Effects of Intra-Couple Bargaining Power on Maternal and Neonatal Health

Krzysztof Zaremba *

(Job Market Paper)

November 11, 2022

Click here for the latest version

Abstract

This paper provides the first causal evidence that bargaining power in a relationship shapes pregnancy outcomes and health disparities in the US. A key driver of bargaining power is the availability of potential non incarcerated male partners in the local dating market, which I define at the race by cohort by county level. Because these sex ratios are endogenous, I use a novel instrument that leverages the randomness in sex at birth and the persistence of local demographics to isolate exogenous variation in the relative availability of men. Greater female bargaining power causes better outcomes: fewer out-of-wedlock births, less chlamydia and hypertension among mothers, and fewer infants with APGAR score below the normal level. The marriage market makes a significant contribution to racial disparities in pregnancy health. Specifically, Black women face relatively poor prospects when looking for a partner compared to White women: while there are 102 White men per 100 White women, only 89 Black men are available per 100 Black women. According to my estimates, Black women's disadvantage accounts for 5-10% of the large racial gap in maternal and neonatal health. The racial difference in male availability is mostly policy-driven, as incarceration accounts for 45% of the gap. A counterfactual policy equalizing county-level incarceration rates for non-violent offenses between Black and White people would prevent 200-700 adverse pregnancy outcomes per year among Black mothers through the bargaining power channel alone.

*Department of Economics, Columbia University. E-mail: kz2303@columbia.edu. I am grateful to Douglas Almond, Pierre-André Chiappori, and Brendan O'Flaherty for their valuable advice and support throughout this project. This project benefited greatly from feedback from Michael Best, Marianna Bitler, Sandra Black, Gautam Gowrisankaran, Suresh Naidu, Bernard Salanié, Pietro Tebaldi, Ebonya Washington, Omar Ahsan, Tantyana Avilova, Naman Garg, Jan Gromadzki, Florian Grosset, Bookang Seol, and seminar participants at the Applied Micro Methods colloquium, and Applied Micro Theory colloquium. I also thank administrators at NCHS Division of Vital Statistics for helping with data access. Formatting according to Chicago Manual of Style

1 Introduction

In the US, Black women experience more than three times the maternal mortality rate of White women, and Black children experience more than twice the infant mortality rate of White children. Black mothers also suffer from higher morbidity and worse birth outcomes. For instance, Black mothers are twice as likely to have hypertension, and Black neonates are 75% more likely to have an APGAR score[1] below a healthy level compared to White infants.

While these health inequalities are persistent and have been well documented, their specific causes have proved difficult to pin down. Black women are exposed to a plethora of factors that may negatively impact pregnancy outcomes. For example, they experience poverty more frequently, live in lower quality neighborhoods, face greater difficulties accessing quality healthcare, and face an unfavorable marriage market. As these adverse conditions are usually correlated, disentangling the specific causes is challenging.

Design-based research has focused on poverty and racial discrimination as major drivers of disparities. Studies have shown that structural racism and discrimination in labor markets led to lower socioeconomic status, which contributes to poor health[2]. Nonetheless, even accounting for differences in socioeconomic variables, health inequalities persist. Kennedy-Moulton et al. (2022) show that the disparity between Black and White infants occurs at all parental income levels. Researchers attributed part of the remaining gap to racial discrimination in the healthcare setting[3], which hampers access to quality care for Blacks.

In this paper, I examine the role of the dating market as a novel source of pregnancy outcomes disparities. In particular, I study how within-romantic-relationship bargaining shapes pregnancy outcomes and, therefore, maternal and neonatal health inequalities. As I argue below, Black women have less bargaining power in relationships than White women. More than 90% of relationships are between two people of the same race, and there are only 89 Black men per 100 Black women compared with 102 White men per 100 White women. If within-relationship bargaining affects women's and children's health, the disparity in the ratio of men to women (henceforth *sex ratio*) should contribute to the inequity of health outcomes. Therefore, this paper aims to (1) investigate the causal link between intra-household bargaining power and maternal and neonatal health in the US and (2) examine the extent to which racial disparities in the dating market contribute to health inequalities.

My empirical strategy relies on the idea that the sex ratio affects partners' outside options and bargaining power in the dating market (Becker (1973); Chiappori et al. (2002)). Consequently, I identify changes in the bargaining power through deviations from a balanced sex composition in a woman's dating market. I focus on heterosexual markets defined as an intersection of county of residence, race, and five-year age groups[4]. 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

[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 for instance Aizer et al. (2004); Lillie-Blanton and Hoffman (2005); Hoynes et al. (2011); Almond et al. (2011); Fryer et al. (2013), Buchmueller et al. (2016); Elder et al. (2016); Carruthers and Wanamaker (2017), Bailey et al. (2021), Lane et al. (2022)

[3] See Almond et al. (2006); Hoffman et al. (2016); Kuziemko et al. (2018), Alsan and Wanamaker (2018), Ly (2021)

[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 4.1.

to violence. A contribution of the present paper is to introduce a novel instrument aimed at overcoming such endogeneity. Specifically, I instrument local, contemporary sex composition with the local sex composition 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, which results in the persistence of local, within-cohort demographics. Particularly in smaller markets where the law of large numbers hasn't fully "kicked in", the chance of more male or female births can create significantly imbalanced sex ratios. Moreover, I provide evidence that the local sex composition at birth is a strong predictor of the local sex composition of the cohort when it enters adulthood. My study uses this variation to measure how changes 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.

I find that female bargaining power plays a vital role in shaping maternal and neonatal health. Women do better when they are scarcer in the dating market. First, I show that the instrument produces results for marital outcomes that are consistent with the existing literature. Increasing the proportion of men in the cohort 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. Next, my estimates show that women who give birth in the markets where men are relatively abundant tend to be healthier. For example, mothers facing a market at the 75th percentile of the proportion of men in the cohort 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, I show that infants born to empowered mothers are healthier. According to my estimates, moving a mother from a market at the 25th percentile to one at the 75th percentile in the abundance of men decreases the chances that the newborn will have a low APGAR score by 0.2 percentage points (compared to the 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. Analysis of the mechanisms suggests that changes in the composition of mothers giving birth accounts for a portion of the results. Women with more bargaining power have lower birth rates, but those who do decide to deliver a baby tend to be healthier, more educated, and have more educated partners than mothers with low bargaining power.

My results suggest that pregnancy outcomes could be improved by increasing the relative availability of men. Contrary to popular intuition, I show that empirical variation in the sex composition, particularly across racial groups, is to a certain degree policy driven. In a decomposition exercise, I quantify the primary factors driving the racial differences in the sex composition in the US. Policy matters for the sex ratio gap. Specifically, incarceration accounts for 40%-52% of the gap, and deaths due to violence for 2%-7%. Section 5.2.2 argues that the disparity in incarceration rates is partly shaped by an interplay of biases and policies. It also discusses literature on specific initiatives aimed at reducing disparities in incarceration. As my results show, focusing on such policies would have a beneficial effect for maternal and neonatal health.

Motivated by the policy sensitivity of sex ratio, I investigate the impact of changing the racial gap in sex composition on health disparities between Black and White mothers. First, I simulate a counterfactual world where Black women face the same dating markets as White women. The results suggest that eliminating Black women's disadvantage would reduce racial health disparities in chlamydia and hypertension among pregnant women 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)). Next, I focus on a more modest policy that equalizes incarceration rates for non-violent offenses between Black and White people. Even this policy could prevent 200-700 adverse pregnancy outcomes per year among Black mothers through its effect on the bargaining power alone. I also 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.

My study contributes to two fields. Firstly, in the field of family economics, it establishes a causal link between within-relationship bargaining and maternal and neonatal health. Secondly, in the field of health economics, it shows that the marriage market is an essential determinant of pregnancy health.

The primary contribution of this paper is to provide the first evidence of the causal impact of female bargaining power on pregnancy outcomes. Previous research has shown that increasing women's bargaining power leads to higher spending on children (Thomas (1990); Lundberg et al. (1997); Calvi (2020)) and improvement in older children's health (Duflo (2003); Thomas et al. (1999)). My results add to this literature by demonstrating that female empowerment positively affects health during pregnancy. Moreover, previous studies identifying the link between bargaining power and health are set in the developing countries. My paper is the first to demonstrate that bargaining still matters for health in upper income countries.

This study also adds to the literature linking the sex ratio in the dating market to the distribution of bargaining power within relationships. Researchers used variation in the local 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)). One strength of my paper is to isolate the exogenous variation in the bargaining power 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 also adds to knowledge around racial differences in demographic structure. Missing a sizable number of men, Black communities' sex ratios are lower. Incarceration and early mortality seem to drive a large part of this gap (Pouget (2017)). Hall (2000) decomposes temporal changes in the sex ratios among Black Americans, but does not account for incarceration. Differences in sex ratios across all races are still poorly understood, and a more systematic decomposition is missing. My paper fills this lacuna by quantifying the primary factors driving the differences in the sex ratio between White people and other races in the US. In doing so, my paper reveals that the essential driver of the gap in the sex ratio between White and Black people is racial disparity in incarceration. This differential stems partly from the bias in the criminal justice system. Policies mitigating such bias could thus ameliorate the sex imbalance.

Lastly, an important contribution of this paper is to provide evidence that the dating market is a source of racial health disparities. Removing Black women's disadvantage in the dating market shrinks 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 has unexpectedly widened racial health disparities in maternal and neonatal outcomes by reducing supply of potential male partners.

My research informs policymakers that empowering women can improve maternal and neonatal health, even in developed countries. 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), Black et al. (2019) , Hoynes et al. (2016)). East et al. (2017) and Giuntella et al. (2022) show that adverse health outcomes at birth 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 provides a literature review. Section 3 presents the conceptual framework. Section 4 describes the data and the sample construction. In section 5, I perform the decomposition of racial differences in sex ratios. Sections 6 and 7 outline the OLS framework and results for the relationship between bargaining power and health outcomes. Sections 8 and 9 present IV framework and results. Section 10 shows the counterfactual scenarios. Sections 11, 12, and 13 discuss the mechanisms, extensions and robustness checks, followed by the conclusion.

2 Literature Review

The impact of the bargaining power on partners' outcomes has been recognized in economics, starting with the insights in Becker (1973). In his seminal work, Becker shows that the scarcity of women on the dating market shifts the gains from a relationship away from men and toward women. Grossbard-Shechtman (1984) extends this intuition to analyze the effects of changes in the sex ratio on the labor supply of spouses. The theoretical framework of couple's decision making has been rigorously developed in the body of work by Chiappori and coauthors (Chiappori (1988), Chiappori (1992), Bourguignon and Chiappori (1994), Browning and Chiappori (1998), Chiappori and Ekeland (2006)). In particular, they extend their collective approach to identify the impact of bargaining power on decision making through incorporating *distribution factors* (Chiappori et al. (2002)). Distribution factors are variables which affect how resources are shared within a household but do not change preferences or budget sets. Examples of such factors are changes in the divorce legislation or sex composition of the dating market. Importantly, they provide additional restrictions to test the unitary model, which does not treat the household as a collection of agents bargaining over decisions. Empirical studies have corroborated the importance of accounting for the bargaining power and the unitary model has been widely rejected (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) use son preference in China and randomness in the sex at birth to show that women whose first born is son enjoy better nutrition and are less often underweight. Armand et al. (2020) use a cash transfer program in Macedonia to demonstrate that household diet becomes more nutritious if the woman is transfer's recipient. Panda and Agarwal (2005) and Rao (1997) provide evidence that stronger female bargaining position translates to fewer occurrences of domestic abuse. Moreover, empowering a woman tends also to improve her children's well-being. Literature documented correlations between female bargaining power, as proxied by assets ownership, and the use of prenatal care (Beegle et al. (2001)) or children morbidity and mortality (Thomas et al. (1999), Maitra (2004)). Nonetheless, these studies do not identify a causal relationship as households with high female assets ownership may differ from households with few female assets on various dimensions. Better identified research exploits exogenous variations in whether the mother or father receives income. Attanasio and Lechene (2002) leverage payments from the PROGRESA program to show that households with large contributions to income from women spend more on children's clothing. Duflo (2003) uses a rollout of pensions in South Africa to show that increasing the income of women, but not men, improves the health of girls in the household.

Among the determinants of spouses' respective bargaining power, the sex ratio has been shown to play a particularly significant role. Chiappori et al. (2002) uses the sex ratio as a distribution factor to provide evidence that the scarcity of women, consistently with the theory, decreases their labor supply. Angrist (2002) find similar effects on labor supply leveraging ethnic homophily and historical immigration flows as an instrument for changes in the sex composition in some groups. Moreover, he shows that a high ratio of men to women improves female marital prospects. Lafortune (2013) uses second-generation Americans to demonstrate that an unfavorable sex ratio decreases marriage stability. Abramitzky et al. (2011), Brainerd (2016), and Alix-Garcia et al. (2022) arrive to similar conclusions using wars as a shock inducing scarcity of men. They provide evidence that the number of unmarried women and out-of-wedlock births increases with the share of women available in the marriage market. Such outcomes are consistent with men being able to avoid commitments and engage in non-monogamous relationships. Unbalanced sex ratio and related distortions on the marriage market have also been linked to increase in crime in China (Edlund et al. (2008)). One of the largest shocks to the sex ratio in the modern US comes from mass imprisonment. It is especially severe among Black populations, where a substantial share of men are missing due to incarceration. Interviews in Banks (2012) share perspective 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)).

The scarcity of men also seems to affect the quantity and the quality of relationships beyond marriage. As women explained during interviews in a qualitative study by Dauria et al. (2015), incarceration decreased the number of men available, and the remaining men are undesirable. Consequently, women tend to engage in shorter partnerships which are more often focused on sex and hence 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 suffer from worse sexual health (Thomas et al. (2008), Johnson and Raphael (2009), Stoltey et al. (2015), Kang and Pongou (2020)). Such research suggests that the sex ratio is important not only for women's dating and marital outcomes but also for their health. Consequently, the racial differences in the sex ratio could potentially contribute to explaining racial disparities in female health. While factors such as structural racism (Williams and Collins (Oct), Bassett (2015), Hoffman et al. (2016), Alsan and Wanamaker (2018), Ly (2021), Bailey et al. (2021)) have been shown to shape racial health inequalities, the role of female disadvantage on the dating market remained unexplored.

3 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 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 A.7, 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. As a result, the competition among men to secure a female partner becomes stronger. Women can be pickier in their choices. Experimental evidence from dating apps indeed shows that people become more selective when they face larger pool of potential mates (Fong (2020)). Consequently, women end up with higher-quality partners. 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. Again, a favorable sex ratio tends to boost women's bargaining position.

All in all, one can expect female health to improve as a consequence of the changes in the dating market, and numerous studies tend to confirm this prediction. Firstly, 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)). Secondly, more bargaining power translates to better nutrition and subsequent improved health (Li and Wu (2011)). Thirdly, studies have also noted that women with strong negotiating position are less exposed to sexually transmitted infections (STIs) (Cornwell and Cunningham (2008); 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 woman cares about her 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, we hypothesize that increasing the proportion of men on the dating market improves female health and, consequently, neonatal health.

4 Sample Construction and Data

4.1 Defining Dating Markets and Computing Sex Composition

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 summary files. In particular, the Census summary table 1 provides the exact population count by race and age group in each census block.

I decided to focus on the proportion rather than the sex ratio because the proportion is symmetric around the balanced sex composition[5]. Nonetheless, 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.2).

I define the dating markets as an intersection of age group, race, and county. In other terms, I assume that people in the same 5-years age cohort, of the same race, and residing in the same county participate in one dating market. Empirically, there are relationships which cross these boundaries. While for methodological reasons I assume them away, the appendix section A.6 shows that relaxing this assumption would make my current estimates conservative. Moreover, my research focuses on people of heterosexual orientation. A substantial part of the population may prefer to date people of their own gender. However, sex ratio would not be a relevant measure of bargaining power for this group and hence my current methodology would not be applicable.

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, states seem implausibly large as the area of search. People usually find partners through friends, at bars, or online (Rosenfeld et al. (2019)). Friendship networks are usually local (Backstrom et al. (2010), Laniado et al. (2018)), and attending the same bar requires proximity. There is also evidence that online dating remains local. While searching for a match, 2/3 of

[5]As an example, consider two dating markets: one with 49 men and 51 women and one with 51 men and 49 women. The markets are symmetric, and the proportion of males is equally far (by 1percentage points) from the balanced share of 50%. However, the sex ratio in these markets is not symmetric around 1

survey respondents said they set their search radius on dating apps to 30 miles or less (Kirkham (2019)). 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). Secondly, thanks to the advances in computing power, I can accurately measure the sex composition at the county level. Previous papers used ACS or Census microdata which is at best a 10% sample and only identifies the location of the individuals up to the state. Using block-level data from the Census Summary Tables, I can compute sex composition among non-incarcerated populations at the county level (details below). Block level data is orders of magnitude larger than county level data and hence requires additional computing power. Nonetheless, this procedure produces more plausibly sized markets and eliminates measurement error due to sampling as it is based on the full count of the population.

Age is the second criterium 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[6]. People tend to date within their own race for either availability or preference reasons. This pattern is clear in the natality data, especially for White and Black mothers (figure A.3 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. Interracial parents 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 (figure A.4 in the appendix).

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 circumvent the lack of incarceration data at the county/race/cohort level. In particular, I first identify *jails and prisons* by finding census blocks where more than 50% of the population is institutionalized [7]. Next, I exclude these blocks from calculating county/race/age-sex composition.

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 8.

[6]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

[7]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. Note that the instrument eliminates this measurement error.

4.2 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.

Having defined the dating markets, I turn to describe the general patterns observed in the data.

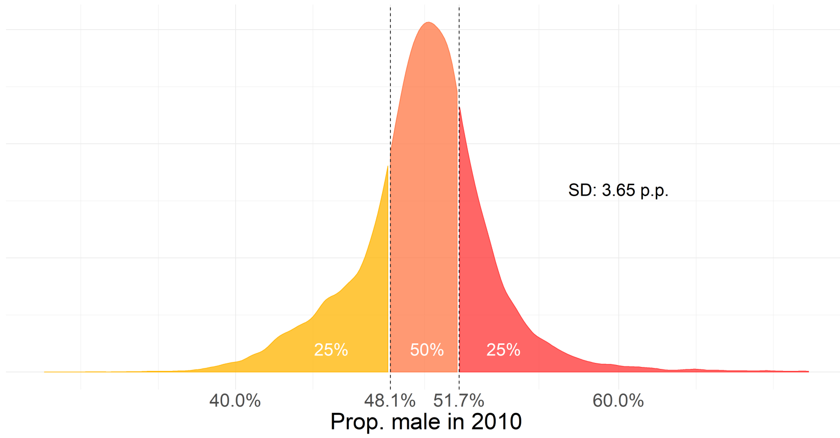
5 Descriptive Statistics: Sex Composition and Health Outcomes

Sex composition in the US dating markets varies substantially. Notably, there are significant racial discrepancies in the sex ratio, which are partially policy driven. It's worth noting that the racial health inequalities coincide with racial differences in the sex ratios. Moreover, maternal and neonatal health outcomes co-vary with the sex composition which hints at a relationship between health and bargaining power.

5.1 Variation in the sex composition of the dating markets

American women can 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 1. 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. Women at a market at the 75th percentile are more fortunate, as they face a proportion male of 51.7%. 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 1: 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%.

