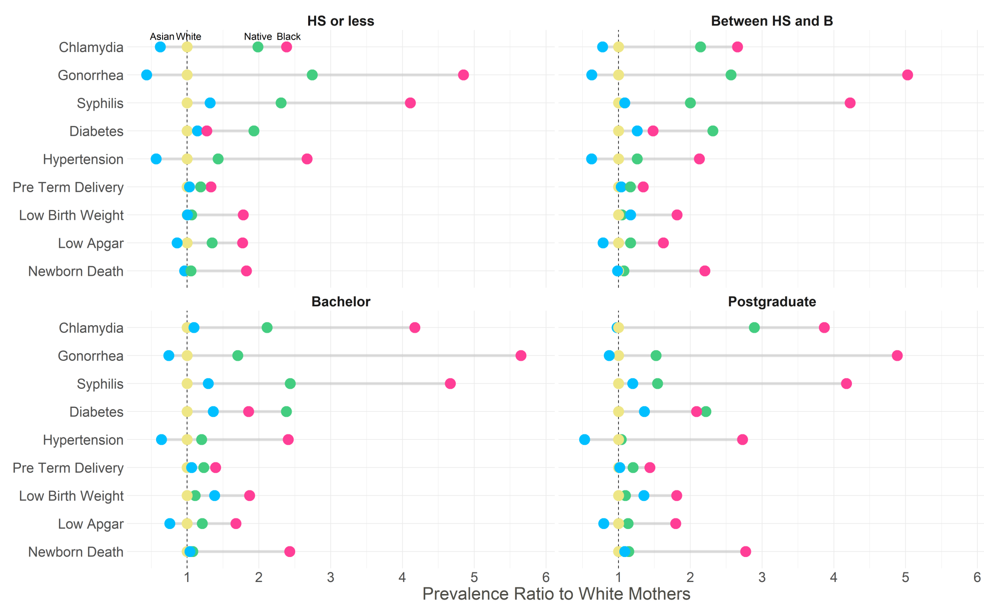
Notes: The figure shows the share of mothers with a given education level in each racial group.

Figure A.13: Educational Disparities by Health Outcomes



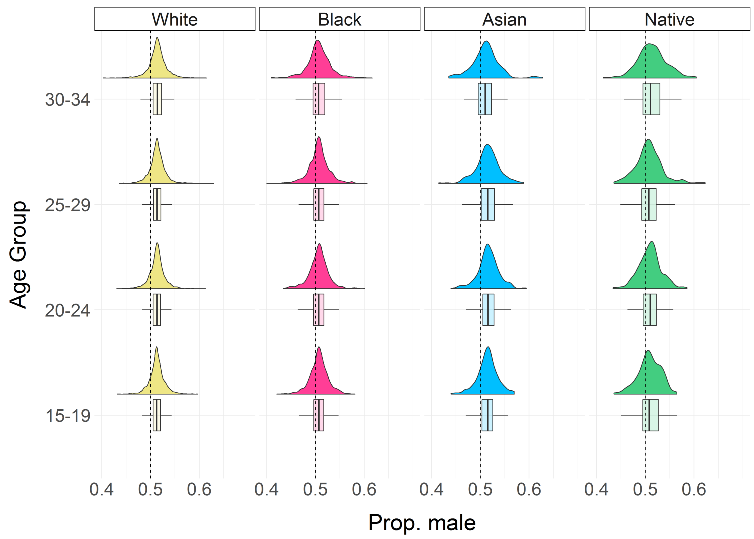
Notes: The lightest dots correspond to the benchmark of mothers with less than high school education. Other dots represent the ratio of the average prevalence among an education group to the average prevalence in among less than high school mothers.

Figure A.14: Racial Disparities in Health Outcomes



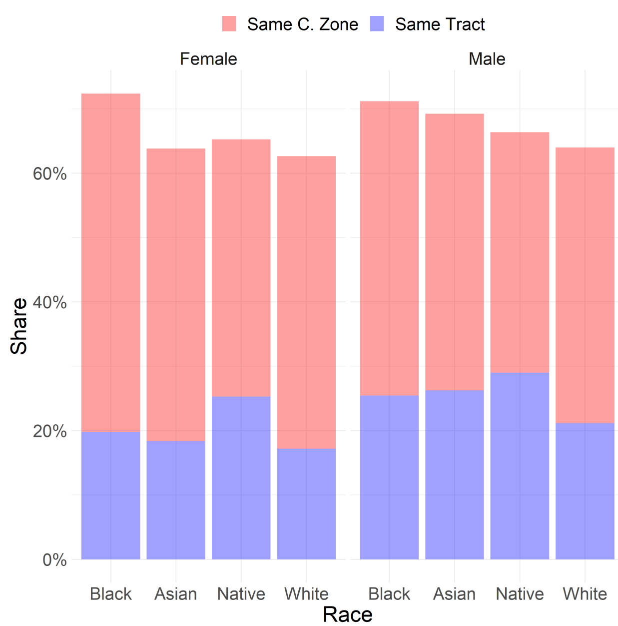
Notes: The light dots on the dashed line correspond to the baseline of the White mothers. Other dots represent the ratio of the average prevalence of a morbidity among a racial group to the average prevalence among White mothers. Blue, green and violet colors represent respectively Asians, Native Americans and Black Americans.

Figure A.15: Density of Proportion Male at Birth



Notes: Figure shows the empirical distribution of the sex composition. Each observation represents the proportion of men among agents on the dating market.

Figure A.16: Geographic Mobility since Childhood

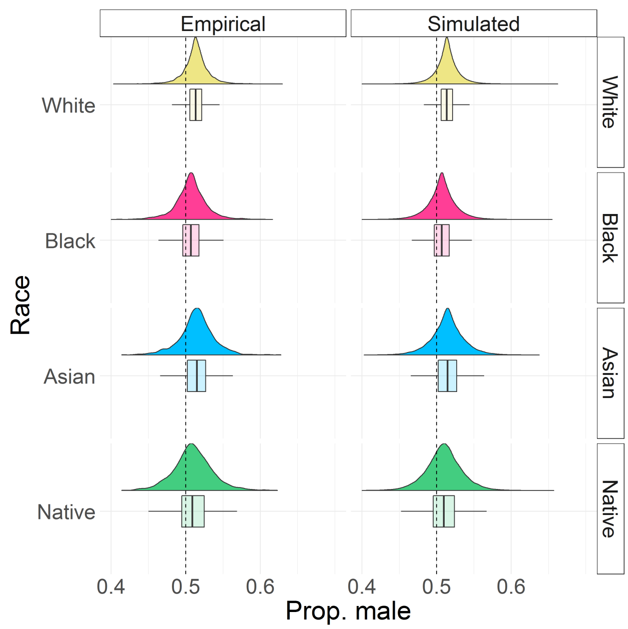


Notes: Figure shows the proportion of people born between 1978 and 1983 who live in their childhood census tract or commuting zone as young adults. Source: Opportunity Insights data.

A.3 Simulated Distribution of Sex Composition at Birth

I perform a exercise showing that empirical and simulated distributions of sex compositions at birth are identical. Figure A.17 visualizes it. First, for each race, I calculate the mean proportion of male births (p_r) in the data. Note that I assume that the sex ratio at birth is only random conditional on race, as there are some racial differences in the propensity of a male birth. Next, for each market, I "toss a coin" n_{cra} times with the probability of success p_r, where n_{cra} is the number of birth on the market. I repeat this procedure 100 times, resulting in a simulated distribution of sex compositions that would arise if sex at birth was a Bernoulli variable. If sex at birth is truly a random "coin toss", the empirical and simulated distribution should be similar[22]. Indeed, the distributions are visually almost identical. This is further confirmed by the Kolgomorov-Smirnov tests, which do not reject the equality of the distributions (table A1). The p-values associated with this test stay above the traditional singnificance levels, although for the Black and White population they are around 0.13-0.15.

Figure A.17: Actual vs Simulated Density of Proportion of Male Births



Notes: The left panel shows the empirical distribution of sex compositions where each observation represents the proportion of male births at a dating market when the cohort was born. The right panel shows the simulated distribution. Simulations are draws from the binomial distribution with parameters p_r and n_{cra}, and divided by n_{cra}.

[22]Note that they mechanically have the same mean

Table A1: Kolgomorov-Smirnov Test

Race	**P-value**
Asian	0.728
Black	0.155
White	0.1303
Native	0.921

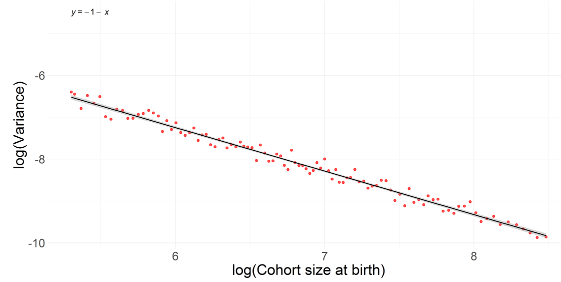
Notes: The table shows p-values from Kolgomorov-Smirnov tests for the hypothesis that the empirical and simulated distributions in the figure A.17 are equal.

A.4 Relationship between Cohort Size and Variation in Sex Composition

One would expect that the deviations from the balanced sex ratio are negligible in large cohorts but can be substantial in small cohorts. Such pattern holds true in the data. Panel a of A.18 plots the theoretical standard deviation by sample size n using p=0.5 and $\sqrt{\frac{p(1-p)}{n}}$. The dots represent the empirical standard deviation by cohort size. Specifically, I divided markets by the percentiles of the size of the birth cohort. Within each percentile I calculated standard deviation of proportion male and plotted it against the average size in this percentile. The theoretical and empirical standard deviation by size are almost identical, which suggests that most of the observed variation in the data comes from the randomness in sex at birth. I also formally test this relationship. Taking logs of the theoretical variance I obtain $log(var) = log(p(1-p)) - log(n)$. Therefore, regressing the log of empirical variance on the log of cohort size should give a coefficient equal to 1, as illustrated in panel b of the figure A.18. I perform such regression in 10000 bootstrap samples where I draw markets with replacement. The mean coefficient is equal to -1.025 with a 95% bootstrap confidence interval (-1.052, -0.998).

Figure A.18: Variation in the Sex Composition

(a) Theoretical and Empirical Standard deviation in Sex Ratio at Birth



(b) Log of Theoretical and Empirical Standard deviation in Sex Ratio at Birth

Notes: The curve in figure A.18a shows the theoretical standard deviation by sample size n using p=0.5 and $\sqrt{\frac{p(1-p)}{n}}$. The dots represent the standard deviation in the data. Specifically, markets were divided by the percentiles of the size of the birth cohort. Each dot represents a group of markets in a percentile. Standard deviation and average size are calculated in each percentile. Figure A.18b shows the relationship between log of the variance in the centiles of data and the average cohort size of the centile, and a fitted regression line.

A.5 First Stage Heterogeneity

Table A2: First Stage by Cohort

Dependent Variable:	Prop. male 2010				
h1	Full sample	15-19	20-24	25-29	30-34
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male at birth	0.2329	0.4267	0.3281	0.0511	0.2040
	(0.0236)	(0.0336)	(0.0489)	(0.0645)	(0.0655)
Fit statistics					
Wald Kleibergen-Paap (IV only)	97.3	160.9	45.0	0.628	9.70
Dependent variable mean	0.496	0.511	0.498	0.486	0.482
Observations	7,138,182	1,966,817	2,486,046	2,033,986	991,687

Controls include cohort size in 2010 and at birth, and fixed effects for county-age, race-age, and county-cohort. Standard errors are clustered at the county-race level.

