The Effect of Dating Markets on Maternal and Neonatal Health

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Abstract

This paper provides causal evidence that the sex composition of dating markets affects maternal and neonatal health. Using a novel instrument that leverages randomness in sex at birth to vary the availability of male partners, I find that a more favorable dating market for women reduces fertility—primarily through fewer out-of-wedlock births—lowers rates of chlamydia and hypertension among mothers, and decreases the incidence of low APGAR scores and a composite index of adverse birth outcomes. These effects appear to operate primarily through changes in relationship dynamics and selection into motherhood. Connecting this to inequalities, racial disparities in partner availability can explain 5–10% of the Black–White pregnancy health gap.

JEL Classifications: J12, J13, J15, I14

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1 Introduction

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

While these health inequalities are persistent and have been well documented (Louis et al. (2015); Hill et al. (2022)), their specific causes have proven difficult to pin down. Black women are exposed to many correlated factors that may negatively impact pregnancy outcomes. For example, they more frequently experience discrimination in healthcare, suffer consequences of structural racism, and are more likely to be poor[3]. Nonetheless, even accounting for differences in socioeconomic variables, racial health inequalities persist Kennedy-Moulton et al. (2022).

An underexplored factor contributing to racial disparities in health and fertility outcomes is the sex composition of dating markets. The relative supply of male and female partners plays a central role in shaping dating, marriage, and partnership dynamics (Becker, 1973), which, in turn, are key determinants of reproductive behavior and birth outcomes. A growing body of evidence documents that a stronger female position in relationships is positively is positively associated with the health and welfare of both women and children (Rao (1997); Stevenson and Wolfers (2006); Li and Wu (2011); Armand et al. (2020)). Accordingly, disparities in the relative supply of partners—and, by extension, in individuals' positions within the dating market—may contribute to differences in health outcomes. This aspect

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

[2] See figure III

[3] See Aizer et al. (2004); Lillie-Blanton and Hoffman (2005); Almond et al. (2006); Buchmueller et al. (2016); Hoffman et al. (2016); Kuziemko et al. (2018); Eli et al. (2023); Alsan and Wanamaker (2018); Ly (2021); Bailey et al. (2021); Lane et al. (2022); Hoynes et al. (2011); Almond et al. (2011); Fryer et al. (2013); Elder et al. (2016); Carruthers and Wanamaker (2017), among many others.

is particularly salient in the US context, where Black women face unfavorable sex ratios in dating markets[4]. More than 90% of relationships involve partners of the same race, and there are only 89 Black men for every 100 Black women, compared with 102 White men for every 100 White women. However, isolating the impact of sex composition in dating markets is challenging due to its endogenous nature. As a result, a significant gap remains in understanding the causal effects of dating market sex ratios on pregnancy outcomes and health disparities.

This paper aims to bridge this gap by providing novel causal evidence that the sex composition of dating markets has meaningful effects on maternal and neonatal health, with strong indications that the dating market is a primary mechanism. Specifically, it has two principal goals: (1) to examine whether imbalances in the sex composition of dating market affect pregnancy outcomes in the U.S., and (2) to evaluate how racial disparities in sex compositions may contribute to persisting health gaps.

The key contribution of this paper is a novel identification strategy that addresses the endogeneity of local sex composition - a longstanding challenge in this area of research. For instance, high levels of violent crime or incarceration can simultaneously deplete the supply of potential male partners and adversely affect health outcomes. To overcome this, I develop an instrumental variables approach that exploits random fluctuations in the probability of male births. Specifically, I focus on heterosexual dating markets defined by the intersection of residence, race, and age groups[5]. Then, I instrument local, adult sex ratios with the cohort sex ratios at birth, exploiting the near-random 50% probability of being born male or female and low spatial mobility. In smaller markets where the law of large numbers hasn't fully "kicked in", this randomness often creates imbalanced sex ratios, which persist into adulthood.

To validate this strategy, I carefully examine potential identification concerns related to

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

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

the endogeneity of sex ratios at birth. First, I present evidence suggesting that maternal health, socioeconomic status, and economic or environmental conditions during pregnancy are not systematically related to the probability of male birth in my sample. Second, I find no indication that sex-selective abortions, stopping rules, or selective migration drive the results. The observed variation in sex ratios at birth aligns precisely with what would be generated by a simple Bernoulli process. Finally, placebo tests suggests that sex ratios at birth predict adult sex ratios within their own cohort but not across other cohorts, even within the same county and racial group, consistent with random variation independent of local factors.