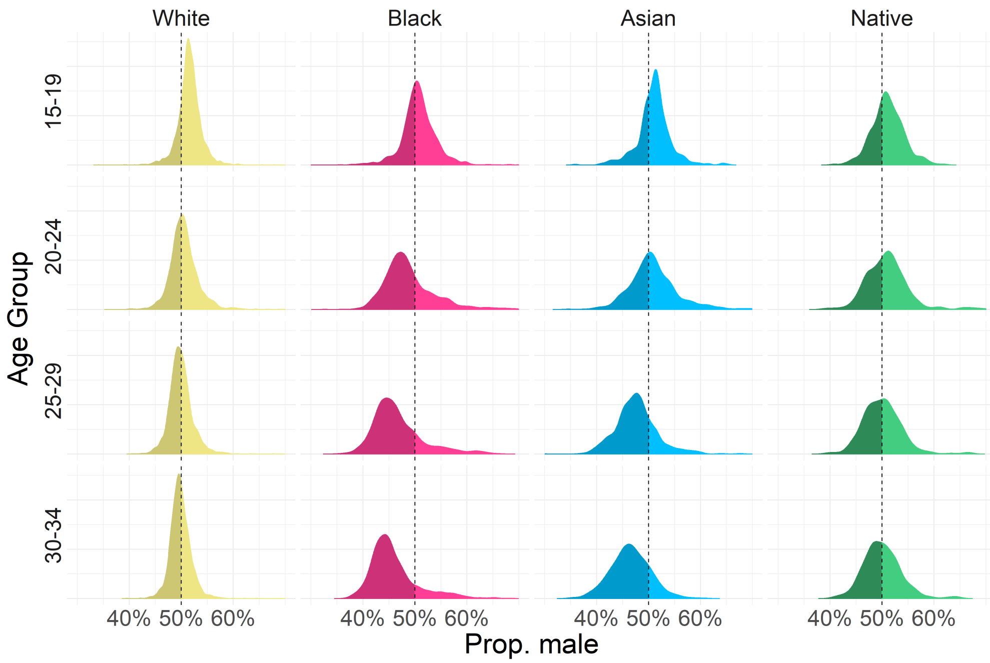
Figure 2 details the distribution of the sex composition in the dating markets. Namely, it shows the densities of the proportion of males in the market within each race and cohort. The vertical dashed lines represent 50% and correspond to a balanced sex composition. Shaded areas to the left of these 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, men have lower survival rates. As a result, there are many markets with a high share of men in the young cohort, but this trend reverses with age.

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 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.

Figure 2: 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. Distributions are divided by the age and race of the cohort. The dashed line represents balanced sex composition of 50%. Shaded area corresponds to markets with too few men. Markets with fewer than 100 people are excluded.

These striking racial disparities invite the question of what are their main drivers. The following subsection addresses this problem.

5.2 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. The results show that the scarcity of Black men stems mainly from mass incarceration, while the abundance of Asian women is a consequence of female-focused migration.

5.2.1 Quantifying Main Drivers of the Differences in the Sex Composition: Method

Racial disparities in the sex composition stem from differences in parameters governing the availability of mates of each gender. Examples of parameters are incarceration rates, mortality rates, and immigration rates, which often vary considerably across races and genders[8]. I analyze the contribution of each parameter by checking how much the racial disparities in sex composition vary when I change the parameter's value. Hall (2000) inspired this method with his analyses of the changes in the sex ratio for Black people in the second half of the XXth century.

[8]Specifically, I consider incarceration, migration patterns, propensity for male births and mortality due to natural, external and violent causes. An example of external causes are accidents or overdoses, while an example of violent causes are homicides

The decomposition proceeds in three steps. First, I model the proportion of men as a function of various parameters whose values differ across races. Second, I pick a parameter and set it equal in two racial groups. Third, I compute the counterfactual gap in the sex compositions under the equality of the parameter. The difference between the actual and counterfactual gap measures the contribution of the parameter under consideration.

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. I quantify the contribution of incarceration by replacing the incarceration rates for Black people with the incarceration rates for White people, while holding all other factors fixed. Next, I compute a counterfactual proportion of men among Black people that would arise if they faced White incarceration rates. Finally, I compare the actual difference in sex compositions between Black and White people to the computed counterfactual difference. The difference between the two measures the incarceration's contribution.

Below I present the derivations for the case of the racial differences at the national level. Nonetheless, the method may be easily further disagregated and in the appendix I present the case disagregated by race and cohort (figure A.9).

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 domestically born number of agents 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 (which eventually cancels out) 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 disagregated 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 disagregated 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 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.

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

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 in the appendix.

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:

$$Pm_r = \frac{N_{rm}}{N_{rm} + N_{rf}} * X_r \tag{1}$$

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 quantify the impact of a parameter on the sex composition of race r by setting its value to what it is for White people. 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. I switch parameter for 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:

1. Replace the incarceration rates for Black men and women by respective incarceration rates for White men and women.
2. Compute the *counterfactual* proportion male for Black people with the new value of the incarceration rate according to equation 1, while keeping other parameters and X_r fixed
3. Compute the *counterfactual* difference in sex compositions
4. The difference between the *counterfactual* and the empirical difference is the contribution of the relevant factor.

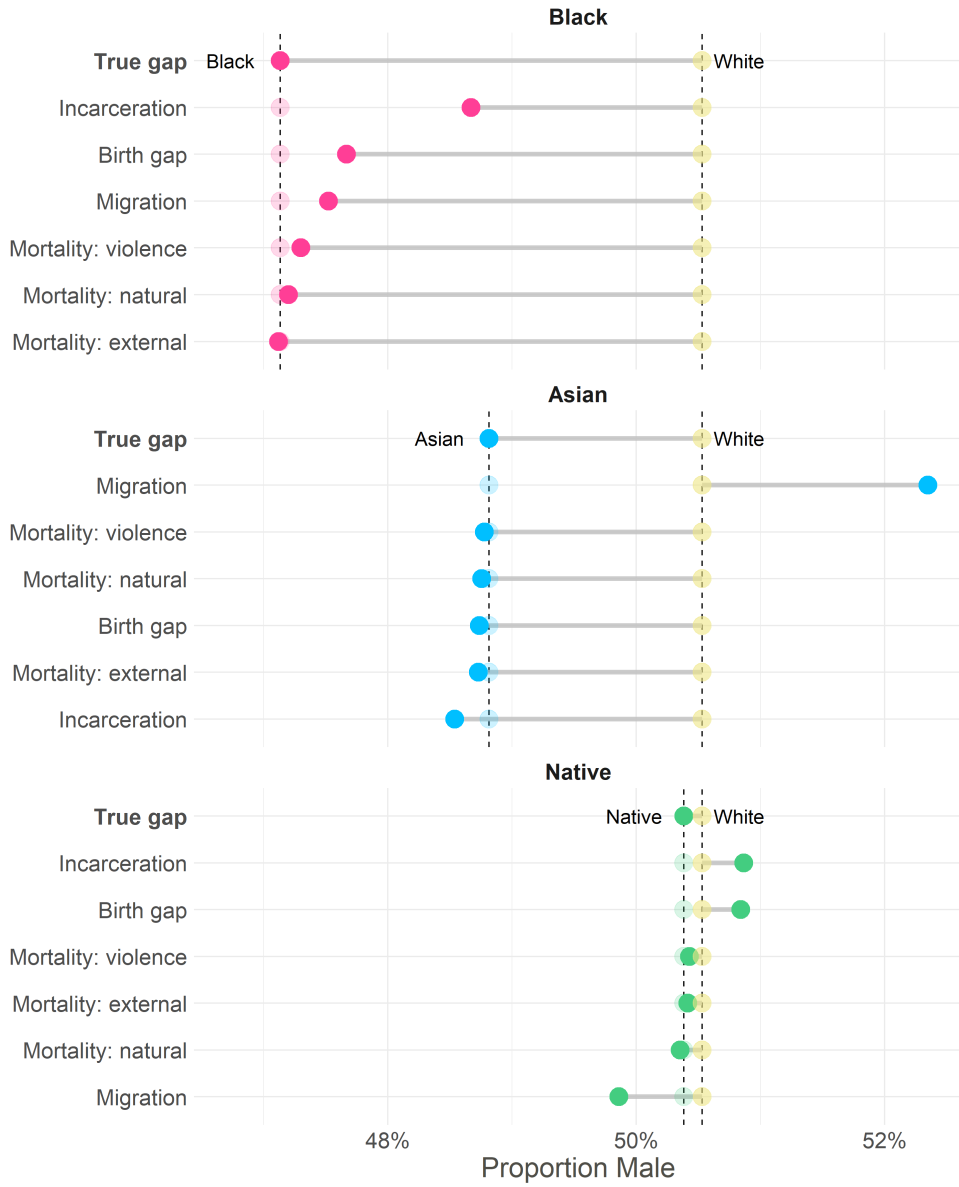
5.2.2 Quantifying Main Drivers of the Differences in the Sex Composition: Results

Figure 3 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. Incarceration rates for Black males are considerably higher than for White males. 10% of Black men aged 30-34 are in prisons, while the equivalent number for White men is 2%. The plot shows that if Black people faced the same incarceration rates as White people, the difference in the sex compositions would shrink by 45%. 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.8 in the appendix). 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. Various 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.

Figure 3: 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. Factors are ordered by the size of the impact

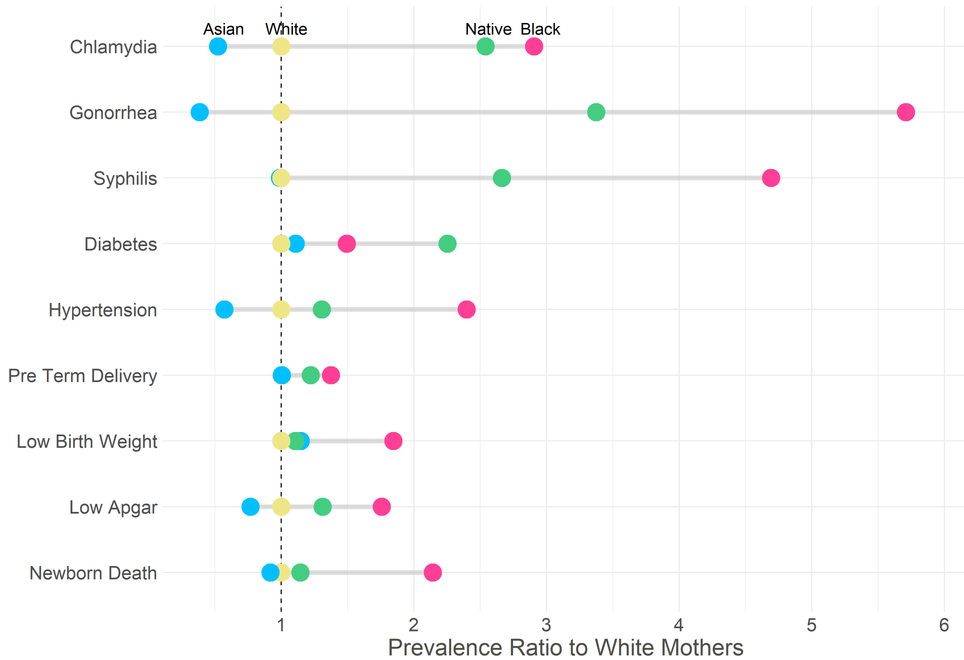
Differences in the migration patterns for Asian people and the disparities in the incarceration rates for Black people largely explain the observed deviations in the sex compositions. While migrants' decisions are voluntary, the gap between Black and White sex composition partly results from an interplay 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)), charged and sentenced more harshly (Rehavi and Starr (2014); Sutton (2013)) compared to similar White people in the same situations. Such biases interact 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[9]. 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 and subsequently the difference in the sex compositions. Hence, decision-makers have an influence over the gap in the sex compositions. For instance, Raphael and Stoll (2014) suggest that abandoning mandatory minumum 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. These policies would shrink the gap in sex ratios and affect not only Black men but also Black women's marriage market prospects and, as this paper argues, the health of Black infants. Indeed, racial differences in sex compositions coincide with racial disparities in health outcomes.

5.3 Large racial disparities in maternal and neonatal health

Pregnancy outcomes of Black mothers are considerably worse than outcomes of White mothers. Figure 4 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, especially after accounting for education (figure A.10 in the appendix). 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 APGAR scores below 7 (a sign that the baby requires medical attention). 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.10 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) In addition, Black women face higher maternal mortality rates (Petersen (2019)).

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

Figure 4: Racial disparities in pregnancy outcomes

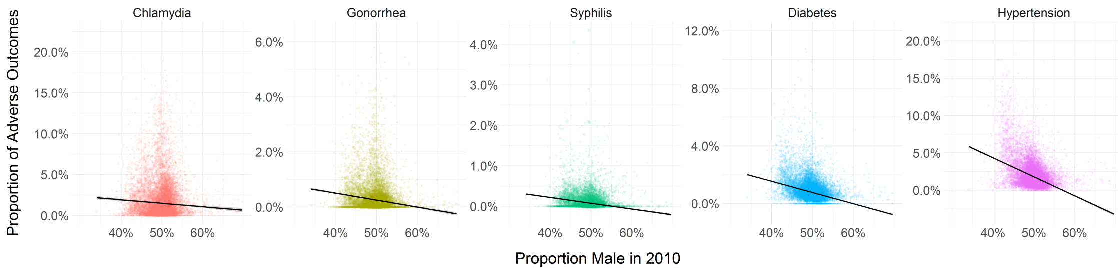


Notes: The light dots on the dashed line correspond to the baseline of the White mothers. Other dots represent the ratio of the average prevalence of a morbidity among a racial group to the average prevalence among White mothers. Blue, green and violet colors represent respectively Asians, Native Americans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

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 (Oct)) and their access to healthcare (Alsan and Wanamaker (2018), Hoffman et al. (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)). Looking at sexual health specifically, researchers identified differences in sexual networks of Black people which likely contribute to the observed disparities in STIs (Laumann and Youm (1999), Adimora et al. (2006), Morris et al. (2009)). They also suggested that the different shapes of the sexual network may be due to low sex ratios.

I believe 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 5, scarcity of men is associated with more frequent adverse effects.

Figure 5: Relationship between sex composition and health outcomes



(a) Maternal Outcomes

(b) Infant Outcomes

Notes: Each dot on the scatterplot 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.

The Black line in figure 5 represents an estimated linear relationship between the outcome's prevalence and the sex composition. It's worth pointing out that it is negative for each outcome, meaning that women and infants are healthier when men are prevalent. This correlation invites a more rigorous analysis which follows in the next sections.

6 Relationship Between Health and Sex Composition: Fixed Effects Framework

In an initial attempt to formally investigate the impact of sex composition on pregnancy health, I turn to the fixed effects framework. In particular, I regress the outcomes on the proportion of men in the dating market relevant to the mother as in equation 2.

$$y_{i,crb} = \beta PM_{crf(b)} + \gamma X_i + \lambda_{c,y-b} + \delta_{r,y-b} + \alpha_{r,2010-b} + \epsilon_i \tag{2}$$

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. I analyze three sets of outcomes. Firstly, I will examine marriage market outcomes. If the proportion of males is a valid distribution factor, 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 [10], whether mother is married and the difference

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

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 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.

The second 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 final set of outcomes contains variables relevant to neonatal health. In particular, I examine whether birth was pre-term (gestation < 37 weeks), wether brithweight was low (weight < 2500g), whether the APGAR score is below 7, whether the baby 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 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 $f(b)$. The notation $f(b)$ is used for the cohort as it is a function of the mother's birth year through her age in 2010. Furthermore, X_i controls for the cohort size in 2010. A large number of observations allow me to include a rich set of fixed effects. Namely, I include *County-Age at birth* fixed effects (y represents the year of child's birth, hence $y - b$ is mother's age at birth of the child), $County - Single$ *age cohort* fixed effects (single age cohort is represented by mother's age in 2010: $2010 - y$) and *Race-Age at birth* fixed effects. 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. The interactions of race and age and race and cohort intend to capture such cross-racial differences flexibly. Hence I leverage within racial groups variation in proportion male. Note that controlling for single years of age helps to reduce the variance of the residuals as pregnancy outcomes vary considerably and non-linearly with age. 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 are available in the data set, I do not control for them in the regression. Covariates such as maternal or paternal education could be affected by the independent variable through the selection into motherhood or matching. Hence, they would constitute bad controls (Angrist and Pischke (2009)).

I estimate the parameters β and γ in the regression equation 2 and I cluster the errors on the $County - Race$ level. The parameter β captures the treatment effect of a higher proportion of men on the market if the variable $PM_{crf(b)}$ is uncorrelated to residuals when conditioning on controls and fixed effects. 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.

7 Relationship Between Health and Sex Composition: Fixed Effects Results

A higher proportion of men on the dating market is associated with improved marital prospects, maternal health, and neonatal outcomes.

Firstly, women giving birth in markets with a higher share of males have stronger relationships and superior quality partners. The first column in table 1 shows that an increase in the proportion of men is associated with a lower likelihood of birth with an unknown father. Mothers at markets with the 75th percentile of proportion male (0.5204) are about 0.7 percentage points more likely to know the father than mothers at the 25th percentile (0.4845). This is a sizeable effect given that only 11% of mothers do not know the father on average. Moreover, parents of babies born in markets with a high share of men are more likely to be married. Given the coefficient in the second column of table 1, moving from the 25th percentile to the 75th percentile of the proportion of male increases the share of married mothers by about 1.1 percentage points The last column in table 1 provides evidence that a high share of men on the market is associated with more educated male partners. As the coefficient is negative, we note a relative increase in the father's education compared to the mother's. One could interpret it as a result of a stronger competition among men who now need to offer more to appeal to women.

Table 1: Mariage outcomes OLS

Dependent Variables:	Unknown Father	Married	Diff. in Edu.(years)
Model:	(1)	(2)	(3)
Variables			
Prop. male 2010	-0.1912***	0.3055***	-0.6211***
	(0.0208)	(0.0329)	(0.0788)
Fit statistics			
Dependent variable mean	0.113	0.650	0.306
Observations	23,299,377	23,818,474	20,174,436

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

This table presents estimates from OLS regression. The outcome variable is indicated on top of the column. The main independent variable is proportion of men on the dating market in 2010. Controls include cohort size and fixed effects for county-age, race-age, and county-cohort. Each observation represents a single birth. Standard errors are clustered at the county-race level.

The results in table 1 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. As the proportion of men affects the marriage market, one could expect that it also impacts mothers' health outcomes through the changes in the bargaining power and differential selection into childbearing. Table 2 shows that, indeed, maternal health is better in places with a higher proportion of men.

Table 2: Maternal outcomes OLS

Dependent Variables:	Chlamydia	Gonorrhea	Syphilis	Diabetes	Hypertension
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0189***	-0.0072***	-0.0022***	-0.0067***	-0.0326***
	(0.0033)	(0.0012)	(0.0007)	(0.0015)	(0.0045)
Fit statistics					
Dependent variable mean	0.015	0.003	0.0008	0.008	0.019
Observations	23,224,271	23,224,271	23,224,271	23,257,824	23,257,824

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

This table presents estimates from OLS regression. The outcome variable is indicated on top of the column.
The main independent variable is proportion of men on the dating market in 2010. Controls include cohort size and fixed effects for county-age, race-age, and county-cohort.
Each observation represents a single birth. Standard errors are clustered at the county-race level.

The first three columns of the table 2 provide evidence that mothers in markets with a low proportion of men are more likely to be diagnosed with sexually transmitted infections (STI) during pregnancy. Women at the 25th percentile of the *PM* have almost 0.07 percentage points higher chance of having chlamydia (compared to the mean of 1.5%) than mothers at the 75th percentile. Analogously, they are 0.03 percentage points more likely to have Gonorrhea (mean of 0.2%) and 0.008 percentage points more likely to have Syphilis (mean of 0.08%). Furthermore, a high proportion of males correlates with better pre-pregnancy health among women. Namely, prospective mothers are less likely to have Diabetes (column 4) and hypertension (column 5). Moving from the 25th percentile of the independent variable to the 75th percentile decreases the likelihood of Diabetes by 0.02percentage points (mean of 0.8%) and hypertension by 0.12percentage points (mean of 1.9%). Improvements in pre-pregnancy health could stem from a higher bargaining power among women, resulting in the resource allocation more favorable to women and lower exposure to negative stimuli such as stress. Nonetheless, the effects on maternal health could also be related to the selection into childbearing and changes in matching. Firstly, in the section *Extensions* (11), I note that the sex composition affects birth rates and I discuss potential selection mechanism. Secondly, higher stability and quality of the relationships could improve female health outcomes through more resources available to the household, especially if the partner is more educated. In any case, the results show that mothers giving birth are healthier, which can have important consequences for neonatal outcomes.