Table A3: First Stage by Racial Group

Dependent Variable:	Prop. male 2010		
Sample	Full sample	White & Asian	Black & Native
Model:	(1)	(2)	(3)
Variables			
Prop. male at birth	0.2329	0.1950	0.3269
	(0.0240)	(0.0242)	(0.0459)
Fit statistics			
Wald Kleibergen-Paap (IV only)	98.0	64.8	50.7
Dependent variable mean	0.496	0.501	0.481
Observations	7,478,536	5,673,531	1,805,005

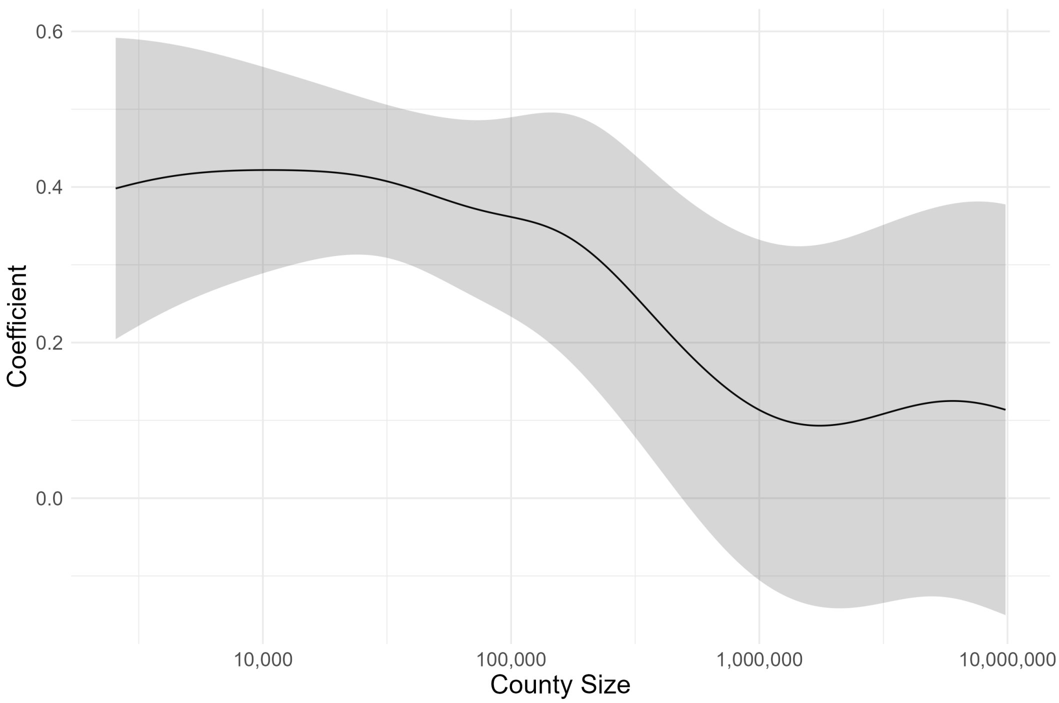
Controls include cohort size at birth, and fixed effects for county-age, race-age, and county-cohort. Standard errors are clustered at the county-race level.

Table A4: First Stage by Rural-Urban Status

Dependent Variable:	Proportion	
Sample	Rural	Urban
Model:	(1)	(2)
Variables		
Prop. male at birth	0.204^{***}	0.449^{***}
	(0.074)	(0.088)
Fit statistics		
R^2	0.88802	0.92488
Observations	6,724	6,032
Dependent variable mean	0.49620	0.50055

Notes: This market level regression includes includes controls for cohort size at birth and in 2010, and fixed effects for county-cohort, and race-cohort. Standard errors are clustered at the county-race level.

Figure A.19: First Stage by County Size



Notes: The graph presents coefficients from running a local linear regression corresponding to the first stage along the log of the county size. County size refers to the total population of the county where the market is located. The regression is fitted using a Gaussian kernel. Standard errors are clustered at the county-race level and only markets with cohorts between 200-5000 were used (while county size might be considerably larger).

Table A5: OLS Results in IV sample

Panel A: OLS RESULTS

Marriage Market Outcomes					
Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*		
Prop. male 2010	-0.2126	0.3976	–0.7418		
	(0.0215)	(0.0407)	(0.1169)		
Dependent variable mean	0.127	0.621	0.360		
Observations	7,166,343	7,478,536	6,105,173		
Maternal Health Outcomes					
Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*
Prop. male 2010	-0.0292	-0.0092	-0.0026	-0.0110	-0.0326
	(0.0033)	(0.0012)	(0.0007)	(0.0015)	(0.0045)
Dependent variable mean	0.019	0.003	0.0008	0.010	0.022
Observations	7,138,182	7,138,182	7,138,182	7,151,592	7,151,592
Infant Health Outcomes					
Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*
Prop. male 2010	-0.0592	-0.0603	-0.0118	-0.0255	-0.0022
	(0.0101)	(0.0085)	(0.0046)	(0.0095)	(0.0014)
Dependent variable mean	0.121	0.087	0.024	0.046	0.003
Observations	7,540,450	7,539,221	7,515,076	7,149,031	7,155,905

Notes: Negative *Diff. in Edu.* means that the father is more educated than the mother. Each regression contains controls for cohort size in 2010, County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample of markets between 200-5000 people. Standard errors clustered at the County-Race level.

A.6 OLS Results

A.7 Results Using the Sex Ratio

Table A6: IV Results: Sex Ratio

First Stage					
Dependent Variables:	*Sex Ratio in 2010*				
Sex ratio at birth	0.2280				
	(0.0228)				
Observations	7,138,182				
Wald Kleibergen-Paap (IV only)	99.602				
Marriage Market Outcomes					
Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*		
Sex ratio in 2010	-0.4025	0.7563	0.0300		
	(0.1311)	(0.1840)	(0.5214)		
Dependent variable mean	0.127	0.621	0.360		
Observations	7,166,343	7,478,536	6,105,173		
Sig. at 5% (Lee et al. 2022)	Yes	Yes	No		
Wald KP (1st stage), Sex ratio in 2010	96.1	98.0	79.7		
Maternal Health Outcomes					
Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*
Sex ratio in 2010	-0.0676	-0.0042	-0.0019	-0.0317	-0.0955
	(0.0266)	(0.0093)	(0.0049)	(0.0169)	(0.0322)
Dependent variable mean	0.019	0.003	0.0008	0.010	0.022
Observations	7,138,182	7,138,182	7,138,182	7,151,592	7,151,592
Sig. at 5% (Lee et al. 2022)	Yes	No	No	No	Yes
Wald KP (1st stage), Sex ratio in 2010	97.3	97.3	97.3	96.6	96.6
Infant Health Outcomes					
Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*
Sex ratio in 2010	-0.0798	-0.0644	-0.0512	-0.0681	-0.0013
	(0.0545)	(0.0461)	(0.0251)	(0.0413)	(0.0084)
Dependent variable mean	0.121	0.087	0.024	0.046	0.003
Observations	7,540,450	7,539,221	7,515,076	7,149,031	7,155,905
Sig. at 5% (Lee et al. 2022)	No	No	Yes	No	No
Wald KP (1st stage), Sex ratio in 2010	97.2	97.5	97.0	96.5	96.0

Notes: Negative *Diff. in Edu.* means that the father is more educated than the mother. The sex ratio in 2010 is instrumented with sex ratio at birth of the cohort. Each regression contains controls for cohort size in 2010 and at birth , County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample of markets between 200-10000 people. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom together with an information whether the coefficient is significant at 5% according to tF statistic (Lee et al. 2022).

A.8 Results Using Larger Sample: Birth Cohorts sized 200-10000

Table A7: IV Results: Larger Markets

Marriage Market Outcomes					
Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*		
Prop. male 2010	-0.3685	0.7678	-0.5424		
	(0.1313)	(0.1860)	(0.5043)		
Dependent variable mean	0.124	0.622	0.354		
Observations	10,548,074	10,973,113	9,011,860		
Sig. at 5% (Lee et al. 2022)	Yes	Yes	No		
Wald KP (1st stage), Prop. male 2010	108.8	111.2	91.7		
Maternal Health Outcomes					
Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*
Prop. male 2010	-0.0765	-0.0047	0.0010	-0.0287	-0.0830
	(0.0274)	(0.0095)	(0.0047)	(0.0163)	(0.0338)
Dependent variable mean	0.018	0.003	0.0008	0.009	0.021
Observations	10,508,996	10,508,996	10,508,996	10,527,013	10,527,013
Sig. at 5% (Lee et al. 2022)	Yes	No	No	No	Yes
Wald KP (1st stage), Prop. male 2010	109.9	109.9	109.9	109.1	109.1
Infant Health Outcomes					
Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*
Prop. male 2010	-0.0955	-0.0778	-0.0534	-0.0662	-0.0033
	(0.0526)	(0.0455)	(0.0237)	(0.0400)	(0.0082)
Dependent variable mean	0.119	0.085	0.024	0.045	0.003
Observations	11,109,756	11,108,124	11,074,088	10,521,957	10,532,750
Sig. at 5% (Lee et al. 2022)	No	No	Yes	No	No
Wald KP (1st stage), Prop. male 2010	110.5	110.8	110.4	109.1	108.6

Notes: Negative *Diff. in Edu.* means that the father is more educated than the mother. The proportion of men in 2010 is instrumented with proportion of men at birth of the cohort. Each regression contains controls for cohort size in 2010 and at birth , County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample of markets between 200-10000 people. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom together with an information whether the coefficient is significant at 5% according to tF statistic (Lee et al. 2022).

A.9 Results Using Smaller Sample: Birth Cohorts sized 200-2000

Table A8: IV Results: Smaller Markets

Marriage Market Outcomes Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*		
Prop. male 2010	-0.4146	0.7849	0.6495		
	(0.1720)	(0.2261)	(0.6442)		
Dependent variable mean	0.132	0.618	0.342		
Observations	3,538,303	3,702,314	2,988,393		
Sig. at 5% (Lee et al. 2022)	Yes	Yes	No		
Wald KP (1st stage), Prop. male 2010	52.9	52.4	43.0		
Maternal Health Outcomes Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*
Prop. male 2010	-0.0891	-0.0142	-0.0030	-0.0465	-0.1088
	(0.0345)	(0.0115)	(0.0062)	(0.0213)	(0.0428)
Dependent variable mean	0.020	0.003	0.0009	0.010	0.022
Observations	3,522,378	3,522,378	3,522,378	3,529,591	3,529,591
Sig. at 5% (Lee et al. 2022)	Yes	No	No	Yes	Yes
Wald KP (1st stage), Prop. male 2010	53.5	53.5	53.5	53.1	53.1
Infant Health Outcomes Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*
Prop. male 2010	-0.0201	-0.0290	-0.0523	-0.0776	0.0008
	(0.0698)	(0.0592)	(0.0336)	(0.0527)	(0.0109)
Dependent variable mean	0.125	0.091	0.025	0.046	0.003
Observations	3,727,677	3,727,204	3,713,742	3,528,853	3,532,839
Sig. at 5% (Lee et al. 2022)	No	No	No	No	No
Wald KP (1st stage), Prop. male 2010	53.3	53.5	53.1	53.1	52.8

Notes: Negative *Diff. in Edu.* means that the father is more educated than the mother. The proportion of men in 2010 is instrumented with proportion of men at birth of the cohort. Each regression contains controls for cohort size in 2010 and at birth , County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample of markets between 200-2000 people. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom together with an information whether the coefficient is significant at 5% according to tF statistic (Lee et al. 2022).