I leverage this variation to examine how differences in the relative availability of males influence fertility as well as maternal and neonatal health across 7 million U.S. births (2011–2019). While my focus is on health outcomes, this identification strategy is broadly applicable to other behaviors shaped by local sex composition, such as migration decisions or household consumption. A concurrent and complementary study by Goldman et al. (2024) uses a similar variation to explore marital homophily by race and class.

I find that a sex ratio favorable to women in the dating market plays a significant role in shaping decisions about childbearing and, subsequently, maternal and neonatal health. First, I observe that a one standard deviation increase in the proportion of men reduces the birth rate per 1000 women by 6.8% relative to the mean, with most of the effect driven by a decline in non-marital births. Second, I find significant shifts in marriage market outcomes. Specifically, a one standard deviation increase in the proportion of men increases the share of married women by around 2.85 percentage points in the general population and by 2.7 percentage points among mothers. It also decreases the share of births with unknown fathers by 1.4 percentage points, reflecting overall positive selection into motherhood. Third, maternal health outcomes improve when women have a more favorable position in the dating market. A one standard deviation increase in the proportion of men reduces the prevalence of chlamydia among women giving birth by 12% and hypertension by 16%, relative to their respective means. Fourth, infants born in markets with a stronger female position exhibit better health outcomes. A one standard deviation increase in the proportion of men reduces the likelihood of a newborn receiving a low APGAR score by 7.8% relative to the mean. While other outcomes, such as birth weight, gestational age, and the need for assisted ventilation, show effects in the expected direction, they remain below conventional levels of statistical significance.

The findings indicate that the sex composition at birth has a meaningful impact on birth outcomes in the next generation. I explore several potential mechanisms through which this effect may operate. The evidence points to the dating market as an important channel: it can shape long-term outcomes—such as maternal health—through selection into motherhood and family formation, as well as short-term outcomes—such as STD exposure—through changes in sexual behavior and partner networks. Both theoretical considerations and empirical patterns are consistent with the dating market playing a central role in this relationship. That said, one cannot be certain it is the sole mechanism. I also examine other plausible channels, including shifts in violent behavior, peer effects, or parental divorce. These and other alternative explanations do not appear to account for a sizable share of the observed effects, though they may still contribute to some extent. Overall, the dating market emerges as a particularly salient pathway linking sex composition to maternal and neonatal health.

The effects are contextualized within policies altering male partner availability. Empirical variation in sex composition, particularly across racial groups, is partly policy-driven. A decomposition shows incarceration explains 40–50% of the Black-White sex ratio gap. Policies reducing incarceration disparities [6] could have positive secondary effects on Black women and children. In line with these findings, Boen et al. (2023) provides reduced-form evidence linking incarceration reforms to improved infant health.

A counterfactual exercise offers insights into the potential scale of health disparities

[6] Section 4.2 reviews literature showing that the disparity in incarceration rates is partly shaped by an interplay of biases and policies. It also discusses specific initiatives aimed at reducing disparities in incarceration.

arising from unequal sex compositions in U.S. dating markets. If Black women faced the same dating markets as White women, disparities in pregnancy outcomes would shrink by 5–10%. A policy modestly narrowing sex ratio disparities, akin to equalizing incarceration rates for non-violent offences between Black and White people, could still prevent 200-700 adverse pregnancy outcomes per year among Black mothers through its effect on the dating market alone. While cautious about extrapolating the causal results to the population of non-violent inmates, I show theoretically that an increase in the supply of men, even of low potential income, benefits all women, with high-income women gaining most due to improved outside options across the income distribution.

The primary contribution of this paper is to offer novel causal evidence on the link between the sex composition of dating markets and pregnancy outcomes. Building on Becker's foundational insight that a scarcity of women shifts relationship gains in their favor (Becker, 1973), later work highlighted how sex ratios shape bargaining power and household decisions. Grossbard-Shechtman (1984) explicitly linked sex ratios to labor supply, while Chiappori (1992) and others[7] developed models of collective decision-making that help explain how shifts in partner availability affect intra-household outcomes. Empirical studies corroborate the link between bargaining power and household outcomes (Blundell et al. (1993), Browning et al. (1994), Lundberg et al. (1997)), showing correlations with female health and safety (Li and Wu (2011); Armand et al. (2020); Rao (1997); Panda and Agarwal (2005); Stevenson and Wolfers (2006)), and child well-being and health (Beegle et al. (2001), Thomas et al. (1999), Maitra (2004), Calvi (2020)). My findings contribute to this literature by providing causal evidence that a sex ratio more favorable for women influences fertility and improves pregnancy health, with the dating market likely playing a key role. Furthermore, this study extends prior work to a high-income context where policy partially shapes dating market composition.