Table 3: Neonatal outcomes OLS

Dependent Variables:	Preterm Birth	Low BW	Low APGAR	Assisted ventilation	Death
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0472***	-0.0486***	-0.0085***	-0.0092*	-0.0022***
	(0.0053)	(0.0046)	(0.0021)	(0.0054)	(0.0007)
Fit statistics					
Dependent variable mean	0.113	0.082	0.021	0.041	0.003
Observations	24,467,061	24,461,432	24,385,422	23,246,802	23,266,090

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

This table presents estimates from OLS regression. The outcome variable is indicated on top of the column. The main independent variable is proportion of men on the dating market in 2010. Controls include cohort size and fixed effects for county-age, race-age, and county-cohort. Each observation represents a single birth. Standard errors are clustered at the county-race level.

OLS estimates in table 3 demonstrate a similarly strong relationship between sex composition and pregnancy outcomes. Column (1) shows that pre-term births occur less frequently in men-dominated markets. The effect is small, though, with a difference of 0.2 percentage points between the 25th and 75th percentile. A higher proportion male is also associated with heavier infants (column (2)). Moving from 25th to 75th percentile of *Prop. Male 2010* decreases slightly share of children with low birth weight by 0.2 percentage points. For the context, this effect is twice as large as the decline in low birth weight stemming from a $1 increase in minimum wage two years prior to birth (0.09 percentage points, Wehby et al. (2016)). The effect is also larger than the impact of one unit change in maternal exposure to Carbon Monoxide (0.089 percentage points, Currie et al.

(2009)). Furthermore, the coefficient for APGAR being low is negative and statistically significant in column (3). Babies at 75th percentile of *Prop. Male 2010* are 0.03 percentage points less likely to have APGAR below seven than those at the 25th percentile. To give some context, Expansion of EITC reduced share of children with low Apgar score by 0.185 percentage points Hoynes et al. (2015).

Most importantly, children born at markets with a scarcity of women are more likely to be alive until the birth certificate is produced (column (5)). The magnitude is small, as very few neonates (less than 0.3%) die in such a short time since birth. While negative, the effect on assisted ventilation (column (4)) is not statistically significant at 5%.

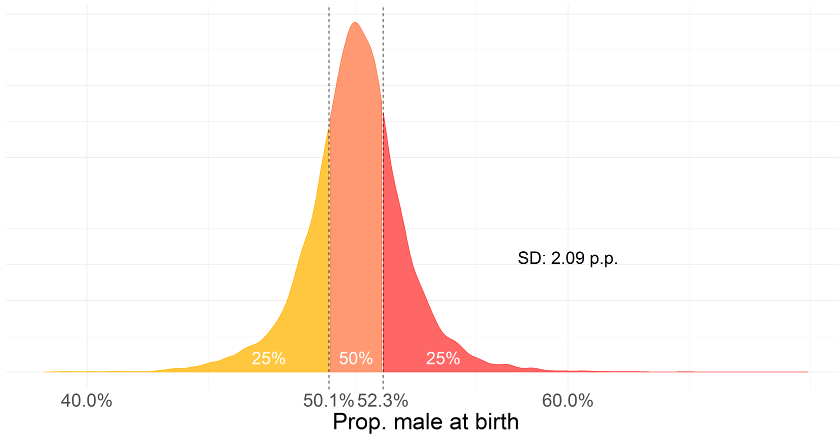
These results overall suggest a tangible link between the conditions in the dating market and pregnancy outcomes. Nonetheless, one should be careful about the causal interpretation of the coefficients. There can be omitted variables affecting both the sex ratio and the outcomes. As an example, consider 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)). 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)). These factors could produce a correlation between sex composition and health outcomes even without bargaining power. Hence, I proceed to the instrumental variable framework to recover the causal parameters.

8 Relationship Between Health and Sex Composition: Instrumental Variables Framework

I isolate the exogenous variation in sex composition by leveraging randomness in the sex ratio at birth. Hence, the instrument for PM_{cra} is the proportion of male births or race r 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 6 shows the distribution of the instrument together with its standard deviation and the first, and the third quartile. Figure A.11 in the appendix shows the distribution of the sex composition at birth by race and cohort.

Figure 6: Density of proportion male at birth



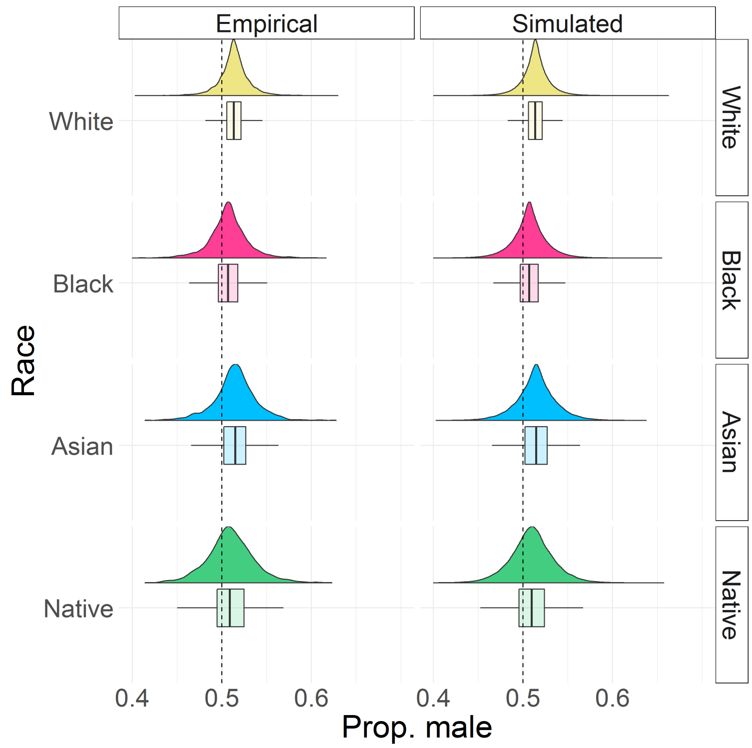
Notes: Figure shows the empirical distribution of the sex compositions. Each observation represents the proportion of men among agents on the dating market. The two vertical lines show the first and the third quartile. Standard deviation is noted on the side. Markets with fewer than 200 and more than 5000 births are excluded.

The primary motivation behind this instrument relies on two facts. First, the exclusion restriction 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. Second, instrument is relevant because a substantial amount of people live close to their childhood homes. Hence, 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.

The second fact 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.12 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. 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.

Regarding the first fact, it can be shown that the empirical distribution of sex composition at birth is similar to the one that would arise if the sex at birth was a random Bernoulli trial. To that end, I perform a simulation exercise visualized in figure 7. 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[11]. Indeed, the distributions are visually almost identical. This is further futher confirmed by the Kolgomorov-Smirnov tests, which do not reject the equality of the distributions (table A1 in the appendix). In the appendix, I also show that the amount of variation is consistent with the theoretical prediction of the binomial distribution (figure A.13).

Figure 7: Actual vs simulated density of proportion of male births



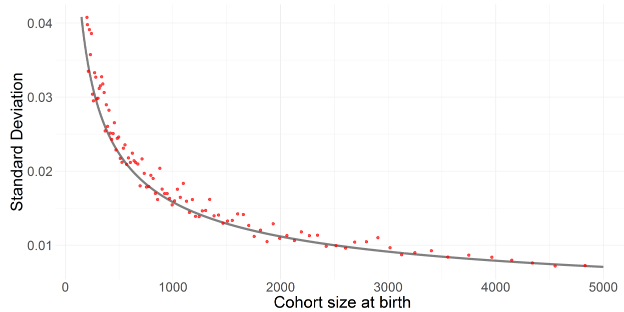
Notes: The left panel shows the empirical distribution of sex compositions where each observation represents the proportion of male births at a dating market when the cohort was born. The right panel shows the simulated distribution. Simulations are draws from the binomial distribution with parameters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

The instrument practically leverages the sampling variation in the mean probability that 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 $\sqrt{\frac{p(1-p)}{n}}$. Hence, 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. 8a plots the theoretical standard deviation by sample size n using p=0.5 and $\sqrt{\frac{p(1-p)}{n}}$. 8b plots the standard deviation in the data. 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 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

[11]Note that they mechanically have the same mean

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 on the figure 8b. 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). Hence, the behavior of the empirical variance is consistent with the sampling variation of bernouilli variable, and hence randomness at birth.

Figure 8: Variation in the sex composition



(a) Theoretical and empirical standard deviation

(b) Log variance and log cohort size

Notes: The curve in figure 8a 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 8b 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

Figure 9 illustrates this pattern using density plots. The sex composition is very close to balance in the largest markets[12]. In the smaller markets, however, there is substantial variation in the proportion of male births. Some cohorts have more male or female births just by chance, and since the cohorts are small, they remain unbalanced. As the instrument exploits sampling variation, I exclude cohorts above 5000 since they do not add meaningful variation. In the robustness section, 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.

[12]Sex ratio at birth is slightly skewed toward men

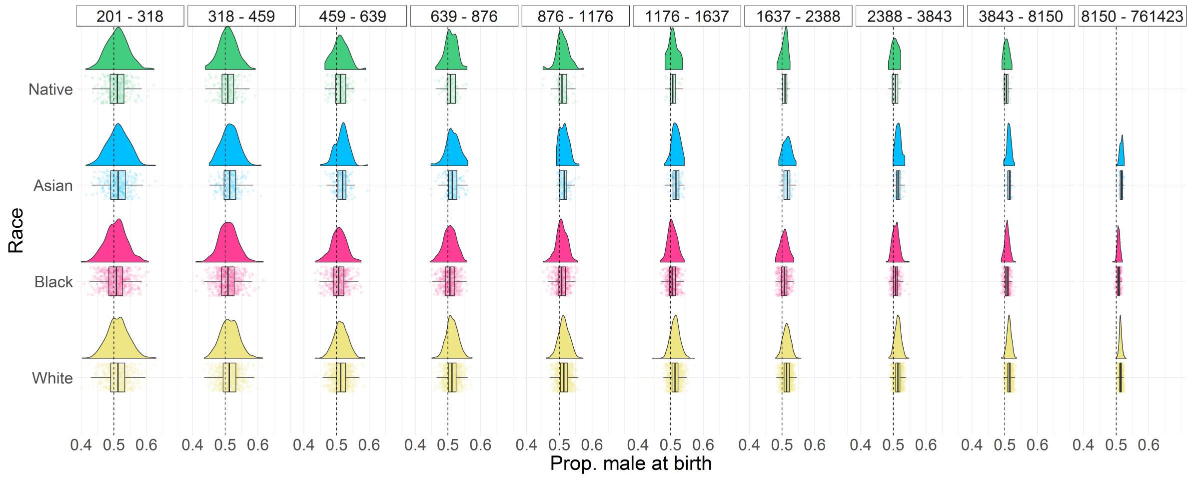


Figure 9: Density of proportion male at birth by cohort size

Notes: Figure shows the empirical distribution of the sex composition. Each observation represents the proportion of men among agents on the dating market. Distributions are divided by the deciles of the size of the cohort with smallest cohorts on the left and largest cohorts on the right.

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.

It is worth noting that focusing on small markets may have implications for the estimated treatment effect. As the impact may be heterogeneous with respect to the cohort size, I estimate a local effect on the population of compliers in small locations. Note that the instrument should be more potent in less geographically mobile cohorts, providing most of the valuable variation. Nonetheless, concentrating on smaller markets involves a trade-off. While I gain variation in the sex composition, people in smaller markets may be more likely to look for partners outside of their county, race or age group. The bounding exercise from the section A.6 would apply with higher $\alpha_{c,c'}$, and my estimates would be conservative. Finally, the variation in the instrument comes from the US born population. Hence, it disregards variation coming from the foreign born migrants.

To provide a consistent estimate, the instrument needs to satisfy two conditions. Firstly, it needs to be relevant, that is, to be correlated with the proportion of men on the market. Secondly, the exclusion restriction needs to hold, that is, it needs to be uncorrelated with other determinants of the pregnancy outcomes conditional on covariates. The correlation between the instrument and the endogenous variable is an empirical question that is analyzed in detail in the next section. Exogeneity, however, cannot be directly assessed. Some argue that sex composition at birth can be determined by socioeconomic factors, which can also impact health outcomes in the next generations. I conduct robustness checks in the section 13 to show that the sex ratio at birth is not predicted by the mother's education, age, relationship status or local economic conditions during pregnancy. Furthermore, I show that adults growing up in locations with unbalanced sex ratios are not different in terms of human capital from the general population. In particular the sex composition is not related to traits such as incarceration or education. Finally, 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.

If the exclusion restriction and relevance hold, the instrument can help eliminate problems in the OLS estimation. Firstly, it isolates 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. 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:

$$\hat{PM}_{i,crf(b)} = \zeta PMB_{i,crf(b)} + \theta X_i + \kappa_{c,y-b} + \pi_{r,y-b} + \tau_{r,2010-b} \tag{3}$$

$$y_{i,crb} = \beta \hat{PM}_{crf(b)} + \gamma X_i + \lambda_{c,y-b} + \delta_{r,y-b} + \alpha_{r,2010-b} + \epsilon_i \tag{4}$$

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 3). 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 4) to estimate the treatment effect β.

9 Relationship Between Health and Sex Composition: Instrumental Variables Results

The IV framework provides evidence that sex composition has a causal impact on maternal and neonatal health. 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 4 reports estimation results of the first-stage equation 3.

Table 4: First stage

Dependent Variable:	Prop. male 2010
Model:	(1)
Variables	
Prop. male at birth	0.2329***
	(0.0236)
Fit statistics	
R^2	0.738
Within R^2	0.065
F-test (IV only)	202,409.9
Wald (IV only)	97.3
Dependent variable mean	0.496
Observations	7,138,182

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

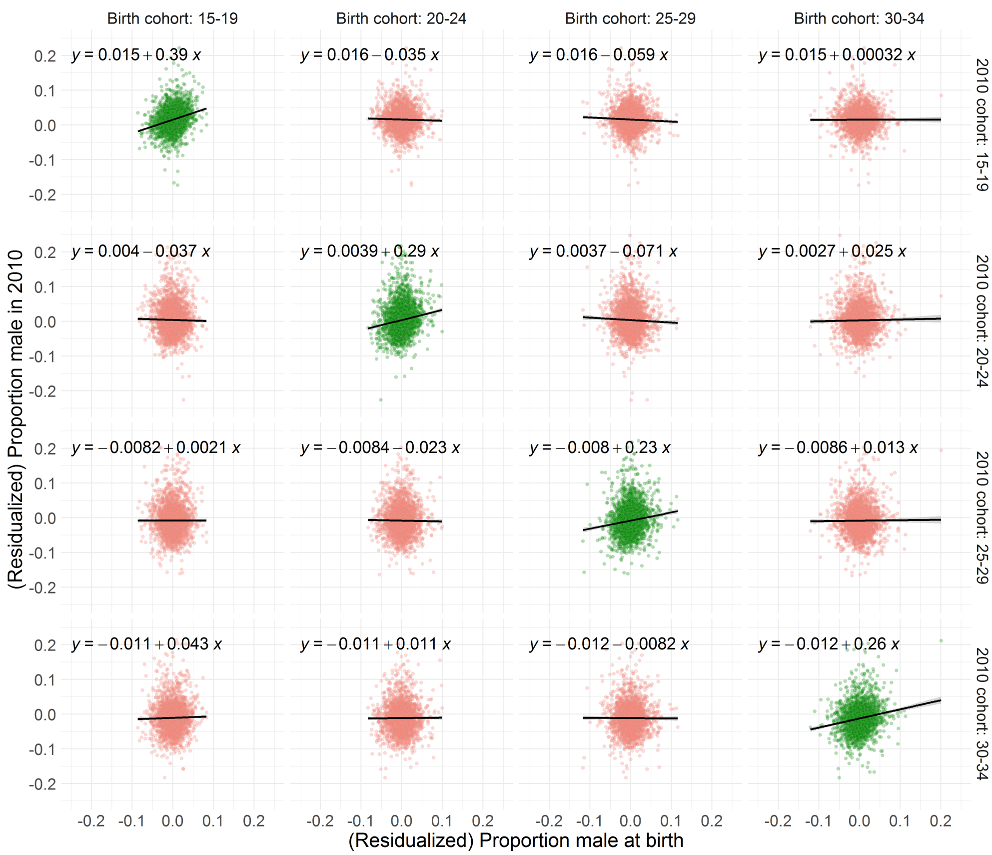
This table presents first stage estimates from the IV framework. In particular, it shows a regression of proportion of men on the dating market in 2010 on the proportion of men at birth of the cohort and covariates. The regression contains controls for cohort size in 2010 and at birth, County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male at birth* correspond to β in equation 3. Each observation represents a single birth. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom.

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 section 12.3.

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 97.75, 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 10 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 and slopes' p-values. All diagonal relationships, as expected, are positive and highly significant with very low p-values. 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.

Figure 10: First stage graph



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 . They approximate the first stage. 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 cohort PM_{crs} with $a \neq s$ (but of the same race and county). The estimated coefficients, R^2 and the p-value for the slope are provided on each graph. Only markets with birth cohorts between 200-5000 births are included.

The IV framework confirms the impact of the sex composition on the marital status of child-bearing women (table 5). They are considerably less likely to give birth to an unkown father and more likely to be married during delivery. The magnitudes are twice as large as in the case of the OLS estimate. 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 Note that both coefficients are significant according to tF standard errors. The coefficient on the difference in education (column 3) is small and not statistically significant. The higher proportion of men on the market has a favorable causal impact on the mother's situation in the marriage market. It's worth noting that this effect extends to the general female population, not just mothers. This generalization is discussed in the extension section 12.2. These results suggest that women in the men-dominated markets have higher bargaining power. Next, I show that it translates to improved maternal health outcomes.

Table 5: Instrumental Variables: Mariage outcomes

Dependent Variables:	Unknown Father	Married	Diff. in Edu.(years)
Model:	(1)	(2)	(3)
Variables			
Prop. male 2010	-0.4025***	0.7563***	0.0300
	(0.1311)	(0.1840)	(0.5214)
Fit statistics			
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 (1st stage), Prop. male 2010	96.1	98.0	79.7

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

This table presents estimates from IV regressions of couple 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. Columns' titles indicate the specific outcomes. 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 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-5000 births are included.

IV results in table 6 provide evidence that the scarcity of women on the dating market ameliorates health during pregnancy. Contrary to the OLS estimates, only two coefficients are statistically significant, although they all have the expected signs. 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 in table 3, which implies that moving from the 25th to 75th percentile of the proportion male decreases the share of mothers with chlamydia by 0.26 percentage points and hypertension by 0.37 percentage points

The causal effect of the scarcity of women can be channeled in two ways. Firstly, women may achieve more favorable household resource allocation. For instance, they could increase spending on healthcare, and nutrition or enforce their partner's fidelity. Secondly, higher bargaining power may affect selection into motherhood. For example, women unwilling to have a child may be more empowered to require condom use. My results could then arise if women who want to pursue pregnancy are healthier. I further discuss the mother's composition change in section 11. Independently of the channel, the health of pregnant women is better, so one can reasonably expect improvements in neonatal outcomes.