A.10 Additional Results

Table A9: Cross-County Effects

	By age							
	24		26		29		32	
	Female	Male	Female	Male	Female	Male	Female	Male
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Prop. male at birth	0.037	0.038	0.029	0.006	0.051	0.071	0.076	0.063
	(0.070)	(0.049)	(0.070)	(0.056)	(0.068)	(0.060)	(0.066)	(0.060)
Fixed-effects								
fips	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
county1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
R^2	0.96128	0.94770	0.96689	0.95354	0.97140	0.96289	0.97197	0.96400
Observations	19,316	19,340	19,316	19,340	19,316	19,340	19,316	19,340
Dependent variable mean	0.31562	0.21905	0.38898	0.30209	0.45456	0.38693	0.48662	0.43618

Notes: The outcome variable is the proportion of men or women married at a given age. Population under consideration was born in 1978-1983 and is assigned to the county where they spent their childhood. Each observation represents a pair of counties *times* gender *times* race. *Prop. male at birth* measures the share of births during period 1978-1983 in the neighboring county and of the same race who were male. Each regression contains controls for log of the cohort size at birth in the outcome county, counties-pair and race fixed effects. Maximum effect, according to 95% confidence interval, of one standard deviation change in sex ratio at birth on neighboring county's marriage rate is in the range: (-0.001,0.0032). Standard errors are heteroskedacticity robust. Source: Opportunity Insights data Chetty et al. (2018)

Table A10: Parity

Dependent Variable:			Male		
Race	Full sample	Asian	Black	Native	White
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Parity	-0.0006**	0.0004**	-0.0005***	-0.0006	-0.0007***
	(0.0001)	(0.0002)	(0.0001)	(0.0004)	(5.94×10^{-5})
Fixed-effects					
Race	Yes	Yes	Yes	Yes	Yes
Fit statistics					
R^2	1.89×10^{-5}	1.66×10^{-6}	3.74×10^{-6}	4.54×10^{-6}	4.84×10^{-6}
Observations	35,229,670	2,521,638	5,767,596	397,335	26,543,101
Dependent variable mean	0.51165	0.51573	0.50782	0.51019	0.51212

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: The outcome variable is the dummy for male birth. Each regression controls for race. The sample includes all births between 2011 and 2019. First column presents the results for the full sample, following columns are for race specific sub samples. Source: Natality Data

Table A11: Prenatal Care IV

Dependent Variables:	Month of Prenatal Care Start	Number of Visits
Model:	(1)	(2)
Variables		
Prop. male 2010	0.1648	-1.129
	(0.4699)	(1.319)
Fit statistics		
Dependent variable mean	2.98	11.3
Observations	6,973,738	7,312,109
Sig. at 5% (Lee et al. 2022)	No	No
Wald KP (1st stage), Prop. male 2010	112.3	115.3

The proportion of men in 2010 is instrumented with the proportion of males at birth of the cohort. Controls include cohort size in 2010 and at birth, and fixed effects for county-age, race-age, and county-cohort. Standard errors are clustered at the county-race level.

A.11 Mechanisms: Change in Composition of Mothers

Conditions in the dating market may affect maternal health through the changes in the composition of mothers. For instance, women with higher bargaining power may opt for childbearing only if it was intended. Hence, women who are not healthy enough or lack resources may not pursue the pregnancies they would otherwise bring to term if their partner had higher bargaining power and insisted. Indeed, as figure A.8 shows, women are usually less willing to have another child compared to men. Childless men are significantly more likely to want a child compared to childless women. While men are still more likely to have more children at a higher parity, the differences are not statistically significant. To investigate this mechanism, I first examine how childbearing rates react to the changes in sex composition. Hence, I regress birth rates on the proportion of men on the market. The birth rate is calculated as a ratio of children born to women on each dating market (between 2011 and 2019) per 1000 of women on that market. The OLS and the IV estimates (table A12) show a considerable decrease in birth rates at the markets where women are scarce. Turning our attention to the IV, most of this decline stems from fewer births to unmarried mothers. This could be either a consequence of fewer women remaining unmarried or women being less likely to have a child without marital commitment. A detailed analysis of the link between bargaining power and fertility is left for further research.

Table A12: Birth rates

	OLS			IV		
	BR	BR (marital)	BR (non-marital)	BR	BR (marital)	BR (non-marital)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Proportion male 2010	-398.8	-292.1	-134.7	-804.2	-277.4	-495.4
	(84.59)	(64.86)	(36.15)	(466.8)	(364.2)	(186.5)
Fit statistics						
Dependent variable mean	500.22	299.40	197.49	414.05	242.51	168.71
Wald KP (1st stage)				119.89	119.89	119.89
Observations	33,604	33,604	33,604	14,203	14,203	14,203

The outcome variable is birth rate (BR) calculated as the number of children born to women on each dating market (between 2011 and 2019) per 1000 of women on that market. The columns 1,2,3 show OLS estimates and columns 4,5,6 show IV estimates. The outcome in columns 2 and 5 is number of children born to married women per 1000 of women on the market and the outcome in columns 3 and 6 is the number of children born to non-married women per 1000 of women. Each regression contains controls for cohort size in 2010 and at birth, and County, and Race-Age group fixed effects. Standard errors are clustered at the County-Race level.

Next, I analyze whether the effect on the birth rate is associated with changes in mothers' characteristics. Table A13 shows that women giving birth at high bargaining positions tend to be healthier and more educated. Namely, mothers with increased bargaining power are less likely to be overweight, more educated, and have more educated partners. I interpret it as empowered women pursuing pregnancy only if there are enough resources in the household. When women lack bargaining power, they may agree to childbearing as a transfer to their male partner. Consequently, it is also evidence for the fact that the average quality of couples deciding to have children does not decrease as supply of men increases.

Table A13: Effect on Composition

Dependent Variables:	Overweight	Age at birth	Mother's Edu.	Fathers's Edu.
Model:	(1)	(2)	(3)	(4)
Variables				
Prop. male 2010	-0.2729	-0.1546	3.246	3.585
	(0.1109)	(0.7672)	(1.286)	(1.464)
Fit statistics				
Dependent variable mean	0.544	28.3	13.9	13.7
Observations	6,973,738	6,973,738	7,119,580	6,116,977
Sig. at 5% (Lee et al. 2022)	Yes	No	Yes	Yes
Wald KP (1st stage), Prop. male 2010	112.3	113.5	99.7	78.9

This table presents estimates from IV regressions of mother's and father's characteristics on proportion of men on the dating market in 2010 and other covariates. Proportion of men in 2010 is instrumented with proportion of men at birth of the cohort. Co Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Errors are clustered at the Race-County level.

B Extensions

B.1 Heterogeneity analysis

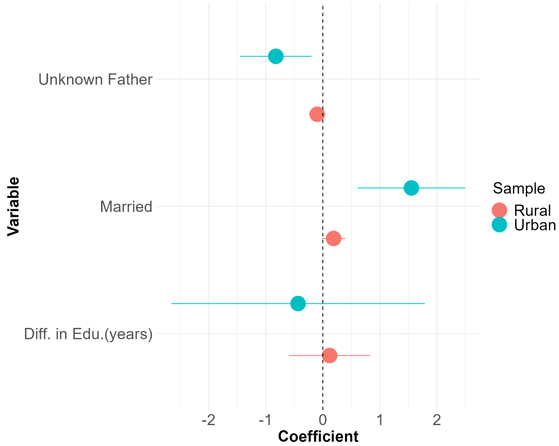
To assess the impact of market definition and sample selection on the results and their generalizability, I investigate heterogeneity in the effects of bargaining. My findings reveal that the most pronounced effects are observed within urban markets and among racial minority populations, suggesting that results would hold in the excluded parts of the sample as well.

B.1.1 Urban markets

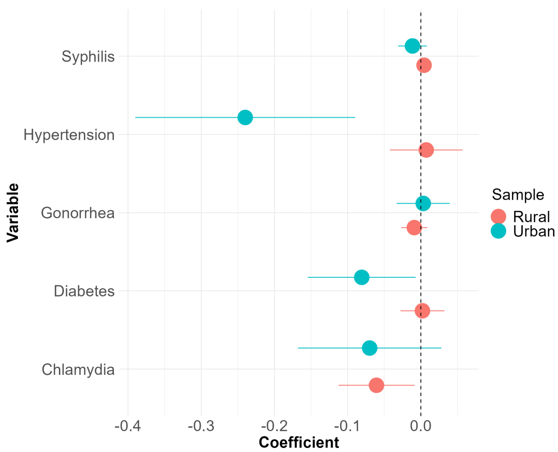
The effect of sex composition on the maternal and neonatal outcomes is mostly driven by the urban markets. Figure B.20 shows results of a heterogeneity analysis in which I split the sample by the type of the market: urban or rural [23].

[23] Counties are classified according to the 2013 Rural-Urban Continuum Codes. Non-metro areas (codes larger than 3) are classifed as rural

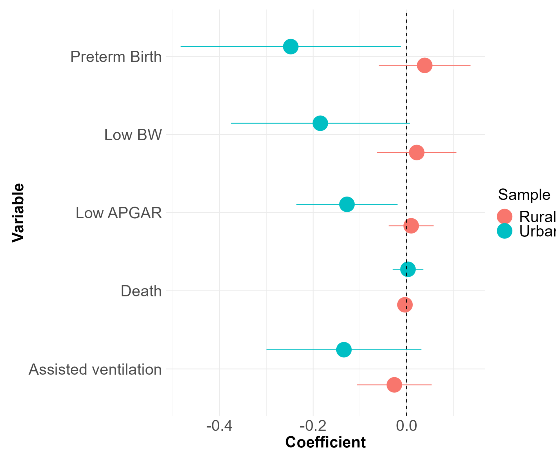
Figure B.20: Heterogeneity: Urban vs Rural Markets



(a) Marriage Market Outcomes



(b) Maternal Health Outcomes



(c) Neonatal Health Outcomes

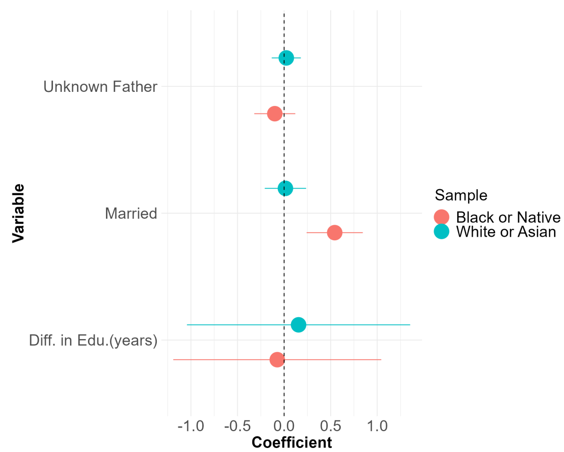
Notes: Each plot depicts coefficients on the variable 'proportion male' from the primary instrumental variable (IV) framework estimated on two distinct subsamples: rural and urban counties. Counties are divided according to the 2013 Rural-Urban Continuum Codes. Non-metro areas are classifed as rural.

The effects of proportion male on unknown father and marital status are considerably stronger in the urban sample, and significant at 5% according to tF standard errors despite the lower first stage compared to the rural sample. Maternal health also seems to be influenced by bargaining more heavily in the urban markets. While the coefficients on chlamydia are similar in both samples, the coefficients on diabetes and hypertension are negative and large only in the urban setting. The same pattern can be observed for neonatal health, with preterm birth and low APGAR score having sizeable negative coefficients in the urban sample. Nonetheless, as sample size is condsiderably smaller, these coefficients are not statistically significant at 5% according to tF standard errors.

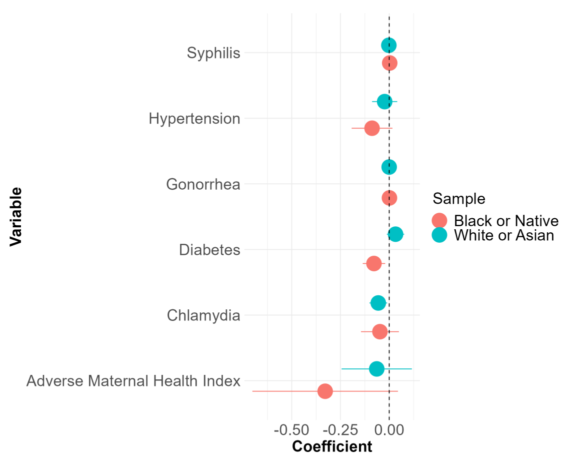
B.1.2 Racial Minorities

Splitting the analysis by racial groups indeed shows that minorities experience stronger effect of bargaining power. In the below analysis I divide the sample into two groups: (1) Black and Native, (2) White and Asian [24]. The absolute value of coefficients is larger in the majority of outcomes for the racial minorities.