Table 6: Instrumental Variables: Maternal Outcomes

Dependent Variables:	Chlamydia	Gonorrhea	Syphilis	Diabetes	Hypertension
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0676**	-0.0042	-0.0019	-0.0317*	-0.0955***
	(0.0266)	(0.0093)	(0.0049)	(0.0169)	(0.0322)
Fit statistics					
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 (1st stage), Prop. male 2010	97.3	97.3	97.3	96.6	96.6

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

This table presents estimates from IV regressions of maternal health outcomes 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. Columns' titles indicate the specific outcomes. Note that Chlamydia, Gonorrhea and Syphilis are dummies equal to one if an infection was diagnosed during pregnancy. Diabetes and Hypertension are dummies equal to one if woman had a disease before the pregnancy. 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 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-5000 births are included.

Indeed, an increase in men's share of the dating market results in healthier newborns, as indicated by a decline in the percentage of infants with a low APGAR score (column 3 in table 7). 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. While other coefficients are of the hypothesized sign, they are not statistically significant at the traditional thresholds.

The results of the IV estimation point to the conclusion that empowering women leads to improvements in maternal and neonatal health. While some of these improvements may stem from the selection into motherhood, they are still important from the policy point of view. The ultimate goal is to ensure good health of infants, as this is a critical period which impacts both adult life (Barreca (2010), Almond and Mazumder (2011), Almond and Mazumder (2005)) and the health of next generations (East et al. (2017)). Ameliorating the health of children who would be born anyways is one way to achieve this goal. Another way is empowering women so they can choose not to pursue pregnancy when they do not want to or when the conditions are not conducive. Both mechanisms are hence relevant for policymakers.

Table 7: Instrumental Variables: Neonatal outcomes

Dependent Variables:	Preterm Birth	Low BW	Low APGAR	Assisted ventilation	Death
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0798	-0.0644	-0.0512**	-0.0681*	-0.0013
	(0.0545)	(0.0461)	(0.0251)	(0.0413)	(0.0084)
Fit statistics					
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 (1st stage), Prop. male 2010	97.2	97.5	97.0	96.5	96.0

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

This table presents estimates from IV regressions of infant health outcomes 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. Columns' titles indicate the specific outcomes. 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 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-5000 births are included

10 Counterfactual scenarios

A policy improving Black women's position in the dating market can ameliorate their pregnancy outcomes and reduce racial inequalities in health. As shown before, Black women face disadvantages in the dating market and experience worse health than White women. In this section, I use my causal estimates and simulations to quantify what share of the racial gap in health outcomes can be attributed to the racial gap in the sex composition. I focus on comparing Black and White mothers because section 5.2.2 shows that their gap in the sex ratios is mostly policy driven. Consequently, a policy could reverse the difference in sex compositions and reduce the health disparities.

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, and whether the newborn had a low APGAR score.

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.

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.

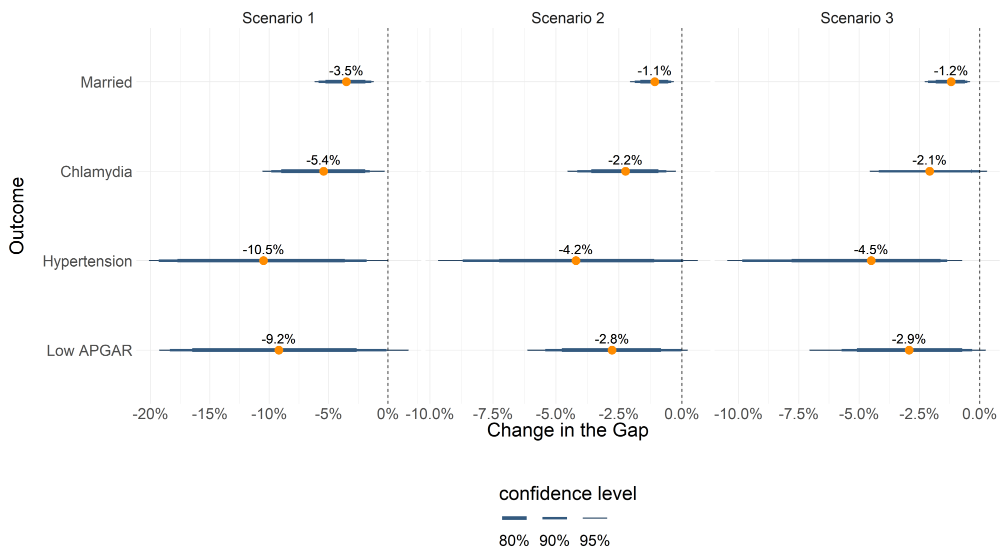
The second scenario focuses on a particular policy driving the sex ratios: incarceration rates for non-violent crimes. The counterfactual assumes that Black men and women are incarcerated for non-violent offenses at the same rate as their White counterparts in the same county and age group. The consequence 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. Focusing on non-violent offenders aims to mitigate this concern by looking at individuals closer in characteristics to the general population.

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 low income individuals to the dating pool still improves outcomes for all women, even those at the top of the income distribution. In the appendix section A.8, I adapt the model from section A.7 to accommodate a variety of assumption on the potential income of incarcerated individuals. My model provides three novel insights regarding the equilibrium effect of increasing the share of men on the market. First, adding men always improves female outcomes under male scarcity, even if new men have low potential income. Second, highest income women always benefit the most, even if only low-quality men are added to the pool. Third, the magnitude of female welfare gains depends relatively little on the quality of men added to the pool. 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 current 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. An additional difficulty is that the census data counts individuals at the location where they are incarcerated. Hence, I use the VERA project data to assign incarcerated individuals to the county where they committed the offense. The details of this procedure are in the appendix section A.5. Next, I recalculate the sex composition, including newly released individuals, and use the model to predict the outcomes and racial disparities.

The third scenario reduces incarceration rates to the level of New York State. State of New York passed a set of reforms which plausibly led to a large decline in its prison population (Raphael and Stoll (2014)). Lawmakers relaxed mandatory minimum sentencing (MMS) (especially related to drug offenses), reduced scope of crimes subject to MMS, delegated larger sentencing discretion to judges, shifted away from policing drug crimes, incentivized good behavior among inmates, and created rehabilitative programs. Between 1999 and 2012 the incarceration declined by about 26% (Raphael and Stoll (2014)). Assuming that 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. Consequently, I effectively top code incarceration rates at the New York level.

The simulations rely on bootstrapping the IV estimation sample and the comparison sample. 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.

Figure 11: Simulations: Reduction in Racial Health Inequality



Notes: Plot shows the reduction in the racial gap in health outcomes under the counterfactual scenarios. Subplot "scenario 1" represents the situation where the proportion male that Black women are facing is set to be the same as for White women. Subplot "scenario 2" correponds to equating incarceration rates for non-violent offenses. "Scenario 3" correponds to censoring the top incarceration at the value of New York incarceratio 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.

Simulations show that a significant share of racial health disparities is due to Black mothers' disadvantage in the dating market. Figure 11 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%. Finally, the racial disparity in the newborns who need medical assistance (low APGAR score) diminishes by 9.2%.

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%.

As a result of the last counterfactual scenario, both Black and White sex compositions would change. Nonetheless, the increase in the proportion of 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% and gap in the low APGAR score by 2.9%.

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 suprplus 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 [13]. 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 stems from a worse situation in dating markets for Black women. Moreover, the simulation shows that the mass incarceration policies have contributed to the racial gap in pregnancy outcomes.

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.14 in the appendix 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 8) 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.

[13] 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

Table 8: 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 (1st stage)				119.89	119.89	119.89
Observations	33,604	33,604	33,604	14,203	14,203	14,203

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

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 9 shows women giving birth at high bargaining positions tend to be healthier and more educated. The first column demonstrates that mothers with increased bargaining power are less likely to be overweight. Pregnant women at the 75th percentile of the sex composition are 1percentage points less likely to be overweight than mothers at the 25th percentile. Columns 3 and 4 show that parents are more educated when the situation in the dating market is more favorable to women. In particular, moving from the 25th to the 75th percentile increases the average education of mothers and fathers by 0.12 and 0.14 years, respectively. 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. I do not find evidence of delaying pregnancies, as there is no effect of the proportion male on the age of mothers at birth (column 2).

Table 9: 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 5Wald (1st stage), Prop. male 2010	112.3	113.5	99.7	78.9

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

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. Columns' titles indicate the specific outcomes. 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 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-5000 births are included.

12 Extensions

I extend my framework to demonstrate that the effect is mostly driven by the urban markets and that the sex composition of the dating market is relevant for outcomes beyond maternal and neonatal health. Firstly, I confirm that my instrument affects other variables that should be sensitive to the distribution factors. In particular, I show that the proportion male at birth changes the marriage rate in the general population. Secondly, I analyze whether men and women actively avoid unfavorable dating markets. My results suggest that there is a migratory response to the sex ratio.

12.1 Heterogeneity analysis

The effect of sex composition on the maternal and neonatal outcomes is mostly driven by the urban markets. Tables 10,11, and 12 show results of a heterogeneity analysis in which I split the sample by the type of the market: urban or rural [14].

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.

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

Table 10: Heterogeneity: Marital Outcomes

Dependent Variables:	Unknown Father		Married		Diff. in Edu.(years)	
County	Rural	Urban	Rural	Urban	Rural	Urban
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Prop. male 2010	-0.0979	-0.8229***	0.1893*	1.553***	0.1197	-0.4334
	(0.0754)	(0.3182)	(0.1052)	(0.4806)	(0.3633)	(1.134)
Fit statistics						
Dependent variable mean	0.128	0.125	0.607	0.632	0.451	0.294
Observations	2,994,976	4,171,367	3,135,086	4,343,450	2,553,632	3,551,541
Sig. at 5% (Lee et al. 2022)	No	Yes	No	Yes	No	No
Wald (1st stage), Prop. male 2010	324.2	23.3	347.7	22.5	278.4	18.6

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

This table presents estimates from IV regression split by rural and urban counties. Counties are divided according to the 2013 Rural-Urban Continuum Codes. Non-metro areas are classifed as rural. The outcome variable is indicated on top of the column. The proportion of men in 2010 is instrumented with the proportion of 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. Each observation represents a single birth. Standard errors are clustered at the county-race level.

Maternal health also seems to be influenced by bargaining more heavily in the urban markets. While the coefficient on hypertension are similar in both samples, the coefficients on Diabetes and hypertension are negative and large only in the urban setting.

Table 11: Heterogeneity: Maternal Health

Dependent Variables:	Chlamydia		Gonorrhea		Syphilis	
County	Rural	Urban	Rural	Urban	Rural	Urban
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Prop. male 2010	-0.0606**	-0.0699	-0.0089	0.0033	0.0044	-0.0114
	(0.0265)	(0.0500)	(0.0091)	(0.0185)	(0.0050)	(0.0100)
Fit statistics						
Dependent variable mean	0.019	0.018	0.003	0.003	0.0006	0.0009
Observations	2,984,182	4,154,000	2,984,182	4,154,000	2,984,182	4,154,000
Sig. at 5% (Lee et al. 2022)	Yes	No	No	No	No	No
Wald (1st stage), Prop. male 2010	323.7	23.5	323.7	23.5	323.7	23.5

Dependent Variables:	Diabetes		Hypertension	
County	Rural	Urban	Rural	Urban
Model:	(7)	(8)	(9)	(10)
Variables				
Prop. male 2010	0.0022	-0.0807**	0.0074	-0.2399***
	(0.0153)	(0.0376)	(0.0253)	(0.0766)
Fit statistics				
Dependent variable mean	0.009	0.010	0.022	0.022
Observations	2,989,596	4,161,996	2,989,596	4,161,996
Sig. at 5% (Lee et al. 2022)	No	No	No	Yes
Wald (1st stage), Prop. male 2010	324.2	23.2	324.2	23.2

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

This table presents estimates from IV regression split by rural and urban counties. Counties are divided according to the 2013 Rural-Urban Continuum Codes. Non-metro areas are classifed as rural. The outcome variable is indicated on top of the column. The proportion of men in 2010 is instrumented with the proportion of 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. Each observation represents a single birth. Standard errors are clustered at the county-race level.

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.

Table 12: Heterogeneity: Neonatal Health

Dependent Variables:	Preterm Birth		Low BW		Low APGAR	
County	Rural	Urban	Rural	Urban	Rural	Urban
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Prop. male 2010	0.0385	-0.2479**	0.0215	-0.1847*	0.0096	-0.1277**
	(0.0500)	(0.1202)	(0.0433)	(0.0977)	(0.0245)	(0.0552))
Fit statistics						
Dependent variable mean	0.119	0.123	0.081	0.091	0.026	0.023
Observations	3,143,069	4,397,381	3,143,244	4,395,977	3,132,255	4,382,821
Sig. at 5% (Lee et al. 2022)	No	No	No	No	No	No
Wald (1st stage), Prop. male 2010	348.9	22.4	348.8	22.5	348.4	22.4

Dependent Variables:	Assisted ventilation		Death	
County	Rural	Urban	Rural	Urban
Model:	(7)	(8)	(9)	(10)
Variables				
Prop. male 2010	-0.0264	-0.1342	-0.0037	0.0028
	(0.0407)	(0.0845)	(0.0083)	(0.0167)
Fit statistics				
Dependent variable mean	0.050	0.043	0.003	0.003
Observations	2,988,427	4,160,604	2,989,889	4,166,016
Sig. at 5% (Lee et al. 2022)	No	No	No	No
Wald (1st stage), Prop. male 2010	323.6	23.2	324.2	23.2

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

This table presents estimates from IV regression split by rural and urban counties. Counties are divided according to the 2013 Rural-Urban Continuum Codes. Non-metro areas are classifed as rural. The outcome variable is indicated on top of the column. The proportion of men in 2010 is instrumented with the proportion of 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. Each observation represents a single birth. Standard errors are clustered at the county-race level.

In my sample, urban markets are disproportionately represented by racial minorities, and rural markets are disproportionately White. This stems partly from the sample definition limiting the maximum birth cohort size to 5000. Many urban White cohorts are larger than this threshold and are excluded from the sample, as they would not provide useful variation in sex ratio at birth. Therefore, this heterogeneity exercise suggests that racial minorities experience more significant effects of relationship bargaining. 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 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.

12.2 Effect on population marriage rates

Sex composition favorable to women increases the marriage rate in the general female population. Table 13, 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 13: 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
Within R^2	0.91850	0.86414	0.94415	0.90228	0.95695	0.93378	0.96146	0.94125

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

The outcome variable measures 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. The variable *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. Regressions are weighted by the population. Standard errors are heteroskedacticity robust. Data 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 3.6p.p more likely to be married than women in the 25th percentile. This result suggests that the increase in married mothers in table 5 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.

12.3 Migratory Respone 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 areas where men are relatively abundant. Census data provides a yearly estimate of the number of men and women[15] 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[16]. Note that the outcome is not disaggregated by race or age. Hence I restrict my sample to racially homogeneous counties. I estimate the following equation:

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

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 14 and 15 presents the estimation results.

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

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

Table 14: 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

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

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 14 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 15: In migration

Dependent Variables: Model:	Male arrival rate (1)	Female arrival rate (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

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

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 15 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 4 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 13.2 that migration is unlikely to drive the main results.

Overall, the instrumented sex composition affects behaviors beyond health outcomes, including marital decisions and location choices.

13 Robustness Checks

Additional analysis shows the robustness of my results to potential identification concerns. First, I investigate whether women tend to look for partners outside of their market if men are scarce in their market. Second, I argue that the migration in reaction to the sex composition does not drive my results. Third, I show that the socialization channel is unlikely to explain the relationship between sex composition at birth and health outcomes. Fourthly, I show that the instrument is exogenous with respect to the socio-economic environment at the time when the cohort was born.

13.1 Effect on partners' characteristics

While my framework assumes that people date within a *race* × *county* × *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 (see appendix section A.6 for the derivation) because the market I consider is only a part of the actual market mothers face. 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 3 and 4 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 16.

Table 16: 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

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

Notes: This table presents estimates from IV regressions of parents' 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. Columns' titles indicate the specific outcomes. 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 4. Each observation represents a single birth. 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). Data source: Natality Data. Only markets with birth cohorts between 200-5000 births are included.

Column (1) in table 16 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. Hence, women do not look for partners in other age groups when the sex ratio in their age group is unfavorable.

According to estimates in column (2), women are slightly more likely to engage in an interracial partnership when the proportion of men on their market is high. The sign of this coefficient goes against the expectation that women would turn to other racial groups when men of their race are scarce. Nonetheless, the magnitude is small, as moving from the 25th percentile to the 75th percentile of the independent variable increases the likelihood of interracial parenthood by only

2percentage points. While it is large compared to the mean value, it does not substantially affect the accuracy of the initial market definition. Moreover, this coefficient is only significant at 10%.

Overall, women tend to have children with men of their race and in their age group, and only a small part of women explores other markets.

13.2 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:

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

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. The regression also includes controls for the size of the cohorts in childhood and 2010 and race and county fixed effects. Table 17 shows the estimation results.

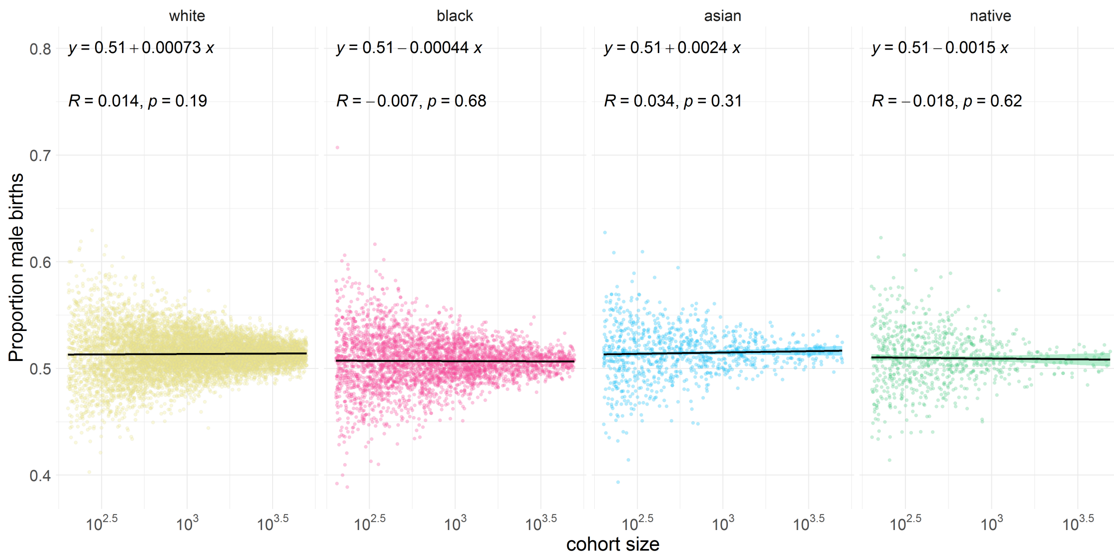
Table 17: RF: Income rank of stayers

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

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

Notes: Each observation correspond to race × county for people born in 1978-1983. The outcome is measured in 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

Figure 12: Birth Cohort Size vs Proportion Male at Birth



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

The income rank of stayers is not related to the instrument. Parameters β for both men and women are small and statistically insignificant. Hence, I treat it as suggestive evidence that the migration in response to the dating market situation does not change the composition of stayers.

13.3 Effects through Channels other than Bargaining Power

One may be concerned that growing up in a location with unbalanced sex composition may impact behaviors through channels unrelated to the dating market. In an example scenario, 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 12 shows that there is no relationship between birth cohort size and proportion of male births.

In an alternative scenario, 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 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 the uneven sex ratio. 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:

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

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 18. 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 18) and who have a college degree (columns 3 and 4).

Table 18: RF: Education and Incarceration

Dependent Variables:	Incarcerated		College	
	Female	Male	Female	Male
Model:	(1)	(2)	(3)	(4)
Variables				
Prop. male at birth	0.002	-0.035	0.279	-0.028
	(0.014)	(0.078)	(0.379)	(0.486)
Fit statistics				
Dependent variable mean	0.00402	0.03926	0.35074	0.25630
Observations	3,558	3,550	3,017	2,912

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

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 population. Controls include cohort size at birth and in the sample, and county 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. 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. These findings lessen the concern that the main results are driven by the effect of growing up in unbalanced sex composition.

13.4 Effects of socio-economic conditions 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. Note that this pattern is a peril only if it holds conditional on the fixed effects.

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 19) and I run an additional regression including all measures together (column 4).

Table 19: 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

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

This table presents regressions of a dummy equal to one if male is birth 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. Each observation represents a single birth. Standard errors are clustered at the County-Race level. Data source: Natality Data. Only markets with birth cohorts between 200-5000 births are included.

The variation in sex composition at birth is not related to 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. 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. For this exercise, 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:

$$Prop.Male_{c,t} = \sum_{lag:0}^{10} \beta^{lag} Unemployment_{c,t-lag} + \gamma_c + \delta_t + \epsilon_{c,t} \tag{9}$$

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 $t - lag$ [17]. 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 [18] and the industry-level national monthly unemployment rates. Table 20 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.

These exercises provide evidence that the sex at birth in the US is not shaped by the individual economic status of the mother (as proxied by education) or by aggregate economic fluctuations (as proxied by unemployment). Hence, these variables do not drive the relationship between sex composition and pregnancy outcomes.

[17] Time is measured in months

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

Table 20: Unemployment and Sex at Birth

Dependent Variable:	Proportion male	
Model:	OLS	IV
	(1)	(2)
Variables		
Unemployment Rate	9.88×10^{-5}	0.001
	(0.0002)	(0.001)
l(lag(Unemployment Rate,1)	-0.0002	-0.002
	(0.0003)	(0.003)
l(lag(Unemployment Rate,2)	0.0001	0.002
	(0.0003)	(0.003)
l(lag(Unemployment Rate,3)	0.0003	0.0004
	(0.0003)	(0.002)
l(lag(Unemployment Rate,4)	-0.0002	-0.003
	(0.0003)	(0.002)
l(lag(Unemployment Rate,5)	2.36×10^{-5}	0.004
	(0.0003)	(0.003)
l(lag(Unemployment Rate,6)	-6.7×10^{-5}	-0.001
	(0.0003)	(0.003)
l(lag(Unemployment Rate,7)	-7.61×10^{-5}	-0.0008
	(0.0003)	(0.002)
l(lag(Unemployment Rate,8)	5.6×10^{-5}	0.0003
	(0.0003)	(0.003)
l(lag(Unemployment Rate,9)	-0.0003	-0.002
	(0.0004)	(0.005)
l(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), l(lag(Unemployment Rate, 1)		39.882
K-P Wald (1st stage), l(lag(Unemployment Rate, 2)		44.713
K-P Wald (1st stage), l(lag(Unemployment Rate, 3)		33.055
K-P Wald (1st stage), l(lag(Unemployment Rate, 4)		33.814
K-P Wald (1st stage), l(lag(Unemployment Rate, 5)		41.963
K-P Wald (1st stage), l(lag(Unemployment Rate, 6)		43.093
K-P Wald (1st stage), l(lag(Unemployment Rate, 7)		36.550
K-P Wald (1st stage), l(lag(Unemployment Rate, 8)		32.239
K-P Wald (1st stage), l(lag(Unemployment Rate, 9)		24.835
K-P Wald (1st stage), l(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 (from Natality data). It is regressed at current month county unemployment rate and its 10 lags (from Fred). 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. K-P (Kleinberg-Paap) Wald statistic show the first stage strength for each instrumented variable. County and time fixed effects are included.

14 Conclusion

This paper provides evidence that a relationship's distribution of bargaining power matters for pregnancy outcomes. I measure female bargaining power with the dating market's sex composition, which determines the availability of alternative partners. My empirical framework identifies the causal effect by leveraging a novel instrument: the cohort's sex composition at birth. The results show that the higher availability of male partners leads to a lower share of out-of-wedlock births, a lower prevalence of maternal hypertension and chlamydia, and fewer occurrences of low APGAR score among newborns.

Two primary mechanisms appear to be driving these results. Firstly, women with more bargaining power can secure a higher quality partner and a larger share of the relationship's surplus. Consequently, their health during pregnancy improves as they can direct additional resources to their safety, nutrition, and healthcare. Secondly, empowered women have more control over whether to have a child. My results reveal that mothers in dating markets favorable to females are more likely to be educated and healthy before pregnancy. Such positive selection into fertility may reflect the mother's decisions not to get pregnant or deliver if her circumstances are disadvantageous.

A limitation of this approach, however, is the inability to distinguish between the respective contributions of these mechanisms. While empowering women leads to healthier mothers and infants, it is difficult to quantify separately the partial effects of matching, household resources' allocation, and selection into fertility. As a deeper understanding of the mechanism is policy-relevant, I intend to explore this as a future research avenue. Additionally, my study is limited by a rigid definition of the dating market stemming from data constraints. Power could be gained and measurement error reduced if one could more accurately measure the dating market relevant to an individual's decisions. Hopefully, the release of big data from dating apps in the near future have the potential to address this issue.

The finding of this project suggests that policies empowering women can improve maternal and neonatal health and fight racial disparities in health. Female bargaining power can be affected by gender-contingent transfers (Duflo (2003)) or laws governing the divorce and division of assets (Chiappori et al. (2002)). My results demonstrate that policy can also influence bargaining power by altering the sex composition of the dating market. Mass incarceration policies resulted in a scarcity of men, especially in Black communities. Racial disparities in incarceration rates account for 45% of the difference in the sex composition between White and Black Americans, with half of it stemming from incarceration for non-violent offenses. According to my estimates, eliminating the disadvantage Black women face in the dating markets could reduce the racial gap in pregnancy outcomes by 5-10%. A smaller policy aiming to equalize the incarceration rate for non-violent Black offenders to the rate experienced by White people has the potential to prevent 200-700 adverse pregnancy outcomes per year among Black mothers. Hence, my findings indicate that racial health disparities are partly an unintended consequence of mass incarceration policies.

I believe that this project points out several interesting research avenues. Firstly, my results show that women migrate in response to the conditions in the dating market. Further research quantifying the trade-off between the marriage market and labor market opportunities involved in migration decisions would be additive. Moreover, according to my findings, fertility negatively correlates with female bargaining power. It is therefore essential to understand better why women who gain power in a relationship are less likely to have children. Finally, my findings show the effects of bargaining in the first 24 hours of a child's life. It is reasonable to expect that the effect of bargaining power continues and accumulates throughout the child's life. I would like to explore whether the adverse health outcomes due to female disadvantage in the dating market persist through childhood and adulthood, as well as whether they persist into the next generation. Understanding the effects' persistence could help address the inter-generational transmission of health inequalities by improving outcomes for the most vulnerable populations.

References

Abramitzky, R., Delavande, A., and Vasconcelos, L. (2011). Marrying Up: The Role of Sex Ratio in Assortative Matching. *American Economic Journal: Applied Economics*, 3(3):124–157.

Abrevaya, J. (2009). Are There Missing Girls in the United States? Evidence from Birth Data. *American Economic Journal: Applied Economics*, 1(2):1–34.

Adimora, A. A., Schoenbach, V. J., Bonas, D. M., Martinson, F. E. A., Donaldson, K. H., and Stancil, T. R. (2002). Concurrent sexual partnerships among women in the United States. *Epidemiology (Cambridge, Mass.)*, 13(3):320–327.

Adimora, A. A., Schoenbach, V. J., and Doherty, I. A. (2006). HIV and African Americans in the southern United States: Sexual networks and social context. *Sexually Transmitted Diseases*, 33(7 Suppl):S39–45.

Aizer, A. (2011). Poverty, Violence and Health: The Impact of Domestic Violence During Pregnancy on Newborn Health. *The Journal of human resources*, 46(3):518–538.

Aizer, A., Lleras-Muney, A., and Stabile, M. (2004). Access to Care, Provider Choice and Racial Disparities.

Alix-Garcia, J., Schechter, L., Valencia Caicedo, F., and Jessica Zhu, S. (2022). Country of Women? Repercussions of the Triple Alliance War in Paraguay. *Journal of Economic Behavior & Organization*, 202:131–167.

Almond, D., Chay, K. Y., and Greenstone, M. (2006). Civil Rights, the War on Poverty, and Black-White Convergence in Infant Mortality in the Rural South and Mississippi.

Almond, D. and Cheng, Y. (2020). Perinatal Health among 1 Million Chinese-Americans.

Almond, D., Hoynes, H. W., and Schanzenbach, D. W. (2011). Inside the War on Poverty: The Impact of Food Stamps on Birth Outcomes. *Review of Economics and Statistics*, 93(2):387–403.

Almond, D. and Mazumder, B. (2005). The 1918 Influenza Pandemic and Subsequent Health Outcomes: An Analysis of SIPP Data. *American Economic Review*, 95(2):258–262.

Almond, D. and Mazumder, B. (2011). Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy. *American Economic Journal: Applied Economics*, 3(4):56–85.

Alsan, M. and Wanamaker, M. (2018). Tuskegee and the Health of Black Men*. *The Quarterly Journal of Economics*, 133(1):407–455.

Andrews, I., Stock, J. H., and Sun, L. (2019). Weak Instruments in IV Regression: Theory and Practice. *Annual Review of Economics*.

Angrist, J. (2002). How Do Sex Ratios Affect Marriage and Labor Markets? Evidence from America's Second Generation. *The Quarterly Journal of Economics*, 117(3):997–1038.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press.

Armand, A., Attanasio, O., Carneiro, P., and Lechene, V. (2020). The Effect of Gender-Targeted Conditional Cash Transfers on Household Expenditures: Evidence from a Randomized Experiment. *The Economic Journal*, 130(631):1875–1897.

Attanasio, O. and Lechene, V. (2002). Tests of Income Pooling in Household Decisions. *Review of Economic Dynamics*, 5(4):720–748.

Backstrom, L., Sun, E., and Marlow, C. (2010). Find me if you can: Improving geographical prediction with social and spatial proximity. In *Proceedings of the 19th International Conference on World Wide Web*, WWW '10, pages 61–70, New York, NY, USA. Association for Computing Machinery.

Bailey, Z. D., Feldman, J. M., and Bassett, M. T. (2021). How Structural Racism Works — Racist Policies as a Root Cause of U.S. Racial Health Inequities. *New England Journal of Medicine*, 384(8):768–773.

Banks, R. R. (2011). *Is Marriage for White People?: How the African American Marriage Decline Affects Everyone*. Penguin.

Banks, R. R. (2012). *Is Marriage for White People?: How the African American Marriage Decline Affects Everyone*. Penguin.

Barcellos, S. H., Carvalho, L. S., and Lleras-Muney, A. (2014). Child Gender and Parental Investments in India: Are Boys and Girls Treated Differently? *American Economic Journal: Applied Economics*, 6(1):157–189.

Barreca, A. I. (2010). The Long-Term Economic Impact of In Utero and Postnatal Exposure to Malaria. *Journal of Human Resources*, 45(4):865–892.

Bassett, M. T. (2015). #BlackLivesMatter — A Challenge to the Medical and Public Health Communities. *New England Journal of Medicine*, 372(12):1085–1087.

Becker, G. S. (1973). A Theory of Marriage: Part I. *Journal of Political Economy*, 81(4):813–846.

Beegle, K., Frankenberg, E., and Thomas, D. (2001). Bargaining Power Within Couples and Use of Prenatal and Delivery Care in Indonesia. *Studies in Family Planning*, 32(2):130–146.

Bharadwaj, P. and Lakdawala, L. K. (2013). Discrimination Begins in the Womb: Evidence of Sex-Selective Prenatal Investments. *Journal of Human Resources*, 48(1):71–113.

Björkman Nyqvist, M. and Jayachandran, S. (2017). Mothers Care More, but Fathers Decide: Educating Parents about Child Health in Uganda. *American Economic Review*, 107(5):496–500.

Black, S. E., Bütikofer, A., Devereux, P. J., and Salvanes, K. G. (2019). This Is Only a Test? Long-Run and Intergenerational Impacts of Prenatal Exposure to Radioactive Fallout. *The Review of Economics and Statistics*, 101(3):531–546.

Blau, F. D., Kahn, L. M., Brummund, P., Cook, J., and Larson-Koester, M. (2020). Is there still son preference in the United States? *Journal of Population Economics*, 33(3):709–750.

Blundell, R., Pashardes, P., and Weber, G. (1993). What do we Learn About Consumer Demand Patterns from Micro Data? *The American Economic Review*, 83(3):570–597.

Borooah, V. K. (2004). Gender bias among children in India in their diet and immunisation against disease. *Social Science & Medicine (1982)*, 58(9):1719–1731.

Bourguignon, F. and Chiappori, P.-A. (1994). Collective Models of Household Behavior. In *Developments in Agricultural Economics*, volume 10, pages 205–216. Elsevier.

Brainerd, E. (2016). The Lasting Effect of Sex Ratio Imbalance on Marriage and Family: Evidence from World War II in Russia. SSRN Scholarly Paper ID 2826924, Social Science Research Network, Rochester, NY.

Browning, M., Bourguignon, F., Chiappori, P.-A., and Lechene, V. (1994). Income and Outcomes: A Structural Model of Intrahousehold Allocation. *Journal of Political Economy*, 102(6):1067–1096.

Browning, M. and Chiappori, P. A. (1998). Efficient Intra-Household Allocations: A General Characterization and Empirical Tests. *Econometrica*, 66(6):1241.

Buchmueller, T. C., Levinson, Z. M., Levy, H. G., and Wolfe, B. L. (2016). Effect of the Affordable Care Act on Racial and Ethnic Disparities in Health Insurance Coverage. *American Journal of Public Health*, 106(8):1416–1421.

Calvi, R. (2020). Why Are Older Women Missing in India? The Age Profile of Bargaining Power and Poverty. *Journal of Political Economy*, 128(7):2453–2501.

Carruthers, C. K. and Wanamaker, M. H. (2017). Separate and Unequal in the Labor Market: Human Capital and the Jim Crow Wage Gap. *Journal of Labor Economics*, 35(3):655–696.

CDC (2022). Diabetes Risk Factors. https://www.cdc.gov/diabetes/basics/risk-factors.html.

Charles, K. K. and Luoh, M. C. (2010). Male Incarceration, the Marriage Market, and Female Outcomes. *The Review of Economics and Statistics*, 92(3):614–627.

Chetty, R., Friedman, J. N., Hendren, N., Jones, M. R., and Porter, S. R. (2018). The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility. Working Paper 25147, National Bureau of Economic Research.

Chiappori, P. and Ekeland, I. (2006). The micro economics of group behavior: General characterization. *Journal of Economic Theory*, 130(1):1–26.

Chiappori, P.-A. (1988). Rational Household Labor Supply. *Econometrica*, 56(1):63.

Chiappori, P.-A. (1992). Collective Labor Supply and Welfare. *Journal of Political Economy*, 100(3):437–467.

Chiappori, P.-A., Fortin, B., and Lacroix, G. (2002). Marriage Market, Divorce Legislation, and Household Labor Supply. *Journal of Political Economy*, 110(1):37–72.

Chiappori, P.-A. and Oreffice, S. (2008). Birth Control and Female Empowerment: An Equilibrium Analysis. *Journal of Political Economy*, 116(1):113–140.

Cornwell, C. and Cunningham, S. (2008). Sex Ratios and Risky Sexual Behavior. SSRN Scholarly Paper ID 1266357, Social Science Research Network, Rochester, NY.

Cortes-Ramirez, J., Naish, S., Sly, P. D., and Jagals, P. (2018). Mortality and morbidity in populations in the vicinity of coal mining: A systematic review. *BMC Public Health*, 18(1):721.

Currie, J. (2009). Healthy, Wealthy, and Wise: Socioeconomic Status, Poor Health in Childhood, and Human Capital Development. *Journal of Economic Literature*, 47(1):87–122.

Currie, J. (2013a). Pollution and Infant Health. *Child development perspectives*, 7(4):237–242.

Currie, J. (2013b). Weathering the Storm: Hurricanes and Birth Outcomes. *Journal of health economics*, 32(3):487–503.

Currie, J., Mueller-Smith, M., and Rossin-Slater, M. (2018). Violence while in Utero: The Impact of Assaults During Pregnancy on Birth Outcomes. Working Paper 24802, National Bureau of Economic Research.

Currie, J., Neidell, M., and Schmieder, J. (2009). AIR POLLUTION AND INFANT HEALTH: LESSONS FROM NEW JERSEY. *Journal of health economics*, 28(3):688–703.

Dauria, E. F., Oakley, L., Arriola, K. J., Elifson, K., Wingood, G., and Cooper, H. L. F. (2015). Collateral consequences: Implications of male incarceration rates, imbalanced sex ratios and partner availability for heterosexual Black women. *Culture, Health & Sexuality*, 17(10):1190–1206.

Deininger, K., Goyal, A., and Nagarajan, H. (2010). Inheritance Law Reform and Women's Access to Capital: Evidence from India's Hindu Succession Act.

Duflo, E. (2003). Grandmothers and Granddaughters : Old-Age Pensions and Intrahousehold Allocation in South Africa. *World Bank Economic Review*, 17(1):1–25.

East, C. N., Miller, S., Page, M., and Wherry, L. R. (2017). Multi-generational Impacts of Childhood Access to the Safety Net: Early Life Exposure to Medicaid and the Next Generation's Health. Working Paper 23810, National Bureau of Economic Research.

Edlund, L., Li, H., Yi, J., and Zhang, J. (2008). More Men, More Crime: Evidence from China's One-Child Policy. SSRN Scholarly Paper 1136376, Social Science Research Network, Rochester, NY.

Ehrenstein, V., Pedersen, L., Grijota, M., Nielsen, G. L., Rothman, K. J., and Sørensen, H. T. (2009). Association of Apgar score at five minutes with long-term neurologic disability and cognitive function in a prevalence study of Danish conscripts. *BMC Pregnancy and Childbirth*, 9(1):14.

Elder, T. E., Goddeeris, J. H., and Haider, S. J. (2016). Racial and ethnic infant mortality gaps and the role of socio-economic status. *Labour Economics*, 43:42–54.

Elliott, B., Brunham, R. C., Laga, M., Piot, P., Ndinya-Achola, J. O., Maitha, G., Cheang, M., and Plummer, F. A. (1990). Maternal gonococcal infection as a preventable risk factor for low birth weight. *The Journal of Infectious Diseases*, 161(3):531–536.

Fong, J. (2020). Search, Selectivity, and Market Thickness in Two-Sided Markets: Evidence from Online Dating.

Fryer, R. G., Pager, D., and Spenkuch, J. L. (2013). Racial Disparities in Job Finding and Offered Wages. *The Journal of Law and Economics*, 56(3):633–689.

Ganatra, B. and Hirve, S. (1994). Male bias in health care utilization for under-fives in a rural community in western India. *Bulletin of the World Health Organization*, 72(1):101–104.

Gelman, A., Fagan, J., and Kiss, A. (2007). An Analysis of the New York City Police Department's "Stop-and-Frisk" Policy in the Context of Claims of Racial Bias. *Journal of the American Statistical Association*, 102(479):813–823.

Ghandnoosh, N. (2015). Black Lives Matter: Eliminating Racial Inequity in the Criminal Justice System. https://www.sentencingproject.org/publications/black-lives-matter-eliminating-racial-inequity-in-the-criminal-justice-system/.

Giuntella, O., La Mattina, G., and Quintana-Domeque, C. (2022). Intergenerational Transmission of Health at Birth: Fathers Matter Too! Working Paper 30237, National Bureau of Economic Research.