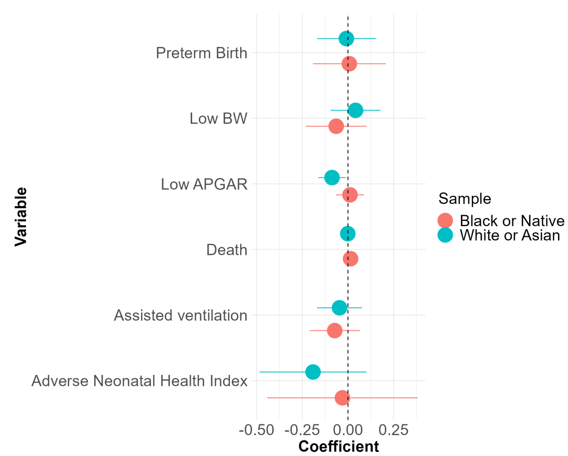
Figure B.21: Heterogeneity: Racial Group



(a) Marriage Market Outcomes



(b) Maternal Health Outcomes



(c) Neonatal Health Outcomes

Notes: Each dot corresponds to the value of the coefficient estimated on a sub-sample specified by the color. The range corresponds to the 95% confidence interval.

Minorities might be poorer or treated differently in the healthcare setting, leaving them more sensitive to other bargaining-related factors. An example could be domestic violence. If mothers from racial minorities are given less care and priority in the hospital, they are more

[24]Splitting by a single racial group leads to power issues

vulnerable to adverse health consequences of domestic violence episodes. Future research could further explore the role of poverty and discrimination in mediating the impact of household bargaining.

B.2 Effect on population marriage rates

Dating market favorable to women increases the marriage rate in the female population. Table A14, based on the Opportunity Insights data (Chetty et al. (2018)), demonstrates this finding. I adapt my framework to this data by constructing a variant of the instrument: the proportion of male births in 1978-1983 in each county and race. Next, I estimate the following reduced form equation:

$$Married^{a}_{crg} = \beta^{ag}\text{Prop. male at birth}_{cr} + \gamma^{ag} X_{cr} + \lambda^{ag}_{c} + \delta^{ag}_{r} + \epsilon^{a}_{crg} \tag{5}$$

Where $Married^{a}_{crg}$ is the share of people married at age a in county c, race r, and of gender g. The main independent variable is the proportion of male births, which varies across counties and races. Note that there are no multiple cohorts per county, as there is only one cohort in the outcome data. The regression also includes controls for the size of the cohorts in childhood and 2010, and race and county fixed effects. The parameter β^{ag} identifies to what extent the sex composition at birth affects the marriage rates at age a in the general population of gender g. I perform only the reduced form regression as the years of births do not correspond to a well defined age cohort in 2010 census.

Table A14: RF: Marriage in the General Population

	Married at the age							
	24		26		29		32	
	Female	Male	Female	Male	Female	Male	Female	Male
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
Prop. male at birth	0.197	0.090	0.180	0.083	0.189	0.072	0.236	0.019
	(0.105)	(0.090)	(0.105)	(0.108)	(0.100)	(0.108)	(0.104)	(0.107)
Fit statistics								
Observations	3,945	3,947	3,945	3,947	3,945	3,947	3,945	3,947
R^2	0.96513	0.95193	0.97390	0.96073	0.97854	0.97017	0.98036	0.97232

Notes: The outcome variable is the proportion of men or women married at a given age. Population under consideration was born in 1978-1983 and is assigned to the county where they spent their childhood. Each observation represents race *times* county *times* gender. *Prop. male at birth* measures the share of births during period 1978-1983 in each county and race who were male. Each regression contains controls for cohort size in 2010 and at birth, County and Race fixed effects. Standard errors are heteroskedacticity robust. Source: Opportunity Insights data Chetty et al. (2018)

Columns 1,3,5,7 show that women are more likely to be married when the proportion of men is high. Only the coefficient for the marriage rate at the age of 32 is significant at 5%, although the magnitudes are similar across ages. In particular, women at the 75th percentile of the proportion male at birth are 3.6 p.p more likely to be married than women in the 25th percentile. This result suggests that the increase in married mothers in table II is not due purely to selection into fertility as all women are more likely to be married. The magnitudes for men are considerably smaller (columns 2,4,6,8), but of the same sign. These results are consistent with findings in Angrist (2002) who also find a positive effect for women but no significant effect for men.

B.3 Migratory Response to Unfavorable Dating Market

Women tend to avoid locations with unfavorable sex composition. I leverage the census data on migration flows to show that they migrate out of places with a scarcity of men and to the areas where men are relatively abundant. Census data provides a yearly estimate of the number of men and women[25] leaving and arriving in each county. I construct yearly departure and arrival rates for both genders using migration flows in 2011-2015. Next, I regress them on the proportion of male births in two aggregated cohorts who were aged 15-24 and 25-34 in 2010[26]. Note that the outcome is not desegregated by race or age. Hence

[25] The data cannot be simultaneously desegregated by race, gender, and age. Hence I focus on gender.

[26] I aggregate the cohorts as the outcome is not desegregated by age and migration is a rare occurrence.

I restrict my sample to racially homogeneous counties. I estimate the following equation:

$$y_c^g = \alpha + \beta_{15-24}^g \text{Prop. male at birth: 15-24}_c + \beta_{25-34}^g \text{Prop. male at birth: 25-34}_c + \gamma^g X_i + \epsilon_c \tag{6}$$

Where y_c^g is the arrival or departure rate for gender g in county c. Rates are defined as the count of departing or arriving individuals divided by the county population. The independent variables are the proportion of male births in the cohorts aged 15-24 and 25-34 in 2010. I control for the cohort size in 2010. The parameters β_{cohort}^g identify the migratory response to the sex composition for gender g. Tables A15 and A16 presents the estimation results.

Table A15: Out Migration

Dependent Variables:	Pr(Male leave)	Pr(Female leave)
Model:	(1)	(2)
Variables		
Prop. male birth: 15-24	-0.0158	0.0295
	(0.0498)	(0.0425)
Prop. male birth: 25-34	-0.0540	-0.0739
	(0.0365)	(0.0361)
Fit statistics		
Dependent variable mean	0.06889	0.06248
Observations	1,735	1,735

Notes: The outcome variable is the count of yearly (male or female) out-migration out of the county (in years 2011-2015) divided by the population size (of men or women). Two independent variable measure the proportion of male births in this county in cohorts 15-24 and 25-34. The sample include counties where 80% of individuals are of the same race. Regressions are weighted by the population. Controls include log of cohort size. Standard errors are heteroskedacticity robust.

Table A15 analyzes the yearly probability of departures from a county for men and women as a function of the sex composition at birth. Column (2) shows that women are less likely to leave the county if the sex composition at birth in cohort 25-34 is favorable. Coefficients for men were also negative, however smaller in magnitude and not statistically different from 0 (column 1).

Table A16: In Migration

Dependent Variables:	Male arrival rate	Female arrival rate
Model:	(1)	(2)
Variables		
Prop. male birth: 15-24	0.0714	0.1167
	(0.0633)	(0.0442)
Prop. male birth: 25-34	-0.0112	0.0072
	(0.0410)	(0.0313)
Fit statistics		
Dependent variable mean	0.06990	0.05890
Observations	1,727	1,727

Notes: The outcome variable is the count of yearly (male or female) in-migration to a county (in years 2011-2015) divided by the population size (of men or women). Two independent variable measure the proportion of male births in this county in cohorts 15-24 and 25-34. The sample include counties where 80% of individuals are of the same race. Regressions are weighted by the population. Controls include log of cohort size. Standard errors are heteroskedacticity robust.

Table A16 shows a symmetric result, albeit for a different cohort. Column (2) shows the rate of female arrivals to a county increases with the proportion of men in cohort 15-24. Coefficients for men (column 1) are again statistically indistinguishable from 0.

The migratory response to the prevalent sex composition partially explains why the magnitude of the first stage in table I is lower than one. As women tend to leave places with unfavorable sex ratios and arrive at places with favorable sex ratios, the sex composition partially evens out. Xiong (2022) observes a similar pattern in China. While the migratory response could change the population composition and hence bias the estimated impact on health, I show in the section C.2 that migration is unlikely to drive the main results.

C Robustness Checks

C.1 Effect on partners' characteristics

While my framework assumes that people date within a *race* $\times$ *county* $\times$ *cohort* cell, one may wonder if women explore other markets when their own has an unfavorable sex ratio. If they do, my estimates would be biased toward zero because the market I consider is only a part of the actual market mothers face (see section C.11 for the derivation). To investigate this issue, I analyze whether the race or age difference between parents is affected by the variation in the sex composition in the mother's dating market. In particular, I use the IV framework in equation 2 and 3 to estimate the impact of *Proportion male* on two additional variables: the absolute difference between the parent's age and a dummy on whether parents are of a different races. Estimation results are in table A17.

Table A17: Effect on Market

Dependent Variables:	abs(Difference in age)	Diff. Race Parents
Model:	(1)	(2)
Variables		
Prop. male 2010	-1.615	0.4240
	(1.087)	(0.2381)
Fit statistics		
Dependent variable mean	3.5818	0.08616
Wald (1st stage), Prop. male 2010	76.913	51.041
Observations	6,259,559	6,300,696
Sig. at 5% (Lee et al. 2022)	No	No

Notes: The first outcome is the absolute value of the difference between parents' ages. The second outcome is a dummy for whether parents are of the same race. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Standard errors are clustered at the County-Race level.

Column (1) in table A17 demonstrates that the age difference among parents does not change with sex composition. The coefficient on *Prop. male 2010* is small in magnitude and statistically insignificant. If taken at face value, one standard deviation in proportion of men on the market would change difference in age by only 0.06 of a year. Hence, women do not look for partners in other age groups when the sex ratio in their age group is unfavorable.

According to the values in column (2), women are slightly more likely to engage in an interracial partnership when the proportion of men on their market is high, although this estimate is noisy. The sign of this coefficient goes against the expectation that women would turn to other racial groups when men of their race are scarce. It could, however, reflect men's higher propensity to look for partners in other racial groups when they face stiff competition. Nonetheless, I remain skeptical of interpreting the sign of this coefficient as it is noisily estimated and the null effect cannot be rejected at (traditional or Lee et al. 2022) 5% significance level.

C.2 Effects of migration on market's composition

The migratory response is unlikely to pose a threat to the identification strategy. It would do so only if female migrants leaving due to the scarcity of men had better potential outcomes than women staying put. Ideally, one would compare the potential outcomes of those who left due to sex ratio and those who stayed. Unfortunately, there is no data to perform such a comparison. However, I can leverage information on the income rank of people staying in their commuting zones of childhood contained in the Opportunity Insights dataset. In particular, suppose that women with better outcomes (as proxied by income rank) are more likely to leave their commuting zone when the sex ratio is unfavorable. Then, the average outcome of women who stay behind should decrease when the sex ratio decreases. Hence, I test whether there exists a positive relationship between the share of men and the income rank of stayers by running the following regression:

$$rank.stayed_{crg} = \beta^g \text{Prop. male at birth}_{cr} + \gamma^g X_{cr} + \lambda_c^g + \delta_r^g + \epsilon_{crg} \tag{7}$$

Where $rank.stayed_{crg}$ represents the average income rank of stayers in county c, race r, and of gender g. The main independent variable is the proportion of male births in county c and race r at the time of cohort's birth. The regression also includes controls for the size of the cohorts in childhood and 2010 and race and county fixed effects. Table A18 shows the estimation results.