Grossbard-Shechtman, A. (1984). A Theory of Allocation of Time in Markets for Labor and Marriage. *Economic Journal*, 94.

Hall, S. D. (2000). An analysis of the trends in and factors affecting African American sex ratios in the United States - ProQuest. https://www.proquest.com/docview/304666384?pq-origsite=gscholar&fromopenview=true.

Hendryx, M. and Ahern, M. M. (2009). Mortality in Appalachian Coal Mining Regions: The Value of Statistical Life Lost. *Public Health Reports*, 124(4):541–550.

Hoffman, K. M., Trawalter, S., Axt, J. R., and Oliver, M. N. (2016). Racial bias in pain assessment and treatment recommendations, and false beliefs about biological differences between blacks and whites. *Proceedings of the National Academy of Sciences*, 113(16):4296–4301.

Hoyert, D. (2022). Maternal Mortality Rates in the United States, 2020. Technical report, Health E-stats.

Hoynes, H., Miller, D., and Simon, D. (2015). Income, the Earned Income Tax Credit, and Infant Health. *American Economic Journal: Economic Policy*, 7(1):172–211.

Hoynes, H., Page, M., and Stevens, A. H. (2011). Can targeted transfers improve birth outcomes?: Evidence from the introduction of the WIC program. *Journal of Public Economics*, 95(7):813–827.

Hoynes, H., Schanzenbach, D. W., and Almond, D. (2016). Long-run impacts of childhood access to the safety net. *American Economic Review*, 106(4):903–34.

Johnson, R. C. and Raphael, S. (2009). The Effects of Male Incarceration Dynamics on Acquired Immune Deficiency Syndrome Infection Rates among African American Women and Men. *The Journal of Law & Economics*, 52(2):251–293.

Kang, Y. and Pongou, R. (2020). SEX RATIOS, SEXUAL INFIDELITY, AND SEXUAL DISEASES: EVIDENCE FROM THE UNITED KINGDOM.

Kennedy-Moulton, K., Miller, S., Persson, P., Rossin-Slater, M., Wherry, L., and Aldana, G. (2022). Maternal and Infant Health Inequality: New Evidence from Linked Administrative Data. *NBER Working Paper series (forthcoming)*.

Kirkham, E. (2019). 2019 Survey on Dating and Distance: How Far Are People Willing to Look for Love? https://blog.hireahelper.com/2019-survey-on-dating-and-distance-how-far-are-people-willing-to-look-for-love/.

Kleibergen, F. and Paap, R. (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics*, 133(1):97–126.

Kochel, T. R., Wilson, D. B., and Mastrofski, S. D. (2011). EFFECT OF SUSPECT RACE ON OFFICERS' ARREST DECISIONS*. *Criminology*, 49(2):473–512.

Kuziemko, I., Meckel, K., and Rossin-Slater, M. (2018). Does Managed Care Widen Infant Health Disparities? Evidence from Texas Medicaid. *American Economic Journal: Economic Policy*, 10(3):255–283.

Lafortune, J. (2013). Making Yourself Attractive: Pre-marital Investments and the Returns to Education in the Marriage Market. *American Economic Journal: Applied Economics*, 5(2):151–178.

Lane, H. M., Morello-Frosch, R., Marshall, J. D., and Apte, J. S. (2022). Historical Redlining Is Associated with Present-Day Air Pollution Disparities in U.S. Cities. *Environmental Science & Technology Letters*, 9(4):345–350.

Laniado, D., Volkovich, Y., Scellato, S., Mascolo, C., and Kaltenbrunner, A. (2018). The Impact of Geographic Distance on Online Social Interactions. *Information Systems Frontiers*, 20(6):1203–1218.

Laumann, E. O. and Youm, Y. (1999). Racial/ethnic group differences in the prevalence of sexually transmitted diseases in the United States: A network explanation. *Sexually Transmitted Diseases*, 26(5):250–261.

Lee, D. S., McCrary, J., Moreira, M. J., and Porter, J. R. (2021). Valid t-ratio Inference for IV. Working Paper 29124, National Bureau of Economic Research.

Li, L. and Wu, X. (2011). Gender of Children, Bargaining Power, and Intrahousehold Resource Allocation in China. *The Journal of Human Resources*, 46(2):295–316.

Lillie-Blanton, M. and Hoffman, C. (2005). The Role Of Health Insurance Coverage In Reducing Racial/Ethnic Disparities In Health Care. *Health Affairs*, 24(2):398–408.

Liu, S. (2020). Incarceration of African American Men and the Impacts on Women and Children. SSRN Scholarly Paper ID 3601259, Social Science Research Network, Rochester, NY.

Lundberg, S. J., Pollak, R. A., and Wales, T. J. (1997). Do Husbands and Wives Pool Their Resources? Evidence from the United Kingdom Child Benefit. *The Journal of Human Resources*, 32(3):463.

Ly, D. P. (2021). Historical Trends in the Representativeness and Incomes of Black Physicians, 1900–2018. *Journal of General Internal Medicine*.

Maitra, P. (2004). Parental bargaining, health inputs and child mortality in India. *Journal of Health Economics*, 23(2):259–291.

Mason, S. M., Wright, R. J., Hibert, E. N., Spiegelman, D., Forman, J. P., and Rich-Edwards, J. W. (2012). Intimate partner violence and incidence of hypertension in women. *Annals of Epidemiology*, 22(8):562–567.

Mastracci, S. (2018). Pulled Over: How Police Stops Define Race and Citizenship, by Charles R. Epp, Stephen Maynard-Moody, and Donald P. Haider-Markel. *International Public Management Journal*, 21(2):326–329.

Mechoulan, S. (2011). The External Effects of Black Male Incarceration on Black Females. *Journal of Labor Economics*, 29(1):1–35.

Mitchell, O. and Caudy, M. S. (2015). Examining Racial Disparities in Drug Arrests. *Justice Quarterly*, 32(2):288–313.

Morris, M., Kurth, A. E., Hamilton, D. T., Moody, J., and Wakefield, S. (2009). Concurrent Partnerships and HIV Prevalence Disparities by Race: Linking Science and Public Health Practice. *American Journal of Public Health*, 99(6):1023–1031.

O'Flaherty, B. (2015). *The Economics of Race in the United States*. Harvard University Press.

Olea, J. L. M. and Pflueger, C. (2013). A Robust Test for Weak Instruments. *Journal of Business & Economic Statistics*, 31(3):358–369.

Panda, P. and Agarwal, B. (2005). Marital violence, human development and women's property status in India. *World Development*, 33(5):823–850.

Petersen, E. E. (2019). Racial/Ethnic Disparities in Pregnancy-Related Deaths — United States, 2007–2016. *MMWR. Morbidity and Mortality Weekly Report*, 68.

Pouget, E. R. (2017). Social determinants of adult sex ratios and racial/ethnic disparities in transmission of HIV and other sexually transmitted infections in the USA. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 372(1729):20160323.

Pouget, E. R., Kershaw, T. S., Ickovics, J. R., and Blankenship, K. M. (2010). Associations of Sex Ratios and Male Incarceration Rates with Multiple Opposite-Sex Partners: Potential Social Determinants of HIV/STI Transmission. *Public Health Reports (1974-)*, 125:70–80.

Rangel, M. A. (2006). Alimony Rights and Intrahousehold Allocation of Resources: Evidence from Brazil. *The Economic Journal*, 116(513):627–658.

Rao, V. (1997). Wife-beating in rural South India: A qualitative and econometric analysis. *Social Science & Medicine*, 44(8):1169–1180.

Raphael, S. and Stoll, M. (2014). A New Approach to Reducing Incarceration While Maintaining Low Rates of Crime. https://nicic.gov/new-approach-reducing-incarceration-while-maintaining-low-rates-crime.

Rehavi, M. M. and Starr, S. B. (2014). Racial Disparity in Federal Criminal Sentences. *Journal of Political Economy*, 122(6):1320–1354.

Rosenfeld, M. J., Thomas, R. J., and Hausen, S. (2019). Disintermediating your friends: How online dating in the United States displaces other ways of meeting. *Proceedings of the National Academy of Sciences*, 116(36):17753–17758.

Ryan, G. M., Abdella, T. N., McNeeley, S. G., Baselski, V. S., and Drummond, D. E. (1990). Chlamydia trachomatis infection in pregnancy and effect of treatment on outcome. *American Journal of Obstetrics and Gynecology*, 162(1):34–39.

Sentencing (2008). Reducing Racial Disparity in the Criminal Justice System: A Manual for Practitioners and Policymakers. https://www.sentencingproject.org/publications/reducing-racial-disparity-in-the-criminal-justice-system-a-manual-for-practitioners-and-policymakers/.

Spencer, M. (2022). Safer Sex? The Effect of AIDS Risk on Birth Rates. *Workin Paper*.

Spohn, C. (2009). Race, Sex, and Pretrial Detention in Federal Court: Indirect Effects and Cumulative Disadvantage.

Sprung-Keyser, B., Hendren, N., and Sonya, P. (2022). The Radius of Economic Opportunity: Evidence from Migration and Local Labor Markets. *CES 22-27 Working paper*.

Stoltey, J. E., Li, Y., Bernstein, K. T., and Philip, S. S. (2015). Ecological analysis examining the association between census tract-level incarceration and reported chlamydia incidence among female adolescents and young adults in San Francisco. *Sexually Transmitted Infections*, 91(5):370–374.

Sutton, J. R. (2013). Structural bias in the sentencing of felony defendants. *Social Science Research*, 42(5):1207–1221.

Thomas, D. (1990). Intra-Household Resource Allocation: An Inferential Approach. *The Journal of Human Resources*, 25(4):635–664.

Thomas, D., Contreras, D., and Frankenberg, E. (1999). DISTRIBUTION OF POWER WITHIN THE HOUSEHOLD AND CHILD HEALTH. page 39.

Thomas, J. C., Levandowski, B. A., Isler, M. R., Torrone, E., and Wilson, G. (2008). Incarceration and sexually transmitted infections: A neighborhood perspective. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, 85(1):90–99.

Ventures, S. (2021). Getting Hyperlocal to Improve Outcomes and Achieve Racial Equity in Maternal Health: The US Maternal Vulnerability Index. Technical report.

VERA (2012). Do Race and Ethnicity Matter in Prosecution? https://www.vera.org/publications/do-race-and-ethnicity-matter-in-prosecution-a-review-of-empirical-studies.

Wehby, G., Dave, D., and Kaestner, R. (2016). Effects of the Minimum Wage on Infant Health.

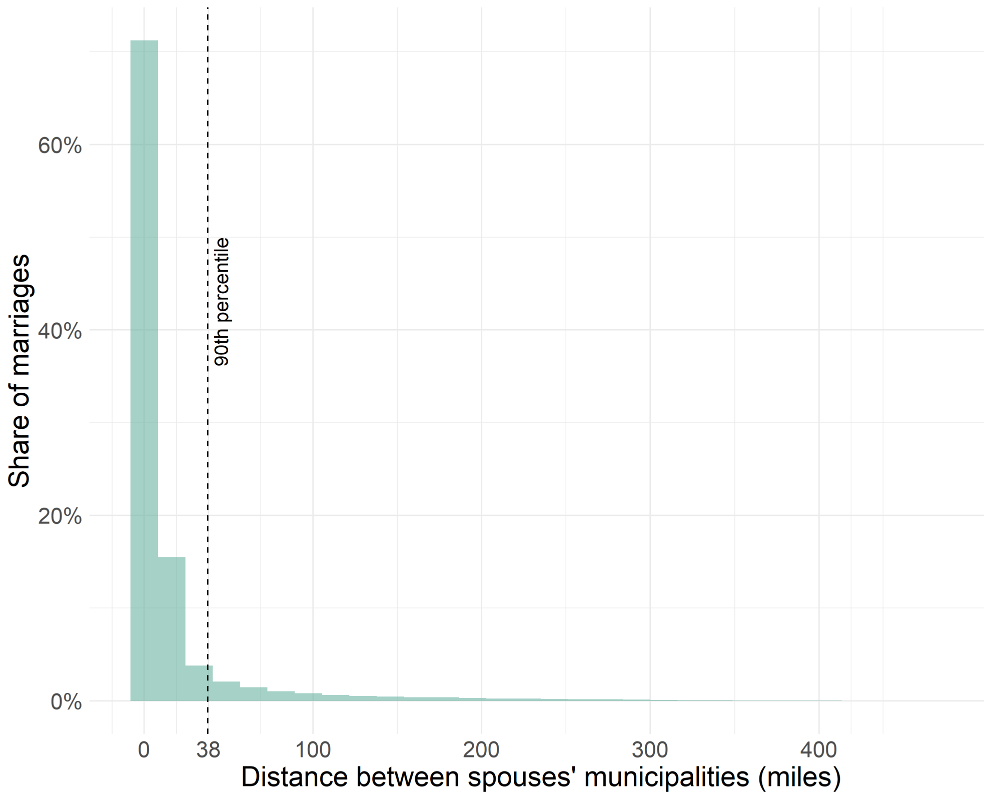
Williams, D. R. and Collins, C. (2001 Sep-Oct). Racial residential segregation: A fundamental cause of racial disparities in health. *Public Health Reports (Washington, D.C.: 1974)*, 116(5):404–416.

Xiong, W. (2022). Dynamics between Regional Sex Ratios at Birth and Sex Ratios at Prime Marriageable Ages in China. *Population and Development Review*, page padr.12476.

Zhang, S., Ding, Z., Liu, H., Chen, Z., Wu, J., Zhang, Y., and Yu, Y. (2013). Association between mental stress and gestational hypertension/preeclampsia: A meta-analysis. *Obstetrical & Gynecological Survey*, 68(12):825–834.

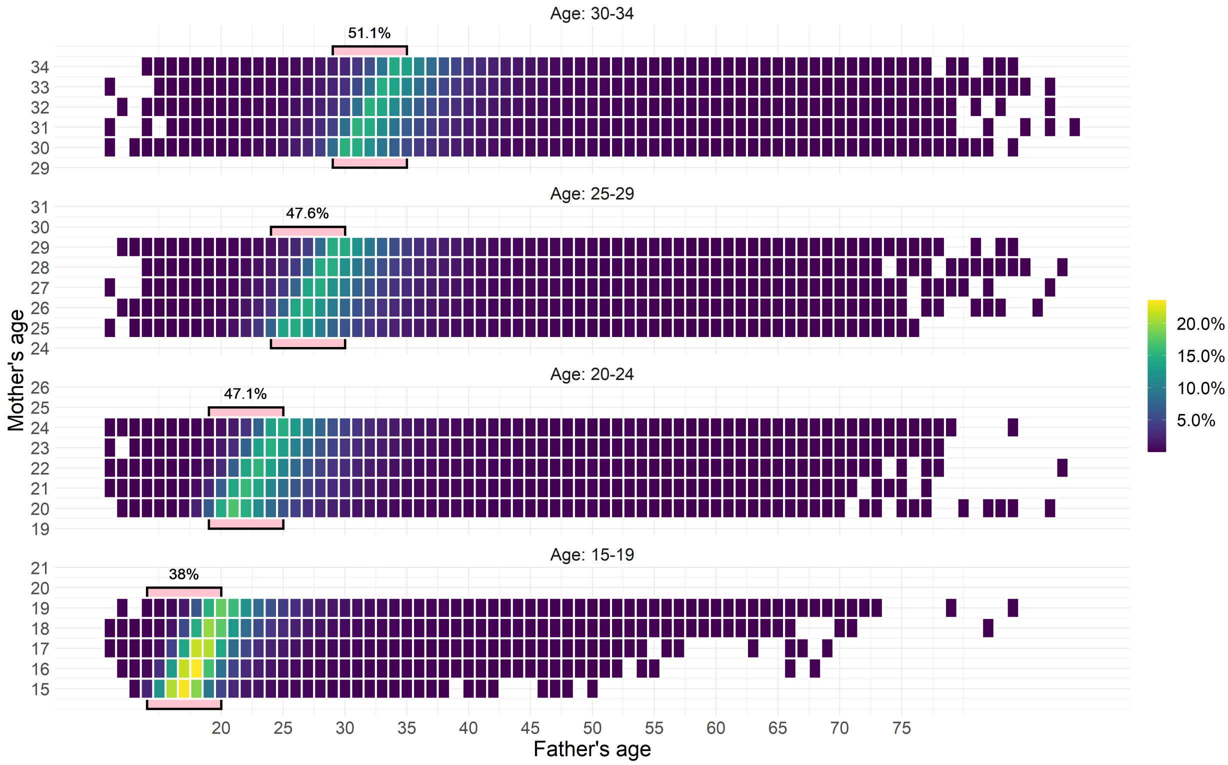
A Appendix

Figure A.1: Histogram of distances between the spouses



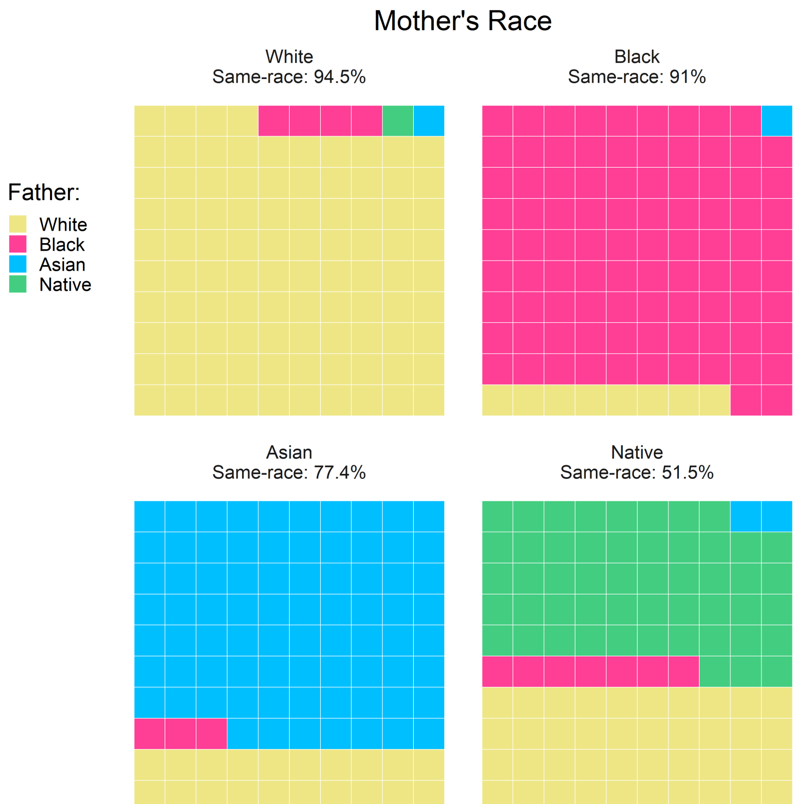
Notes: Figure plots histogram of distances between spouses municipalities before marriage. Polish Marriage Certificates contain information on the municipality where each spouse was registered before the marriage. The distance between each pair of municipalities was calculated and assigned to each married couple based on their municipality of residence. Source: Polish Marriage Certificates 2017-2019