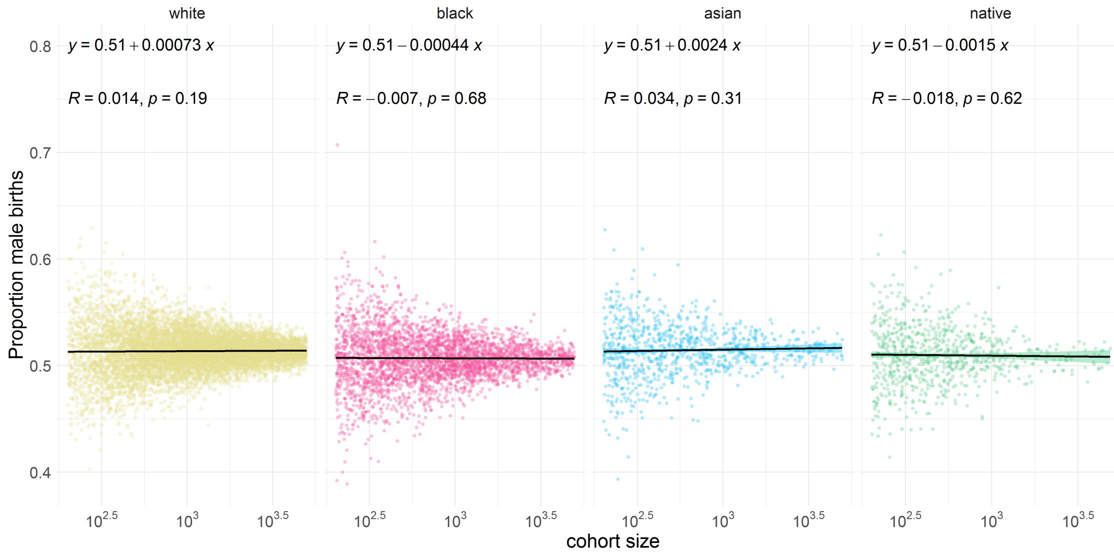
Table A18: RF: Income Rank of Stayers

Model:	Female (1)	Male (2)
Variables		
Prop. male at birth	0.184	0.106
	(0.116)	(0.113)
Fit statistics		
Dependent variable mean	0.45266	0.43570
Observations	3,493	3,503

Notes: Each observation correspond to race × county for people born in 1978-1983. The outcome is measured as the average income rank of those who still leave in the commuting zone of their childhood. The rank is relative to all children in their cohort. Controls include cohort size at birth and in the sample, and county and race fixed effects. Standard errors are Heteroskedasticity-robust. Data source: Opportunity Insights

The income rank of stayers is not related to the instrument. Parameters β for both men and women are small and statistically insignificant. If taken at face value, one standard deviation change in proportion of male births would have an effect of 0.0067 on female and 0.0038 on male income rank. Hence, I treat it as suggestive evidence that the migration in response to the dating market situation does not change the composition of stayers.

Figure C.22: Birth Cohort Size vs Proportion Male at Birth



Notes: Each dot on the figure represents a dating market. It plots birth cohort size vs proportion of male births. A regression line is fitted and its coefficients and p value are shown on top.

C.3 Stopping rules

Stopping rule does not seem to play a role in shaping sex ratio at birth in my sample. The concern stems from the fact that son preference and a stopping rule would result in more boys in smaller cohorts. Smaller cohorts may also benefit from more intensive human capital investments. Nonetheless, figure C.22 shows that there is no relationship between birth cohort size and proportion of male births in none of the racial group.

C.4 Effects Education and Incarceration

One may be concerned that growing up in a location with unbalanced sex composition may impact behaviors through channels unrelated to the dating market. Suppose that boys in mostly female cohorts could have different attitudes toward women than boys in mostly male cohorts. As I lack data for attitudes, this problem has to be acknowledged as a limitation of the study. Nonetheless, I attempt to partially address this issue by showing that outcomes not directly related to the dating market do not differ across locations with high versus low share of men. I focus on two plausible candidates which could be affected by upbringing in an uneven sex ratio setting. Firstly, I analyze whether sex composition at birth affects the share of people who are incarcerated. One would expect such relationship if, for instance, men growing up in cohorts dominated by male were more violent. Secondly, I look at the share of individuals how finished a 4 years college. Relationship between sex composition of a cohort and education could arise through peer effects, as women are more likely to attend college. Note that both outcomes to some extend measure human capital and hence address the previous scenario as well. I test the above mentioned hypothesis by estimating the following equation:

$$y_{crg} = \beta^g \text{Prop. male at birth}_{cr} + \gamma^g X_{cr} + \delta_r^g + \epsilon_{crg} \tag{8}$$

Where y_{crg} represents either the share of incarcerated or college educated in county c, race r, and gender g. Otherwise, the regression is analogous to the one in the previous subsection. Results are contained in the table A19. The parameter β^g identifies the impact of the sex composition at birth on the share of individuals of gender g who are incarcerated (columns 1 and 2 in table A19) and who have a college degree (columns 3 and 4).

Table A19: RF: Education and Incarceration

Dependent Variables:	Incarcerated		College	
	Female	Male	Female	Male
Model:	(1)	(2)	(3)	(4)
Variables				
Prop. male at birth	0.002	0.007	-0.0007	-0.031
	(0.005)	(0.026)	(0.130)	(0.114)
Fixed-effects				
Race	Yes	Yes	Yes	Yes
Fit statistics				
Dependent variable mean	0.00402	0.03937	0.35074	0.25554
R^2	0.12758	0.71730	0.39477	0.44805
Observations	3,558	3,555	3,017	2,993

Notes: this table presents regressions of education and incarceration outcomes on proportion of males at birth of the cohort and covariates. Population under consideration was born in 1978-1983 and is assigned to the county where they spent their childhood. Each observation represents race *times* county *times* gender. The variable *Prop. male at birth* measures the share of births during period 1978-1983 in each county and race who were male. Outcome Incarcerated measures the incarcerated share of the cohort in each gender (columns 1 and 2). Outcome college measures share of ACS respondents in the cohort who had a college degree at age 25 or more by gender (columns 3 and 4). Regressions are weighted by the cohort size. Controls include cohort size at birth and in the sample, and race fixed effects. Standard errors are heteroskedacticity robust. Data source: Opportunity Insights

Estimation results show no relationship between outcomes unrelated to the dating market and the sex composition at birth. According to estimates in columns (1) and (2), the proportion of men in the birth cohort is not related to adult incarceration rates. With 95% confidence, it is possible to rule out the impact of a one standard deviation shift in the sex ratio leading to changes in incarceration rates exceeding 0.02 percentage points for women and 0.1 percentage points for men. This null effect provides reassurance that growing up in an unbalanced sex ratio is not associated with violence. Furthermore, there is no evidence that educational achievements are shaped by the sex composition at birth, as estimates of β in columns (3) and (4) are not statistically significant. With 95% confidence, it is possible to discount any effects of a one standard deviation shift in the sex ratio on college completion rates that are larger than 0.5 percentage points for both genders. These findings lessen the concern that the main results are driven by the effect of growing up in unbalanced sex composition.

C.5 Effects on Social Networks

It could be argued that growing up in an environment with an unbalanced sex ratio might affect the development of soft skills, which subsequently affect health. Soft skills, however, are inherently difficult to measure. However, these skills may be partially reflected in social behaviors, such as the formation of social networks or engagement in volunteering activities. Leveraging data from Opportunity Insights on social capital, based on Facebook, I examine the reduced-form impact of the sex ratio at birth within a cohort on their social behavior later in life.

Specifically, I focus on two measures: first, the clustering of high school friendships, which indicates how cohesive social networks are and whether friendships are supported by mutual friends; second, civic engagement, which measures the likelihood of individuals being members of civic organizations or volunteering groups. I estimate the following regression:

$$y_c = \alpha + \beta \text{Prop. male at birth}_c + \gamma^g X_{cr} + \epsilon_{crg} \tag{9}$$

where y_c represents one of the social behavior outcomes in county c. The coefficient β captures the effect of an imbalanced sex ratio at birth on these measures of social behavior. The results are presented in the table A20.

Table A20: Reduced Form: Social Networks

Dependent Variables:	Clustering	Volunteering Rate
Model:	(1)	(2)
Variables		
P	0.012	0.054
	(0.158)	(0.045)
Fit statistics		
R^2	0.03590	0.00032
Observations	4,124	4,113
Dependent variable mean	0.59015	0.05815

Heteroskedasticity-robust standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents regressions of social network and civic engagement outcomes on the proportion of males at birth within the cohort, controlling for covariates. The population under consideration was born between 1986 and 1996 and is assigned to the county where they attended high school. Each observation represents a county. Controls include the log of the cohort size at birth. Standard errors are heteroskedasticity-robust. Data source: Opportunity Insights.

As shown in the table, there is no significant relationship between the sex ratio at birth and these social behavior measures. The maximum impact of a standard deviation change in the sex ratio, according to the 95% confidence interval, would range from -0.0033 to 0.0036 for social networks clustering and from -0.00038 to 0.0016 for social networks volunteering, which is negligible compared to their means. These findings suggest that an unbalanced sex ratio at birth does not significantly affect social network formation or civic engagement later in life.

C.6 Effects on Divorce in Instrument's Parents Generation

A potential concern in examining the effects of the sex ratio at birth is its possible influence on marital stability within the parents' generation. For instance, Dahl and Moretti (2008) show that parents of first born daughters are more likely to divorce. This might potentially have an impact on the health of the children. To explore this, I examine the reduced-form impact of the sex ratio at birth of children generation on the divorce probability in older generation using county-level data from the 2010 American Community Survey (ACS).

The analysis is conducted across cohorts aged 35-39, 40-44, 45-49, and 50-54 in 2010, to capture variations in the timing of divorce across potential parents of generations aged 15-34 in 2010. The variable *Prop. male at birth* measures the proportion of male births in a given county and cohort. The outcome variable indicates whether an individual was divorced at the time of the survey. I estimate the following regression model:

$$y_{c,a} = \sum_{a'} \beta^{a'} \text{Prop. male at birth}_{c,a'} + \gamma X_{c,a} + \epsilon_{c,a} \tag{10}$$

where $y_{c,a}$ represents the divorce probability in county c, and cohort a. The coefficient $\beta^{a'}$ captures the effect of the sex ratio at birth in cohort a' on the likelihood of divorce in an older cohort a. The results are presented in the table below:

Table A21: RF: Parent's Divorce

	Age in 2010			
	35-39	40-44	45-49	50-54
Model:	(1)	(2)	(3)	(4)
Variables				
Prop. birth 15-19	0.012	-0.009	0.104	0.049
	(0.083)	(0.087)	(0.074)	(0.077)
Prop. birth 20-24		0.118	0.065	0.030
		(0.082)	(0.081)	(0.074)
Prop. birth 25-29			0.011	0.080
			(0.085)	(0.078)
Prop. birth 30-34				-0.072
				(0.074)
Fit statistics				
Adjusted R^2	0.00909	0.00192	0.00144	0.00665
R^2	0.00945	0.00246	0.00216	0.00754
Observations	5,584	5,578	5,576	5,558
Dependent variable mean	0.13797	0.16062	0.17352	0.17484

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Notes: This table presents regressions of a divorce probability in a cohort on the proportion of males at birth in a younger cohort Each observation represents a county *times* cohort combination. The variable *Prop. male at birth* measures the share of births in a given younger cohort and county who were male. Controls include log of cohort size at birth. Standard errors are clustered at the county level. Data source: American Community Survey 2010

The results indicate that there is no significant relationship between the sex ratio at birth and the probability of divorce in parental generations. The maximum impact of a one standard deviation change in the sex ratio, according to the 95% confidence interval, ranges from -0.0037 to 0.0044. These findings imply that an unbalanced sex ratio at birth does not have a substantial impact on the likelihood of divorce among parents.

C.7 Effects of socio-economic conditions and environmental factors on sex at birth

My main results rely on the assumption that no third variable drives the cohort's sex composition at birth and the pregnancy outcomes about 20 years later when the cohort enters the childbearing age. An example of such omitted variable could be a socio-economic environment, which according to the fragile-male hypothesis, can affect the sex of a newborn. This relationship would endanger the identification strategy if the socio-economic background at birth also influenced maternal health in adulthood.