Figure A.2: Age composition of parents



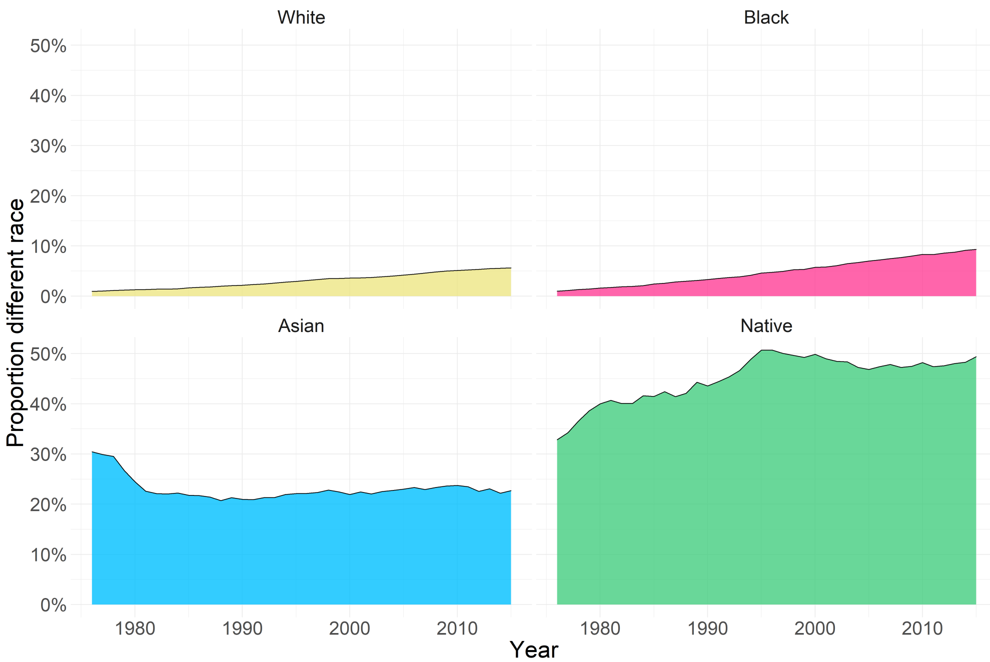
Notes: Each small box on the figure represents a couple with a father's age a_f and mother's age a_m. The color corresponds to the share of all mothers of age a_m who had a baby with a father of age a_f. Light colors on the diagonal indicate that most of women have children with men of their age. The 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. Source: Natality data 1976-2016

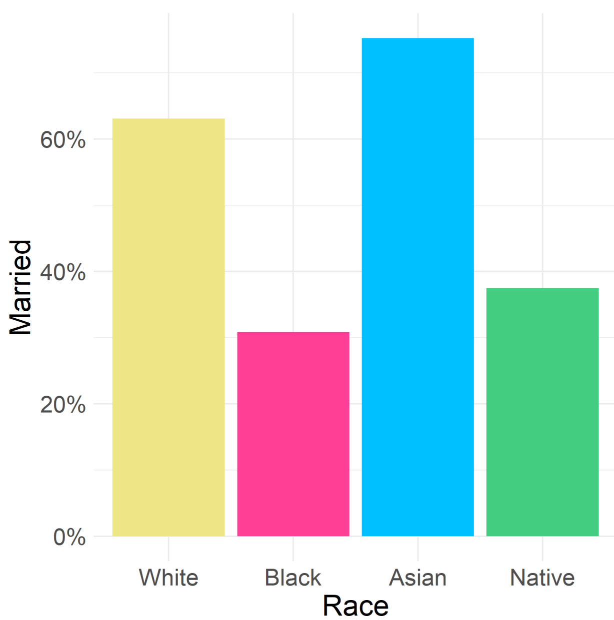


Figure A.5: Marital Rates by Race

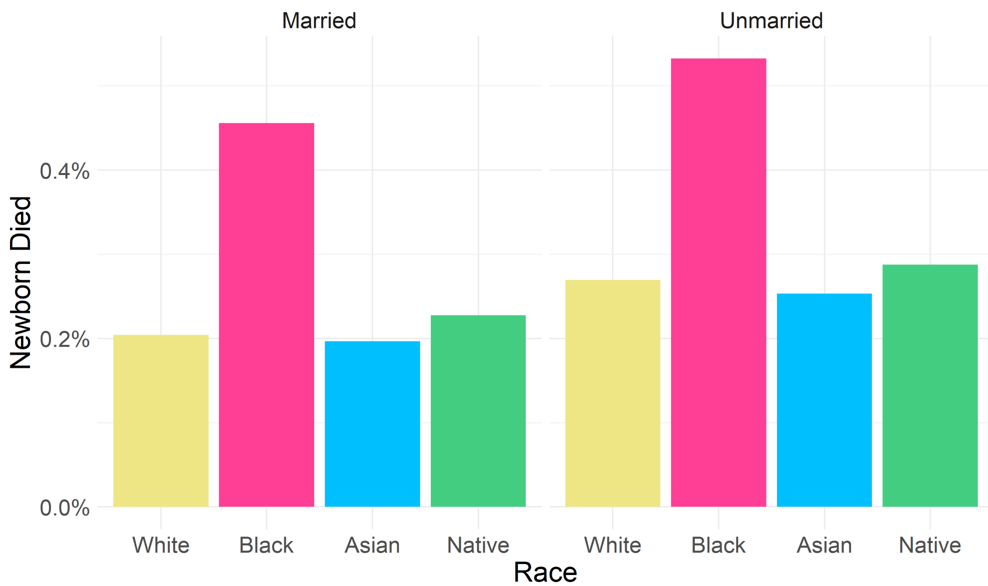
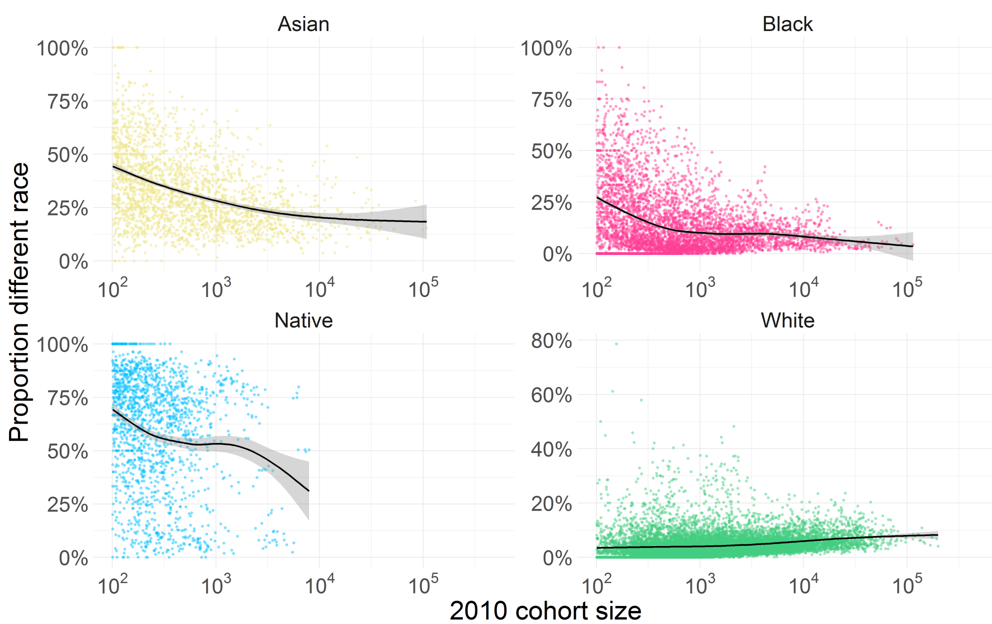


Figure A.6: Neonatal Deaths by Race and Marital Status

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.

A.1 Details on the decomposition of racial differences in the sex composition

Parameters computations

Incarceration 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 [19].

Mortality 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.

Sex of birth 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 immigrants 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

Gender of immigrants 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

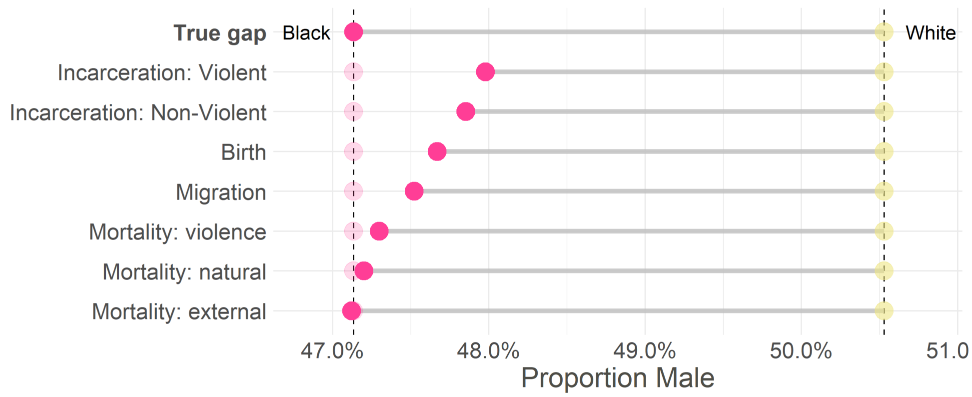
Additional assumptions

Several simplifying assumptions need to hold, mostly due to data limitations:

1. Death rates and incarceration rates are the same for local born and immigrant population. I can't distinguish between US born and foreign born in mortality datasets
2. 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.
3. 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.
4. I do not change relative share of US born/foreign born population.
5. I am not considering the interactions (i.e. changing more than 1 parameter at a time).

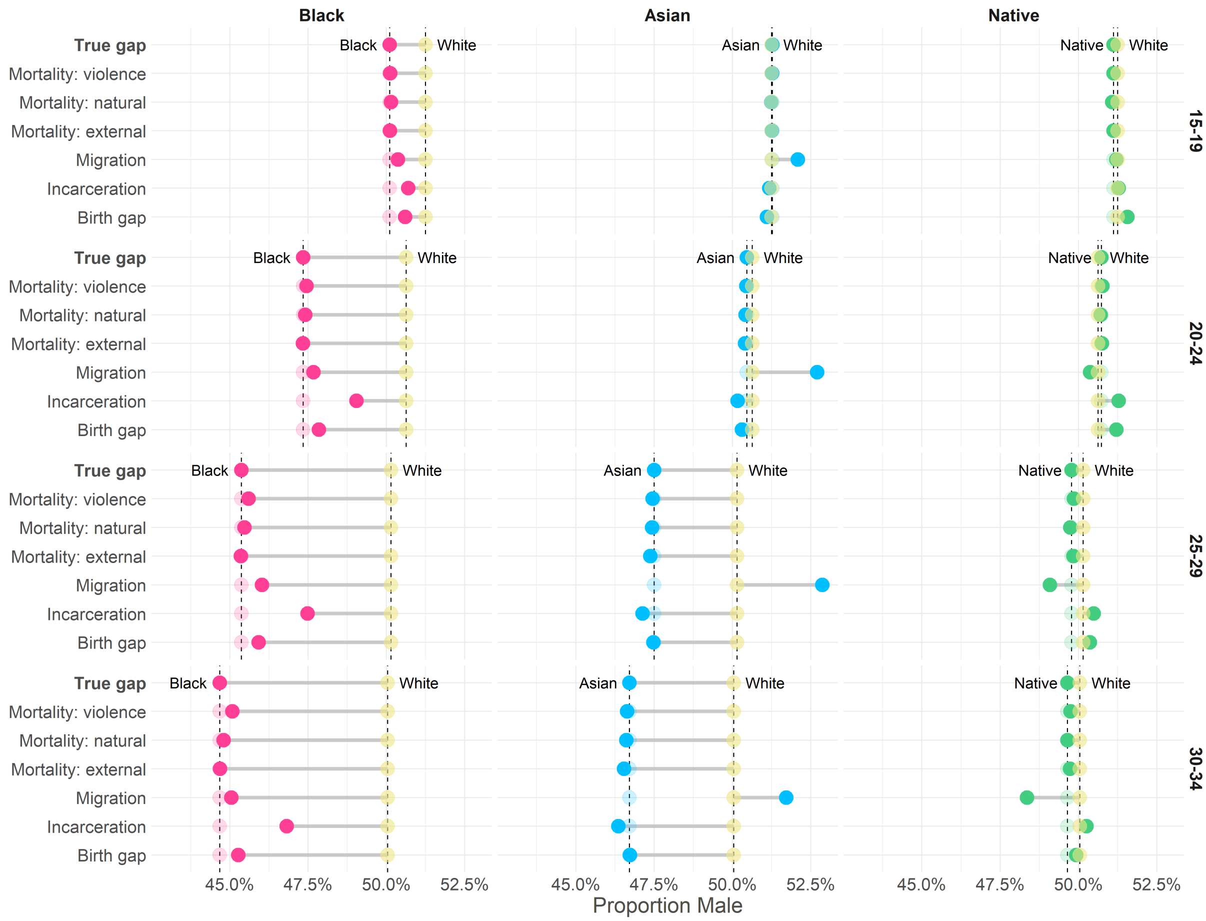
[19] https://csat.bjs.ojp.gov/advanced-query

Figure A.8: Counterfactual gaps in sex the composition



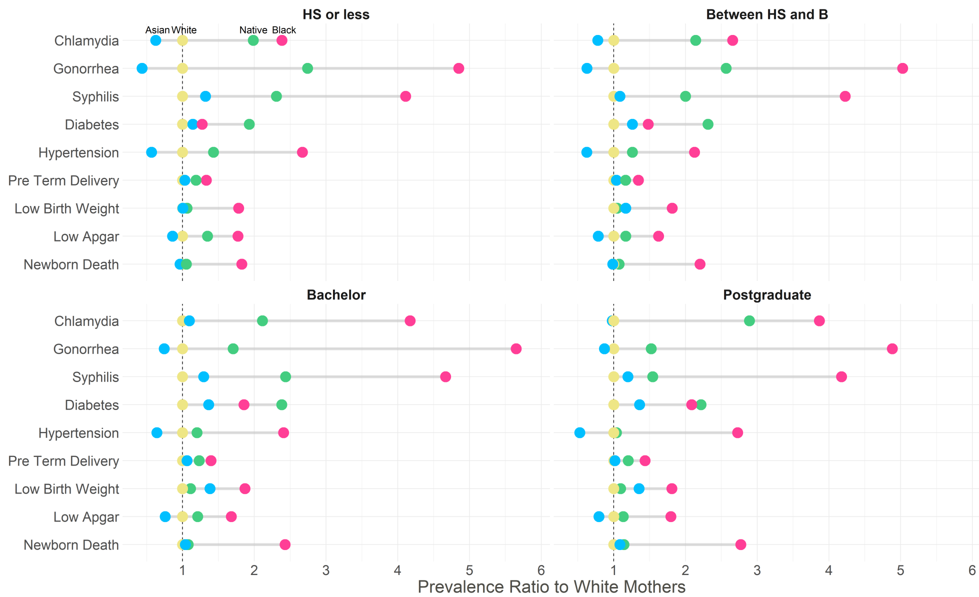
Notes: Each line on the figure shows the counterfactual gap (for the cohort 15-34 in 2010) that would arise if rates for a given factor were equlized to the value of White people. The dashed lines and the semi-transparent dots represent the true sex compositions.Factors are ordered by the size of the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

Figure A.9: Counterfactual gaps in the sex composition: by cohort



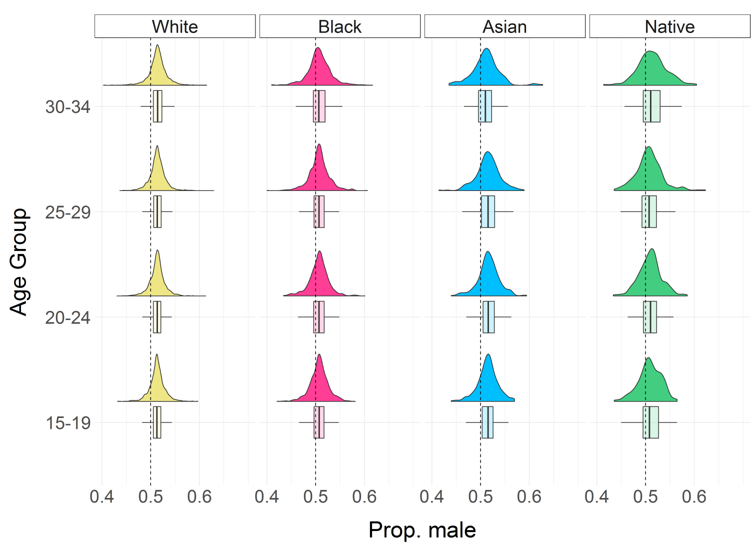
Notes: Each line on the figure shows the counterfactual gap (for the cohort 15-34 in 2010) that would arise if rates for a given factor were equlized to the value of White people. The dashed lines and the semi-transparent dots represent the true sex compositions.

Figure A.10: Racial disparities in health outcomes



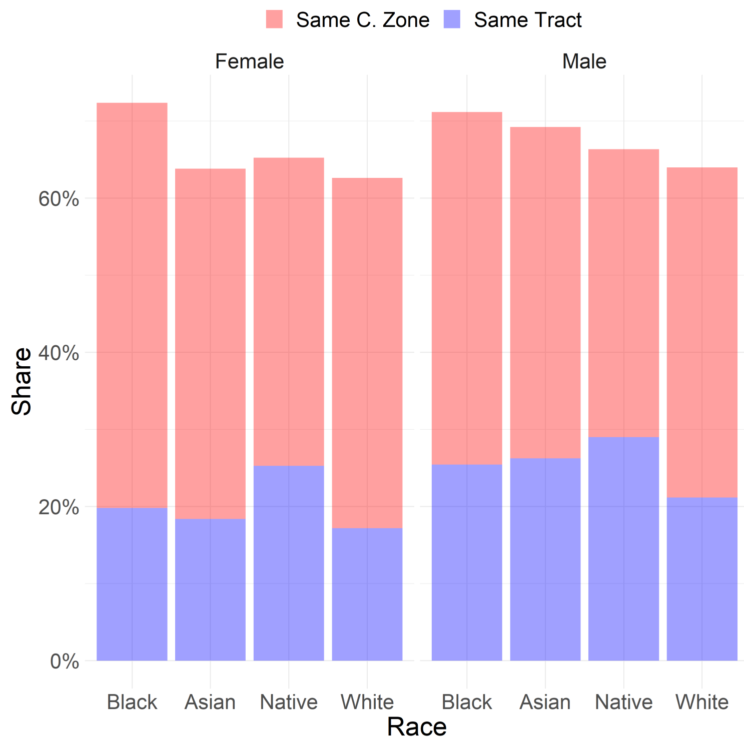
Notes: The light dots on the dashed line correspond to the baseline of the White mothers. Other dots represent the ratio of the average prevalence of a morbidity among a racial group to the average prevalence among White mothers. Blue, green and violet colors represent respectively Asians, Native Americans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

Figure A.11: 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. Distributions are divided by the age and race of the cohort.

Figure A.12: Geographic mobility since childhood



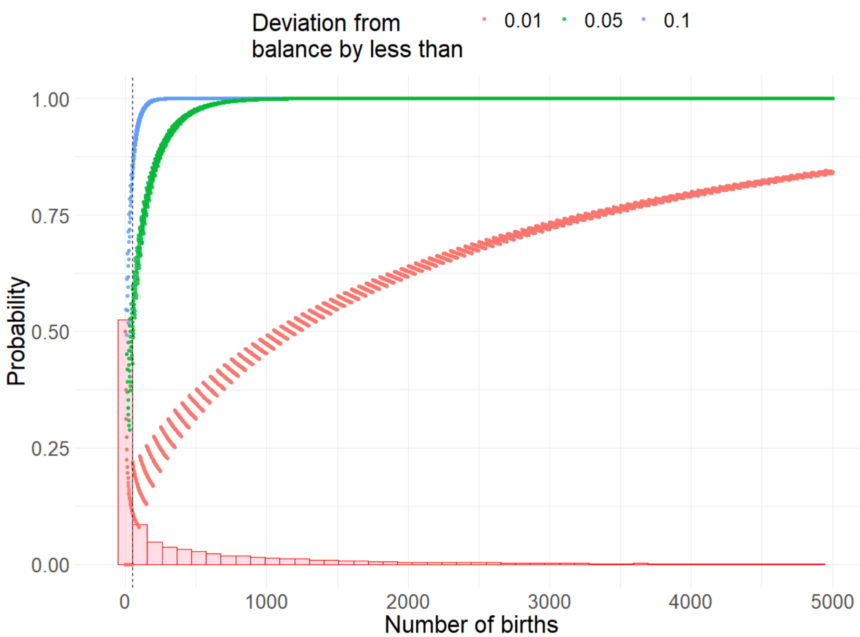
Notes: Figure shows proportion of people born between 1978 and 1983 who live in their childhood census tract or commuting zone as young adults. The blue color show share of people living in the same census tract, while red correspond to share living in the same commuting zone. Data is disagregated by race and gender. Based on Opportunity Insights data.