To alleviate these concerns, I provide evidence that in the US, sex at birth is not related to socio-economic variables. In particular, I focus on several measures: the mother's education, marital status, age, and the county's unemployment during her pregnancy.

First, using my primary analysis sample of the Natality Data, I show no relationship between a mother's education, marital status or age and her newborn's sex. Here, the mother's education is a proxy for her economic status as income and education are highly correlated. In each instance, I regress whether newborn is male on the relevant covariates and fixed effects (columns 1,2,3 in table A22) and I run an additional regression including all measures together (column 4).

Table A22: Education and Sex at Birth

Dependent Variable:	Male birth			
Model:	(1)	(2)	(3)	(4)
Variables				
High School	0.0010			0.0009
	(0.0006)			(0.0006)
Between HS and C	0.0010			0.0010
	(0.0006)			(0.0006)
College or more	0.0011			0.0011
	(0.0007)			(0.0007)
Married		-0.0003		-0.0003
		(0.0004)		(0.0005)
Age at birth			-4.64×10^{-5}	-8.65×10^{-5}
			(7.46×10^{-5})	(7.92×10^{-5})
Fixed-effects				
County-Age at birth	Yes	Yes		
Race-Single age cohort	Yes	Yes	Yes	Yes
Race-Age at birth	Yes	Yes		
County			Yes	Yes
Race			Yes	Yes
Fit statistics				
Dependent variable mean	0.512	0.512	0.512	0.512
Observations	7,546,442	7,478,536	7,546,442	7,478,536

Notes: Outcome variable is a dummy equal to one if a male is born on mother's education (column 1), marital status (2), age (3) and all together (4). Mother's education can have 4 levels: (excluded) less than high school, high school, between high school and college, and college or more. Standard errors are clustered at the County-Race level. Data source: Natality Data.

The variation in sex composition at birth is not related to a differential education, marital status or age among mothers. None of the coefficients are significant at traditional levels. Even if taken at face value, the coefficients are all small in magnitudes. For instance, 10 p.p. increase in mothers with College Education would only increase proportion male by. 0.01 p.p. Considering 95% confidence interval, the impact of having college or more on the probability of male birth would be between $-0.000272, 0.002472$ and that of being married $-0.00128, 0.0006$ Hence, socio-economic characteristics are unlikely to drive the relationship in the data.

Next, I show that the economic conditions proxied by unemployment during any stage of pregnancy do not influence sex composition. I regress the sex composition of births on the unemployment level at the time of the delivery and all months during pregnancy. Such specification allows for a differential effect depending on the timing of the exposure to unemployment. The monthly county-level sex composition for 2003-2020 comes from the Natality data, and the analogous unemployment data was downloaded from FRED. I estimate both an OLS and an IV model using a Bartik-type instrument. OLS follows the equation:

$$Prop.Male_{c,t} = \sum_{lag:0}^{10} \beta^{lag} Unemployment_{c,t-lag} + \gamma_c + \delta_t + \epsilon_{c,t} \tag{11}$$

The outcome variable represents the proportion of male births in county c in month-year t. The main independent variable is $Unemployment_{c,t-lag}$ which shows the (lagged) unemployment level in county c and time $t - lag$ [27]. Lag equal to 0 corresponds to the unemployment level during the delivery month, while lag equal to 10 is the unemployment ten months before the delivery. I also include county γ_c and time fixed effects δ_t.

The IV framework uses a shift-share instrument to capture the exogenous variation in unemployment stemming from differential exposures to industries across counties. The instrument is a weighted average of county industry shares [28] and the industry-level national monthly unemployment rates. Table A23 presents the estimation results.

The regressions show no evidence that unemployment during pregnancy relates to sex at birth. All estimated OLS coefficients in column (1) are close to 0. Note that they also have tight confidence bands. The results are similar to the IV framework. First, note that the instrument is far from weak, as evidenced by sizeable Kleinberg-Paap Wald statistics of the first stage. Again, coefficients on all unemployment lags are close to 0 and insignificant. Hence, I conclude that the exposure to booms and recessions, as proxied by unemployment during pregnancy, does not influence sex at birth. Considering 95% confidence interval, the largest positive and negative impact (among all lags) of 1% change in unemployment on the probability of male birth would be { -0.001084, 0.000888}.

[27] Time is measured in months

[28] Industry shares come from the table P049 in 2000 Census summary file

Table A23: Unemployment and Sex at Birth

Dependent Variable:	Proportion male	
Model:	OLS	IV
Variables		
Unemployment Rate	9.88×10^{-5}	0.001
	(0.0002)	(0.001)
lag(Unemployment Rate,1)	-0.0002	-0.002
	(0.0003)	(0.003)
lag(Unemployment Rate,2)	0.0001	0.002
	(0.0003)	(0.003)
lag(Unemployment Rate,3)	0.0003	0.0004
	(0.0003)	(0.002)
lag(Unemployment Rate,4)	-0.0002	-0.003
	(0.0003)	(0.002)
lag(Unemployment Rate,5)	2.36×10^{-5}	0.004
	(0.0003)	(0.003)
lag(Unemployment Rate,6)	-6.7×10^{-5}	-0.001
	(0.0003)	(0.003)
lag(Unemployment Rate,7)	-7.61×10^{-5}	-0.0008
	(0.0003)	(0.002)
lag(Unemployment Rate,8)	5.6×10^{-5}	0.0003
	(0.0003)	(0.003)
lag(Unemployment Rate,9)	-0.0003	-0.002
	(0.0004)	(0.005)
lag(Unemployment Rate,10)	0.0003	0.002
	(0.0003)	(0.004)
Fit statistics		
Dependent variable mean	0.51182	0.51182
Observations	108,030	108,030
K-P Wald (1st stage), Unemployment Rate		27.781
K-P Wald (1st stage), lag(Unemployment Rate, 1)		39.882
K-P Wald (1st stage), lag(Unemployment Rate, 2)		44.713
K-P Wald (1st stage), lag(Unemployment Rate, 3)		33.055
K-P Wald (1st stage), lag(Unemployment Rate, 4)		33.814
K-P Wald (1st stage), lag(Unemployment Rate, 5)		41.963
K-P Wald (1st stage), lag(Unemployment Rate, 6)		43.093
K-P Wald (1st stage), lag(Unemployment Rate, 7)		36.550
K-P Wald (1st stage), lag(Unemployment Rate, 8)		32.239
K-P Wald (1st stage), lag(Unemployment Rate, 9)		24.835
K-P Wald (1st stage), lag(Unemployment Rate, 10)		24.021

Clustered (County) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

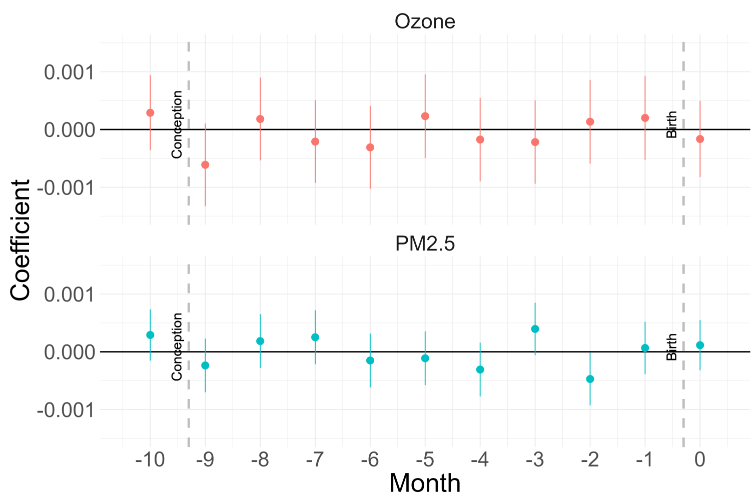
The outcome variable is sex composition of births at the month-county level . It is regressed at current month-county unemployment rate and its 10 lags. Column (1) estimates the OLS relationship. In column (2) the unemployment rate is instrumented with a weighted average of county industry shares and the industry-level national monthly unemployment rates. County and time fixed effects are included. Errors are clustered at the county level.

Similarly, one might argue that the relationship between pollution and the sex ratio at birth could be a confounder, as pollution is associated with a variety of other outcomes. However, I demonstrate that in my sample, pollution levels around the time of pregnancy are not associated with the sex ratio at birth. Specifically, I regress the proportion of male births in a county on the lagged Air Quality Index (AQI) for Ozone and PM2.5, mirroring the specification in Equation 11:

$$Prop.Male_{c,t} = \sum_{lag:0}^{10} \beta_P^{lag} AQI_{c,t-lag} + \gamma_c + \delta_t + \epsilon_{c,t} \tag{12}$$

Here, β_P^{lag} represents the impact of a change in the average Air Quality Index in the *lag* months before birth on the probability of a newborn being male. The results, presented in Figure C.23, show no significant relationship between pollution levels and the sex ratio at birth.

Figure C.23: Pollution and Sex at Birth



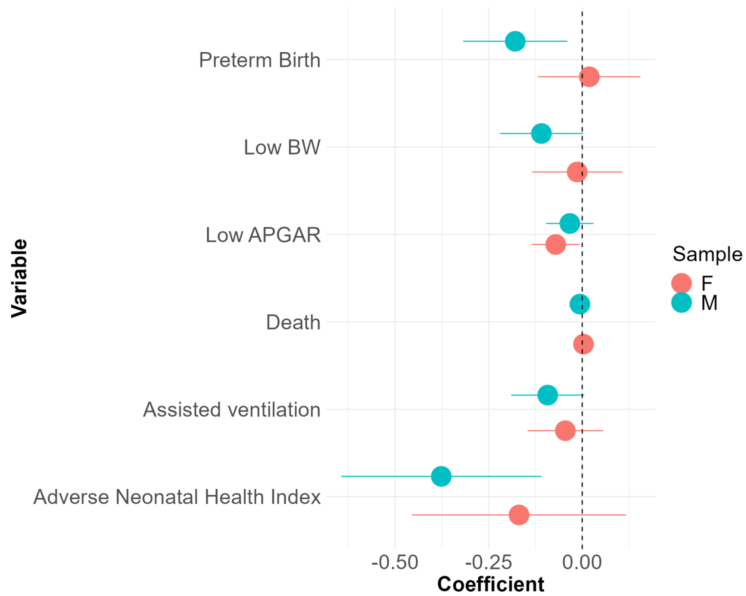
Notes: Each plot depicts coefficients from the regression 12. Estimated on the sample between years 2003 and 2020.

Considering 95% confidence interval, the largest positive and negative impact (among all lags) of 1 unit change in the AQI on the probability of male birth would be { -0.00133,0.00095}.

These exercises provide evidence that the sex at birth in the US is not shaped by the individual economic status of the mothe, by aggregate economic fluctuations (as proxied with unemployment), or by pollution (as proxied with AQI).

C.8 Additional Heterogeneity results

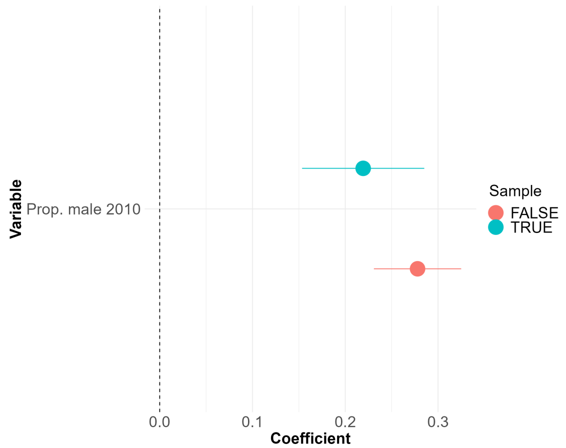
Figure C.24: Heterogeneity by Sex of the Child



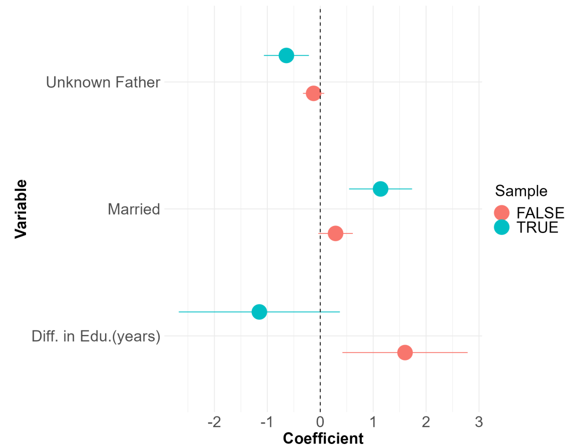
Notes: Notes: Each plot depicts coefficients on the variable 'proportion male' from the primary instrumental variable (IV) framework estimated on two distinct subsamples. One subsample pertains to female children (F), while the other corresponds to male children (M).

C.8.1 Segregation

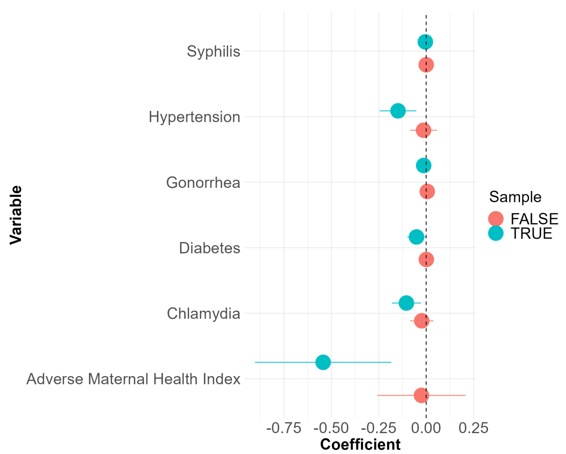
Figure C.25: Heterogeneity by Racial Segregation: Above Median Dissimilarity Index



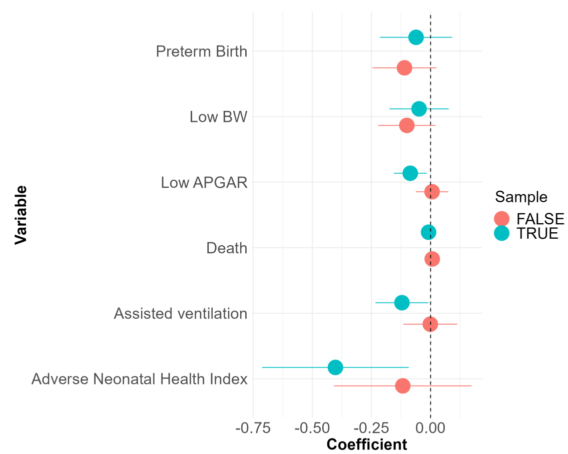
(a) First Stage



(b) Marriage Market Outcomes



(c) Maternal Health Outcomes

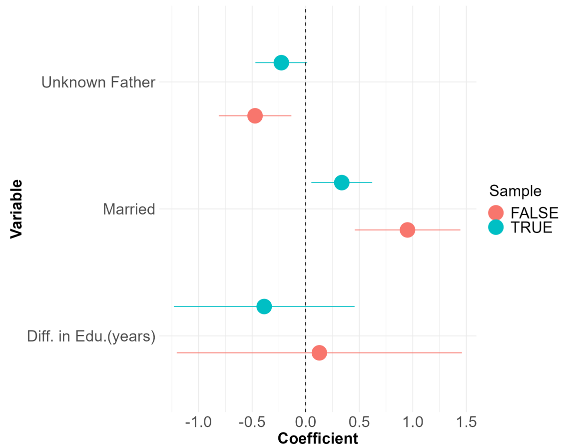


(d) Neonatal Health Outcomes

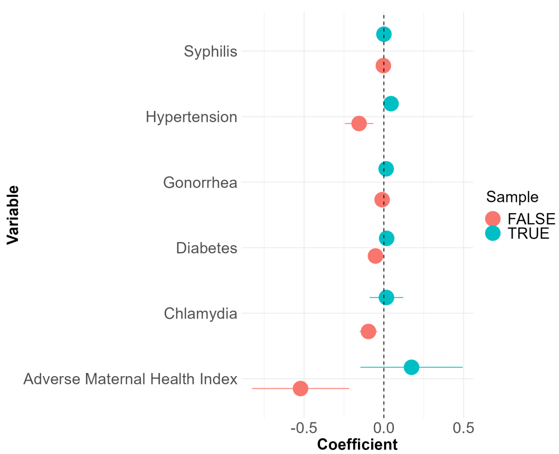
Notes: Each plot depicts coefficients on the variable 'proportion male' from the primary instrumental variable (IV) framework estimated on two distinct subsamples. One subsample pertains to counties with above-median levels of segregation (TRUE), while the other corresponds to counties with below-median levels of segregation (FALSE). Segregation is quantified using the dissimilarity index, which is available on the FRED website. This index quantifies the share of the non-Hispanic White population in a county that would need to relocate within the county to achieve an even distribution of racial groups within each census tract. Higher index corresponds to higher segregation.

C.8.2 Young mothers

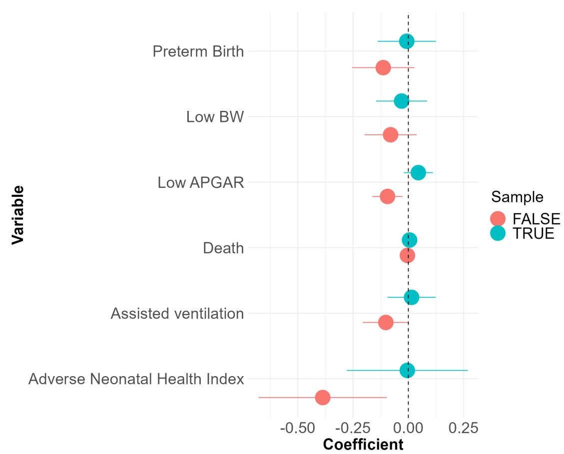
Figure C.26: Heterogeneity: Young Mothers



(a) Marriage Market Outcomes



(b) Maternal Health Outcomes



(c) Neonatal Health Outcomes

Notes: Each plot depicts coefficients on the variable 'proportion male' from the primary instrumental variable (IV) framework estimated on two distinct subsamples. One subsample pertains to young mothers (TRUE), below age 25, while the other corresponds to mothers with age equal or above to 25 (FALSE).

C.9 Assigning Incarcerated Individuals to Their Communities

I first use the prison blocks from the census data to calculate the number of incarcerated individuals in each state, race (Black and White), gender, and age group Inc_census_{srga}. I assume that all individuals are incarcerated in their state of residence. The limitation of such assumption is this it may not hold for the federal prisons. Nonetheless, federal prisons house small share of all inmates. Next, I use Vera (2022) data which provides inmates count by year, race and the county of commitment. Let Inc_vera_{cr} be the number of inmates in jails and prisons of race r who committed a crime in the county c. Note that I average the counts across years 2008-2012 to relieve missing data issues. Next, I compute the share of inmates in each race contributing to the stock of inmates in their state which is $Share^s_{cr} = \frac{Inc\_vera_{cr}}{\sum_{c \in s} Inc\_vera_{cr}}$. I will use this to redistribute them to counties. In particular, I assume that count of inmates from county c, race r, age group a and gender g is $Inc\_census_{crga} = Share^s_{cr} * Inc\_census_{srga}$.

The simulation aims to equate the incarceration rates for non-violent offenses between Black and White people. As this statistic is not available at the granular geographic level, I use the national race and gender specific share of inmates sentenced for non-violent offenses $Share\_NV_{rg}$ provided by the BJS CSAT system. Next, I assume that the number of inmates incarcerated for non violent offenses is $Inc\_census\_NV_{crga} = Share\_NV_{rg} * Inc\_census_{crga}$. Using this number I can calculate the share of the dating market participants who are incarcerated for non-violent crimes.

C.10 Bootstrap

The IV estimation sample comes from the original IV sample, representing all mothers from the markets between 200 and 5000 people. The comparison sample comprises Black and White mothers from all the markets such that there were at least 200 people on the market, and both groups were present in the same county and age group. Each bootstrap iteration proceeds in two steps. In the first step, I draw with replacement the same number of clusters ($county \times race$) as in the original sample. Next, I run the IV regression on this sample and save the estimates. In the second step, I draw with replacement the same number of counties as in the entire comparison sample and calculate the empirical gap in health outcomes. Then, using the estimates from the first step and the counterfactual sex composition, I predict the counterfactual health outcomes for all mothers. Finally, I compute the counterfactual racial gap in health. I repeat the bootstrapping for 1000 iterations.

C.11 Impact of the Market Misdefinition on the Coefficients

Call the proportion of men at the true market PM^T and assume that a woman from a county c search partners across multiple counties which belong to a set C (similar argument can be made about market expanding to other races or age groups). Let n_{cra} be population of age a, race r, and from county c and let n^m_{cra} be the number of men in this group. Let $\alpha_{c,c'}$ measure how often women from county c link with men from county c' and let it sum up to one across C. Assume that the proportions of men across markets are independent. Then, the relationship between the true market and the market limited to own county can be expressed as:

$$\begin{aligned}
\underbrace{PM^{T}_{cra}}_{\substack{\text{Proportion Male}\\ \text{At the True Market}}} &= \frac{\sum_{c'\in C}\alpha_{c,c'}n^{m}_{c'ra}}{\sum_{c'\in C}\alpha_{c,c'}n_{c'ra}} == \sum_{c'\in C}\underbrace{\frac{\alpha_{c,c'}n_{c'ra}}{\sum_{c'\in C}\alpha_{c,c'}n_{c'ra}}}_{\gamma_{c'}}\frac{n^{m}_{c'ra}}{n_{c'ra}} = \\
&= \gamma_c\frac{n^{m}_{cra}}{n_{cra}} + \sum_{c'\neq c}\gamma_{c'}\frac{n^{m}_{c'ra}}{n_{c'ra}} = \underbrace{\gamma_c}_{\gamma_c<1}\frac{n^{m}_{cra}}{n_{cra}} + e_{cra} = \gamma_c \underbrace{PM_{cra}}_{\substack{\text{Proportion Male}\\ \text{At the Limited Market}}} + e_{cra}
\end{aligned} \tag{13}$$

Now assume that health outcomes Y_{cra} are a function of the proportion male at the true market, with true coefficient β. Regressing Y_{cra} on the proportion male at the limited market will give conservative estimate of the true effect:

$$Y_{cra} = \beta PM^{T}_{cra} + \epsilon_{cra} = \beta\gamma_c PM_{cra} + \beta e_{cra} + \epsilon_{cra} = \hat{\beta}PM_{cra} + v_{cra} \tag{14}$$

Since γ_c is lower than one, $\hat{\beta}$ is lower than β.

Note that IV strategy does not eliminate this bias. Now assume conversely that the measured market is too large. In this case a classical measurement error arises, which is eliminated by the IV.

C.12 Dating market model

In this section I solve a dating market model which demonstrates the effect of sex ratio on the equilibrium female welfare. Suppose that there is a population of men and women. Each person i has a utility function composed of a private good q and a public good Q and it has the form:

$$u_i\left(q_i, Q\right) = q_i Q$$

Price of the private good is normalized to 1 and price of public good is p. Income (which can be conceived also as quality or human capital) of an individual is drawn from a uniform distribution $y_g \sim U(1,2)$, where g is gender and $g \in \{m, f\}$. Mass of women is normalized to 1 and mass of men is equal to S which reflects the sex ratio. Without loss of generality, let's assume that $S < 1$, i.e. there is surplus of women on the dating market. Men and women can form couples in which case they maximize joint utility $(q_m + q_f)Q$. The main benefit of being in a couple stems from sharing the public good Q. However, the allocation of resources toward private goods, and hence the final utility, is a result of matching and bargaining in equilibrium. The goal of each woman (man) is to find a partner who maximizes her utility. The natural constrain is that partners must accept each. These two forces, together with the distribution of partners, drive the equilibrium outcomes. With this model, I aim to show

how changes in the sex composition affect female utility in equilibrium. The equilibrium of the dating market is defined as the matching and resource allocation such that no man or woman would prefer a partner different than their match.