Table A1: Kolgomorov-Smirnov test

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

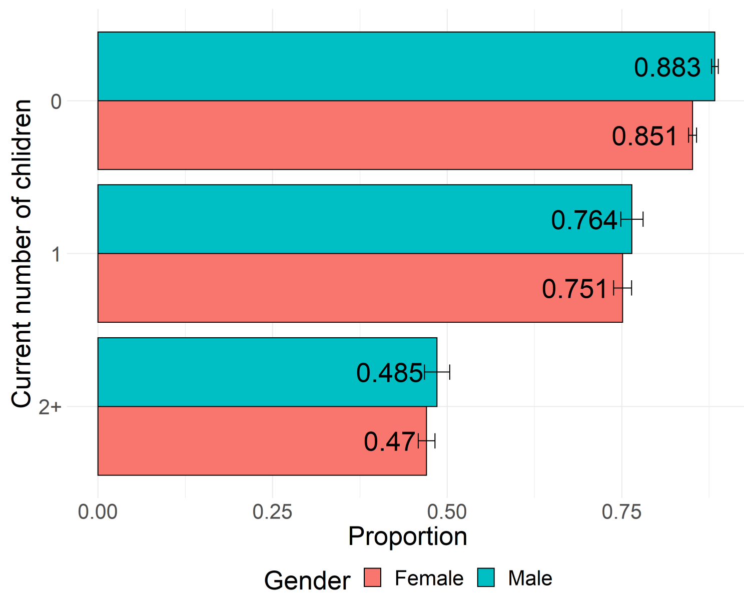
Notes: The table shows p-values from Kolgomorov-Smirnov tests for the hypothesis that the empirical and simulated distributions in the figure 7 are equal.

Figure A.13: Histogram of cohort sizes and probability that the sex ratio does not deviates from balance by x percentage points



Notes: Figure shows theoretical probabilities of deviations from a balanced sex composition derived from the binomial distribution with probability of success 0.5 and number of trials equal to number of births (on x axis). Red dots show probability that the deviation from 0.5 is smaller than 0.01, green dots that the deviation is smaller than 0.05, and blue dots that the deviation is smaller than 0.1. Histogram represent the empirical distribution of the size of cohorts in the data. As the size of the cohort increases, probability of any deviations being very small converges to 1. Nonetheless, in small cohorts there is still substantial amount of deviations.

Figure A.14: Do you want to have another child?



Notes: Figure shows proportion of respondents who want to have an additional child. Blue represents male respondents and red respresents female respondents. The proportions are further stratified by the number of chlidren already born to the respodent (*current number of children*). Based on National Survey of Family Growth 2011-2019.

A.2 Results Using the Sex Ratio

Table A2: First Stage and Sex Ratio

Dependent Variable:	Sex Ratio in 2010
Model:	(1)
Variables	
Sex ratio at birth	0.2280***
	(0.0228)
Fit statistics	
Observations	7,138,182
R^2	0.73134
Within R^2	0.06101
F-test (IV only)	176,232.4
Wald (IV only)	99.602

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

Notes: This table presents first stage estimates from the IV framework. In particular, it shows a regression of sex ratio at the dating market in 2010 on the sex ratio at birth of the cohort and covariates. The regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and 2010 and controls for cohort size at birth and in 2010. Each observation represents a single birth. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom.Only markets with birth cohorts between 200-5000 births are included.

Table A3: IV: Mariage Outcomes and Sex Ratio

Dependent Variables:	Unknown Father	Married	Diff. in Edu.(years)
Model:	(1)	(2)	(3)
Variables			
Sex ratio in 2010	-0.4025***	0.7563***	0.0300
	(0.1311)	(0.1840)	(0.5214)
Fit statistics			
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 (1st stage), Sex ratio in 2010	96.1	98.0	79.7

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

This table presents first stage estimates from the IV framework. In particular, it shows a regression of sex ratio at the dating market in 2010 on the sex ratio at birth of the cohort and covariates. The regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. Each observation represents a single birth. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom.Only markets with birth cohorts between 200-5000 births are included.

Table A4: IV: Maternal Outcomes and Sex Ratio

Dependent Variables:	Chlamydia	Gonorrhea	Syphilis	Diabetes	Hypertension
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Sex ratio in 2010	-0.0676**	-0.0042	-0.0019	-0.0317*	-0.0955***
	(0.0266)	(0.0093)	(0.0049)	(0.0169)	(0.0322)
Fit statistics					
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 (1st stage), Sex ratio in 2010	97.3	97.3	97.3	96.6	96.6

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

This table presents estimates from IV regressions of infant health outcomes on sex ratio on the dating market in 2010 and other covariates. Sex ratio in 2010 is instrumented with sex ratio at birth of the cohort. Columns' titles indicate the specific outcomes. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010.. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom. Only markets with birth cohorts between 200-5000 births are included.

Table A5: IV: Neonatal Outcomes and Sex Ratio

Dependent Variables:	Preterm Birth	Low BW	Low APGAR	Assisted ventilation	Death
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Sex ratio in 2010	-0.0798	-0.0644	-0.0512**	-0.0681*	-0.0013
	(0.0545)	(0.0461)	(0.0251)	(0.0413)	(0.0084)
Fit statistics					
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 (1st stage), Sex ratio in 2010	97.2	97.5	97.0	96.5	96.0

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

This table presents estimates from IV regressions of maternal health outcomes on sex ratio on the dating market in 2010 and other covariates. Sex ratio in 2010 is instrumented with sex ratio at birth of the cohort. Columns' titles indicate the specific outcomes. Note that Chlamydia, Gonorrhea and Syphilis are dummies equal to one if an infection was diagnosed during pregnancy. Diabetes and Hypertension are dummies equal to one if woman had a disease before the pregnancy. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. Each observation represents a single birth. Standard errors are clustered at the County-Race level. Wald statistic (Kleibergen-Paap) for the first stage is presented at the bottom. Only markets with birth cohorts between 200-5000 births are included.

A.3 Results Using Larger Sample: Birth Cohorts sized 200-10000

Table A6: Marriage Outcomes IV: Large Cohorts

Dependent Variables:	Unknown Father	Married	Diff. in Edu.(years)
Model:	(1)	(2)	(3)
Variables			
Prop. male 2010	-0.3685***	0.7678***	-0.5424
	(0.1313)	(0.1860)	(0.5043)
Fit statistics			
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 (1st stage), Prop. male 2010	108.8	111.2	91.7

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

This table presents estimates from IV regressions of marital outcomes of birthing women 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. Columns' titles indicate the specific outcomes. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-10000 births are included.

Table A7: Maternal Outcomes IV: Large Cohorts

Dependent Variables:	Chlamydia	Gonorrhea	Syphilis	Diabetes	Hypertension
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0765***	-0.0047	0.0010	-0.0287*	-0.0830**
	(0.0274)	(0.0095)	(0.0047)	(0.0163)	(0.0338)
Fit statistics					
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 (1st stage), Prop. male 2010	109.9	109.9	109.9	109.1	109.1

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

This table presents estimates from IV regressions of maternal health outcomes 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. Columns' titles indicate the specific outcomes. Note that Chlamydia, Gonorrhea and Syphilis are dummies equal to one if an infection was diagnosed during pregnancy. Diabetes and Hypertension are dummies equal to one if woman had a disease before the pregnancy. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-10000 births are included.

Table A8: Neonatal Outcomes IV: Large Cohorts

Dependent Variables:	Preterm Birth	Low BW	Low APGAR	Assisted ventilation	Death
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0955*	-0.0778*	-0.0534**	-0.0662*	-0.0033
	(0.0526)	(0.0455)	(0.0237)	(0.0400)	(0.0082)
Fit statistics					
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 (1st stage), Prop. male 2010	110.5	110.8	110.4	109.1	108.6

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

This table presents estimates from IV regressions of infant health outcomes 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. Columns' titles indicate the specific outcomes. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-10000 births are included.

A.4 Results Using Smaller Sample: Birth Cohorts sized 200-2000

Table A9: Mariage outcomes IV: Small Cohorts

Dependent Variables:	Unknown Father	Married	Diff. in Edu.(years)
Model:	(1)	(2)	(3)
Variables			
Prop. male 2010	-0.4146**	0.7849***	0.6495
	(0.1720)	(0.2261)	(0.6442)
Fit statistics			
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 (1st stage), Prop. male 2010	52.9	52.4	43.0

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

This table presents estimates from IV regressions of marital outcomes of birthing women 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. Columns' titles indicate the specific outcomes. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-2000 births are included.

Table A10: Maternal Outcomes IV: Small Cohorts

Dependent Variables:	Chlamydia	Gonorrhea	Syphilis	Diabetes	Hypertension
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0891***	-0.0142	-0.0030	-0.0465**	-0.1088**
	(0.0345)	(0.0115)	(0.0062)	(0.0213)	(0.0428)
Fit statistics					
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 (1st stage), Prop. male 2010	53.5	53.5	53.5	53.1	53.1

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

This table presents estimates from IV regressions of maternal health outcomes 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. Columns' titles indicate the specific outcomes. Note that Chlamydia, Gonorrhea and Syphilis are dummies equal to one if an infection was diagnosed during pregnancy. Diabetes and Hypertension are dummies equal to one if woman had a disease before the pregnancy. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-2000 births are included.

Table A11: Neonatal Outcomes IV: Small Cohorts

Dependent Variables:	Preterm Birth	Low BW	Low APGAR	Assisted ventilation	Death
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Prop. male 2010	-0.0201	-0.0290	-0.0523	-0.0776	0.0008
	(0.0698)	(0.0592)	(0.0336)	(0.0527)	(0.0109)
Fit statistics					
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 (1st stage), Prop. male 2010	53.3	53.5	53.1	53.1	52.8

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

This table presents estimates from IV regressions of maternal health outcomes 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. Columns' titles indicate the specific outcomes. Note that Chlamydia, Gonorrhea and Syphilis are dummies equal to one if an infection was diagnosed during pregnancy. Diabetes and Hypertension are dummies equal to one if woman had a disease before the pregnancy. Each regression contains County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects and controls for cohort size at birth and in 2010. The coefficient on *Prop. male 2010* correspond to β in equation 4. Each observation represents a single birth. 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). Only markets with birth cohorts between 200-2000 births are included.

A.5 Assigining 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 **?** 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 commited 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 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.

A.6 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 county c search partners across multiple counties which belong to a set C (similar argument can be made about the 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 $\alpha_{c,c'}$ measures how often women from county c link with men from county c' and it sums 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:

$$\begin{aligned}
\underbrace{PM^T_{cra}}_{\substack{\text{Proportion Male}\\ \text{At the True Market}}} &= \frac{\sum_{c'\in C}\alpha_{c,c'}n^m_{c'ra}}{\sum_{c'\in C}\alpha_{c,c'}n_{c'ra}} = \\
&= \sum_{c'\in C}\underbrace{\frac{\alpha_{c,c'}n_{c'ra}}{\sum_{c'\in C}\alpha_{c,c'}n_{c'ra}}}_{\gamma_{c'}}\frac{n^m_{c'ra}}{n_{c'ra}} = \\
&= \gamma_c\frac{n^m_{cra}}{n_{cra}} + \sum_{c'\neq c}\gamma_{c'}\frac{n^m_{c'ra}}{n_{c'ra}} = \underbrace{\gamma_c}_{\gamma_c<1}\frac{n^m_{cra}}{n_{cra}} + e_{cra} = \\
&\gamma_c \underbrace{PM_{cra}}_{\substack{\text{Proportion Male}\\ \text{At the Limited Market}}} + e_{cra}
\end{aligned} \tag{10}$$

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:

$$Y_{cra} = \beta PM^T_{cra} + \epsilon_{cra} = \beta\gamma_c PM_{cra} + \beta e_{cra} + \epsilon_{cra} = \hat{\beta}PM_{cra} + v_{cra} \tag{11}$$

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

Note that IV strategy does not eliminate this bias. In particular, assume the first stage relationship:

$$PM_{cra} = \delta PMB_{cra} + \tau_{cra}$$

. Then the IV estimate is:

$$\begin{aligned}
\hat{\beta}_{IV} &= \frac{cov(PMB_{cra}, y_{cra})}{cov(PMB_{cra}, PM_{cra})} = \frac{cov(PMB_{cra}, \beta PM^T_{cra} + \epsilon_{cra})}{cov(PMB_{cra}, \delta PMB_{cra} + \tau_{cra})} \\
&= \frac{cov(PMB_{cra}, \beta\gamma_c PM_{cra} + \beta e_{cra} + \epsilon_{cra})}{\delta var(PMB_{cra})} \\
&= \frac{cov(PMB_{cra}, \beta\gamma_c\delta PMB_{cra} + \beta\gamma_c\tau_{cra} + \beta e_{cra} + \epsilon_{cra})}{\delta var(PMB_{cra})} \\
&= \frac{\beta\gamma_c\delta var(PMB_{cra})}{\delta var(PMB_{cra})} = \beta\gamma_c < \beta
\end{aligned} \tag{12}$$

Now assume conversely that the measured market is too large. In this case a measurement error arises, which is eliminated by the IV. Finally, both errors can be present, in which case IV eliminates measurement error but does not eliminate the error stemming from too small market definition.

A.7 Dating market model

In this section I solve a dating market model which demonstrates the effect of sex ratio on 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:

$$u_i(q_i, Q) = q_i Q$$

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 an 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 am 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:

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

   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 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, the second highest income man with the second 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:

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

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. While we now know how matches with whom in equilibrium, we still do not now how the resources are allocated among private goods within a couple.

3. **Individual utility allocation**

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

   (a) Marriage participation constraint

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

   The first condition states that for any pair of man and woman, their individual 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 equilibrium, and it is an equality for couples matched in equilibirum. This condition is related to the stability of matching: switching partners could never generate enough of surplus to make a 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.

Using the above conditions pins 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 in the sex ratio. There are two channels leading to this result. First, through matching. As there are more men available on the market, woman can secure a higher quality partner. Second, through resource allocation. As there is more competition among men, they need to provide women with higher private consumption to sustain the partnership.

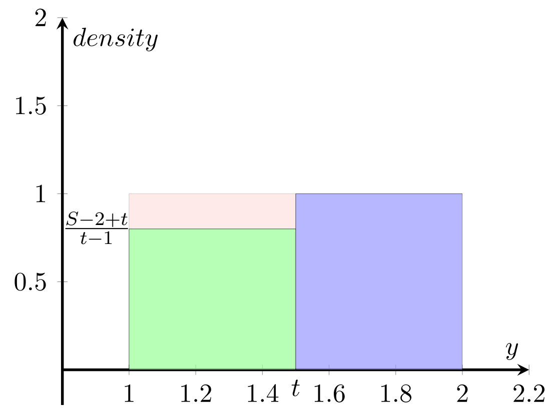


Figure A.15: Distribution of men

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.

A.8 Dating market model: restrictions on men available

The previous model assumes that we add men from all around the income distribution. Would the effect be different if we only add men at 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 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 at the bottom utility are added to the dating pool. In fact, women at the top of the distribution benefits the most, independently of the quality of men added.

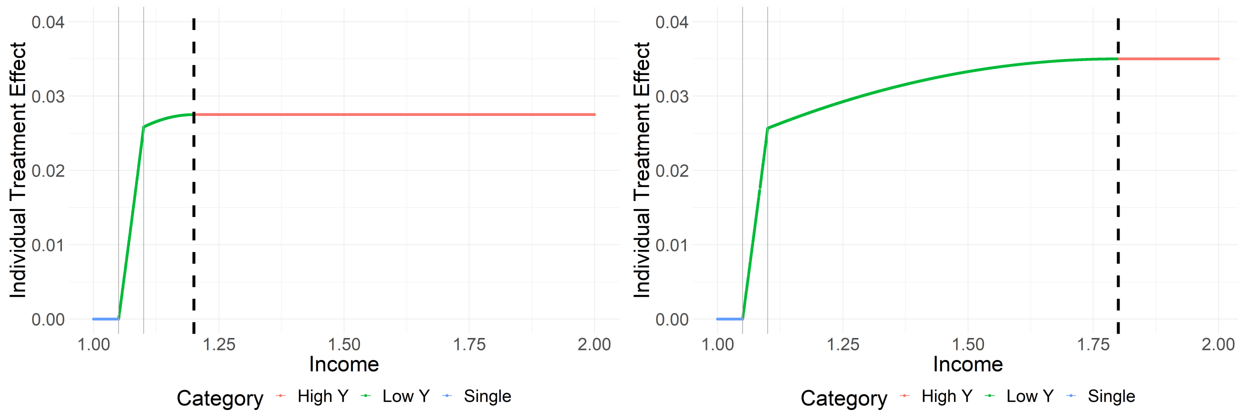
The new assumption of male distribution is schematically illustrated in the figure A.15. The mass of men with income $y_m > t$ (blue rectangle) never changes. When once changes S, it is only through removing or adding men with income $y_m < t$. The green rectangle on figure A.15 represents men with income 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 A.7.

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

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

We 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 $t \in \{1.2, 1.8\}$[20]. The first value, $t = 1.2$, corresponds to the situation where only low-human capital 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 of individual female utility (*individual treatment effect*) resulting from the increase in the sex ratio. Figure A.16 illustrates the results.



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

Figure A.16: Individual Treatment Effect

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 sublot 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 decomposed in 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 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 market0). 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 higher utility to their partner. Hence, current partners of women with $y_f > t$ need to allocate more resources

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

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. Although their partners don't necessarily change, they benefit from a better outside option, and hence they enjoy a more favorable resource allocation in equilibrium.

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.

We 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 A.17. It plots the ratio of average treatment effect (ATE) for a given level of t compared to ATE at $t = 2$. Even at the lowest value of t, so adding only men with very low potential income, the ATE is still higher than 75% of the baseline ATE when men across the distribution are added to the pool.

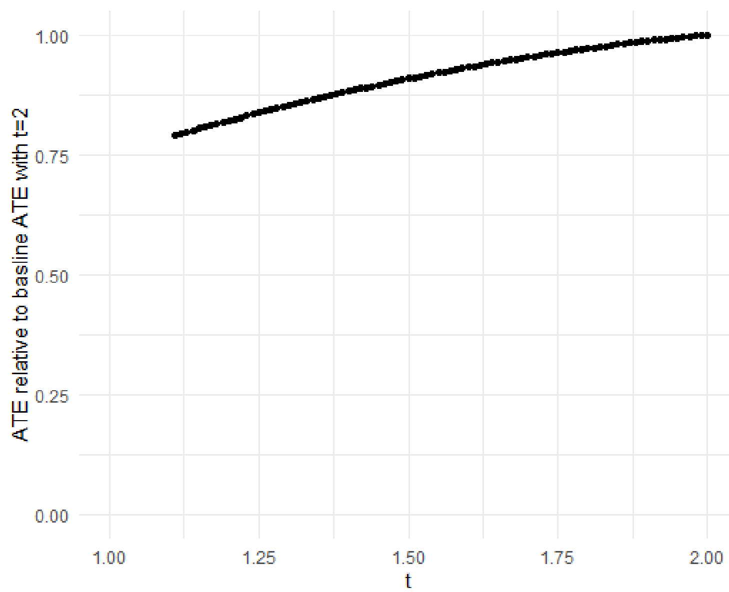


Figure A.17: ATE(t) relative to ATE(2)

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.