To solve for the equilibrium I proceed in three steps:

1. **Within couple maximization**

   Couples maximize their joint surplus S subject to the budget constraint:

   $$S\left(y_f, y_m\right) = \max_{q_f, q_m, Q} \left(q_f + q_m\right) Q \qquad \text{s.t. } H_f + H_m + PQ = y_m + y_f$$

   For this particular form $S = \frac{(y_m+y_f)^2}{4P}$, that is, surplus is supermodular in incomes. Mathematically, it translates to second derivative being positive: $\frac{\partial^2 S}{\partial y_m \partial y_f} > 0$. Intuitively, it means that an increase in surplus from additional income of a woman (man) is higher if their partner has high income as well.

2. **Matching**

   As the surplus is supermodular, it is a well known property of the matching models that matching will be assortative in incomes. That is, the highest income man matches with the highest income woman, and so on. Let the match of woman y_f be $\theta(y_f)$. Given the uniform distribution of income, assortativity requires that the mass of women with income above y_f must equal the mass of men with income above $\theta(y_f)$. Hence, the match of women is:

   $$s(2 - y_m) = 2 - y_f \qquad y_m = \theta(y_f) = 2 - \frac{2 - y_f}{s}$$

   This equation shows the first channel through which the sex composition affects female outcomes. The higher relative abundance of men, the better partner a woman can secure.

3. **Individual utility allocation**

   To solve for the allocation of resources toward private goods within the couple, I use two conditions that need to be satisfied in the equilibrium.

   (a) Marriage participation constraint

$$U_m^m(y_m) + U_f^m(y_f) \geq S(y_m, y_f) \qquad \forall y_m, y_f$$

It states that for any pair of man and woman, their individual equilibrium utilities must be higher or equal to the surplus they would create as a couple. The inequality is strict for any couple not matched in the equilibrium, and it is an equality for couples matched in the equilibrium. This condition is related to the stability of matching: switching partners could never generate enough of surplus to make the new couple better off.

(b) No surplus for last woman in a relationship

Since there is more women than men, some women at the bottom of the income distribution remain single. This condition states that last married women is indifferent between being single and being in a relationship.

The above conditions pin down female utility in equilibrium. In particular it is equal to:

$$U(y_f) = \frac{1}{2P}\left((\frac{x^2}{2} - \frac{(2-s)^2}{2})\frac{s+1}{s} + (x-2+s)\frac{2(s-1)}{s} \right) + \frac{(2-s)^2}{4P}$$

Importantly, it can be shown that:

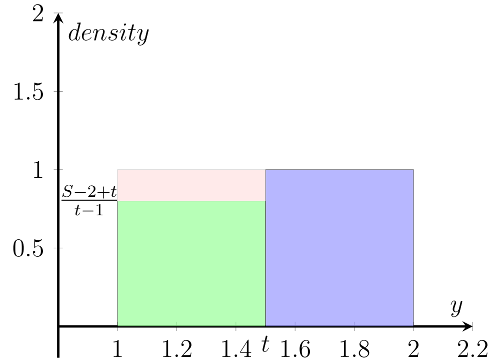
$$\frac{\partial U(y_f)}{\partial S} > 0$$

That is, female utility in equilibrium increases with the sex ratio. There are two channels leading to this result. The first one is matching. As there are more men available on the market, woman can secure a higher quality partner. The second one is the resource allocation. As there is more competition among men, they need to provide women with higher private consumption to sustain the partnership.

C.13 Dating market model: restrictions on men available

The previous model assumes that we add men from all around the income distribution when increasing the sex ratio. Would the effect be different if the increase in supply comes from the bottom of the income distribution? That scenario could correspond to releasing incarcerated individuals, if we assume that people in prison have lower potential income. To understand the implication of such scenario, I adapt the model from the previous subsection by assuming

Figure C.27: Distribution of Men



Notes: Plot shows the distribution of men on the dating market. The blue rectangle shows men with income above t, with mass equal to $2-t$. The green rectangle represents men with income below t on the market. The mass of men with $y_m < t$ is equal to $\frac{S-2+t}{t-1} * (t-1)$. The red rectangle correponds to the "missing" men.

that adjustment to sex ratio occurs only through men with income below some threshold t. I solve for equilibrium utilities in such a model and show that all women's utility increases, even if only men from the bottom of the income distribution are added to the dating pool. In fact, women at the top of the distribution benefit the most, independently of the quality of men added.

The new assumption of male distribution is schematically illustrated in the figure C.27. The mass of men with income $y_m > t$ (blue rectangle) never changes. When once changes S, it is only through removing or adding men with income $y_m < t$. The green rectangle on figure C.27 represents men with income below t on the market. The red rectangle correponds to the "missing" men. The only effect of increasing S would be to reduce the red rectangle and expand the green rectangle. Choosing t allows to flexibly capture a set of assumption on the potential income of, for instance, incarcerated men. The lower t, the lower is the potential income of men newly appearing on the market. Note that $t = 2$ corresponds to the baseline scenario from the subsection C.12.

Solving for equilibrium female utility using this new distribution, we obtain:

$$U(y_f) = \frac{1}{2P}\left((\frac{x^2}{2} - \frac{(2-s)^2}{2})\frac{s-3+2t}{s-2+t} + (x-2+s)\frac{t(s-1)}{s-2+t} \right) + \frac{(2-s)^2}{4P}$$

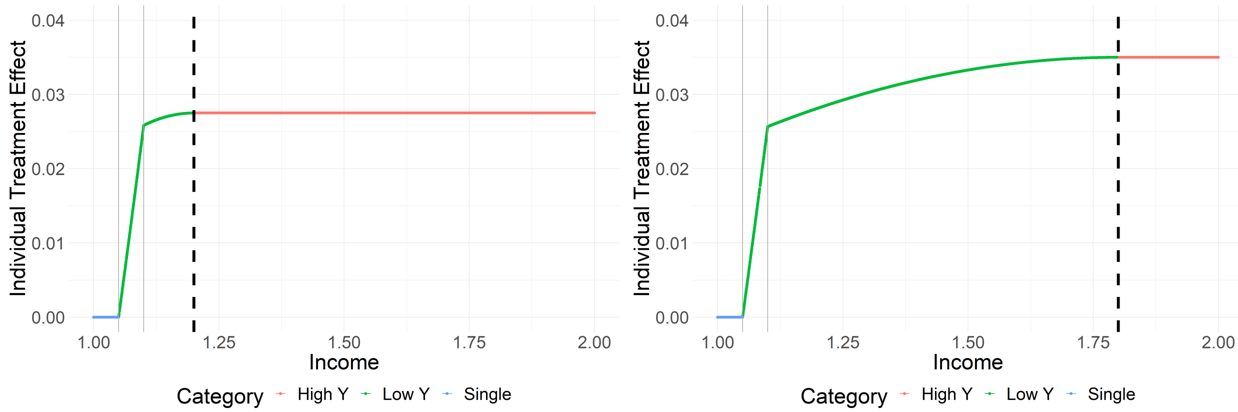
I can now use it to investigate the impact of changing the sex ratio under a variety of assumption on men who are added to the dating pool. In particular, I investigate a scenario of increasing the sex ratio from 0.9 to 0.95 (or proportion of men from 47% to 49%) under two values of $t \in \{1.2, 1.8\}$[29]. The first value, $t = 1.2$, corresponds to the situation where

[29] I set price of public good $P = 1$

only low- income men are added to the pool. The second value, $t = 1.8$ describes a scenario where both high and low income men are added.

For each t I calculate the change in the individual female utility (*individual treatment effect*) resulting from the increase in the sex ratio. Figure C.28 illustrates the results.

Figure C.28: Individual Treatment Effect



(a) Change in Female Utilities for t=1.2 (b) Change in Female Utilities for t=1.8

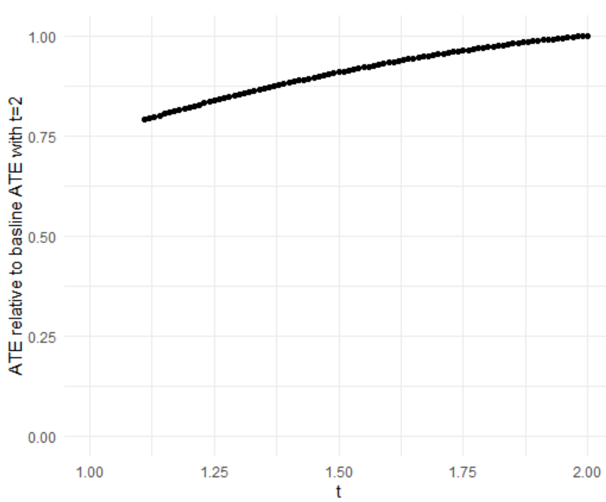
Notes: Plots show the change in female utility as the result of an increase in the sex ratio from 0.9 to 0.95. The left subplot shows the change in utility when $t = 1.2$ and the right plot when $t = 1.8$. The dashed line shows the value of t. The colors represent three groups of women. Blue shows women who were previously single and remain single. Green represent women below income t who have a partner. Women between two grey lines did not have partner before and now have a partner. Red represents women who have income above t.

The impact of the change in the sex ratio can be divided into four groups. First, there are women who were single before and are still single. They are at the bottom of the income distribution and represented with the blue line. Their utility does not change. Next, there are women with income below t who did not have partner before, but now have a partner. They are located between the two continuous grey lines. They experience increase in the utility, because they benefit from being in a relationship. Next, there are women with income below t who previously had a partner. These women have higher utility after the increase in the sex ratio. This increase comes from two sources. First, they can find a slightly better partner. Second, they have a better outside option. Note that previously, the outside option of the last woman in this group was to be single. Now, her outside option is to be married to the man just below her current partner (previously such man was not on the market). As a result, her current partner needs to provide her with higher utility (more private good) to prevent her from switching to the outside option. Intuitively, her bargaining position improved and she can negotiate a more favorable allocation of rescources. Finally, there is a set of women with income above t represented with the red line. Their partner does not change, but their utility still increases. In fact, they experience the highest increase in the utility. This increase comes entirely from a better outside option. Women with $y_f > t$ can threaten their current partner to leave and date a man just below who now provides a higher utility to their partner. Hence, current partners of women with $y_f > t$ need to allocate more resources to female private good to maintain the relationship. Therefore, increasing pool of available men always improves the welfare of women at the top of the distribution.

Comparing the sublpot (a) and (b) one can notice that the change in utilities are not drastically different. The main increase in the utility comes from women who were previously single and are now married, and they improve the outside option for all subsequent women. An additional source of utility in subplot (b) is more women who switch to a higher quality partner, but the resulting rise in utility is small compared the the switching from singlehood to marriage.

I can calculate average increase in the utility across female income distribution (*Average Treatment Effect*) and compare them across different values of t. This is illustrated in the figure C.29. It plots the ratio of average treatment effect (ATE) for a given level of t compared to the ATE at $t = 2$. Even at the lowest value of t, so adding only men with very low potential income, the ATE is still more than 75% of the baseline ATE when men across the whole distribution are added to the pool.

Figure C.29: ATE(t) relative to ATE(2)



Notes: Plot shows the ratio of average treatment effect (ATE) for a given level of t compared to ATE at $t = 2$. The average treatment effect is the average change in the female utility across the income distribution for a change in the sex ratio from 0.9 to 0.95.

Therefore, I conclude that the quality of men added to the dating pool has relatively little effect on the magnitude of increase in the utility and always affect women with high incomes.