This study also contributes to the literature examining the impact of sex ratios in dating

[7]See also Bourguignon and Chiappori (1994), Chiappori et al. (2002), Chiappori and Ekeland (2006).

markets on relationship dynamics by exploiting a unique source of variation. While most prior work has relied on cross-sectional measures of local sex ratios (Chiappori et al., 2002; Cornwell and Cunningham, 2008; Adimora et al., 2002; Kang and Pongou, 2020) or on historical shocks to address endogeneity concerns (Angrist, 2002; Lafortune, 2013; Abramitzky et al., 2011; Brainerd, 2016; Liu, 2020; Alix-Garcia et al., 2022; Battistin et al., 2022), this paper instead leverages natural variation in cohort-level sex ratios at birth. A closely related concurrent study by Goldman et al. (2024) employs a similar identification strategy to examine patterns of marital sorting. By contrast, this paper focuses on fertility and health outcomes that are potentially shaped by relationship dynamics in response to sex ratio imbalances.

Lastly, this paper contributes by providing evidence that the sex composition of the dating market might be a non-negligible source of racial health disparities, revealing that mass incarceration may have unexpectedly exacerbated these gaps by reducing the supply of potential male partners.

My research informs policymakers that a dating market with a sex composition more favorable to women can lead to improvements in maternal and neonatal health — a crucial insight given that the U.S. faces significantly higher maternal and infant mortality rates than comparable countries (Ventures (2021)). Furthermore, early-in-utero and early life health disadvantages persist into adulthood, affecting social, educational, and economic outcomes[8] and can extend into subsequent generations, perpetuating inequalities (Andrews and Logan (2010); East et al. (2017); Giuntella et al. (2022)). This literature highlights that policies enhancing health during pregnancy yield high returns and may reduce racial health disparities. Studies in developing countries demonstrate 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)). This paper suggests that addressing racial disparities in sex ratios is an important avenue for improving early

[8]See Almond and Mazumder (2011); Barreca (2010); Currie (2009); Hoynes et al. (2016); Butikofer et al. (2016); Black et al. (2019).

health. These disparities may stem from institutional factors, such as mass incarceration.

The paper proceeds as follows. Section 2 presents the conceptual framework. Section 3 describes the data and the sample construction. In section 4, I perform the decomposition of racial differences in sex ratios. Sections 5 and 6 outline the empirical framework and results for the relationship between bargaining power and health outcomes. Section 7 explores potential mechanisms, and Section 8 presents counterfactual simulations. Section **??** concludes.

2 Conceptual Framework

While the sex composition may influence health through multiple channels, this section focuses on a particularly vital mechanism: the dating market. Section 7 explores additional pathways. 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 can influence matching and intra-household decision-making in various ways. A mechanism that has been thoroughly investigated operates through equilibrium on the marriage market. In the appendix section C.11, I motivate such mechanism by solving a simple dating market model. Focusing on intuition, suppose that there is an increase in the supply of men relative to women on the dating market. Women are now more likely to find and sustain a partnership. Moreover, the competition among men to secure a female partner becomes stronger. Experimental evidence from speed dating and dating apps indeed shows that women become more selective when they face larger pool of potential mates (Fisman et al. (2006); Fong (2020)). Consequently, a woman ends up with a higher-quality partner. A priori, whether it increases or decreases the quality of an average match is an empirical question, because it can mean that previously single, low quality woman can now find (a low quality) partner. Nonetheless, such mechanism would require strong monogamy, which is also an endogenous outcome subject to bargaining. Moreover, in economic terms, men have to "pay a higher price" for a match. Practically, the price will consist of a shift in decision power within the household, from men to women. This shift, in turn, may have diverse translations: financial transfers, more leisure time, higher partner fidelity, fewer occurrences of domestic violence, better healthcare, or shift in a decision whether to have children. While such a marriage market equilibrium mechanism requires some minimum level of intertemporal commitment, it is by no means the sole justification for the importance of the sex ratio. To take just one example, suppose an opposite (and somewhat extreme) world in which no commitment is feasible so that spouses are constantly bargaining about their joint decisions. The threat points—particularly the situation of each spouse after a hypothetical divorce—play a vital role in determining the outcome. A favorable sex ratio strengthens women's bargaining position by making it easier to find a new partner post-divorce, as matching and bargaining power are unseparably linked; the ability to secure a desirable partner enhances a woman's bargaining position. Therefore, it is reasonable to assume that the marriage market continuously influences a woman's position within a relationship, not merely at the time of its formation.

Overall, one can expect favorable shifts in the dating market to enhance female well-being and pregnancy health—a prediction supported by numerous studies through various mechanisms over both short- and long-term horizons.

First, the positive effect may result from gaining a committed partner. Two-adult households benefit from specialization and resource pooling, leading to higher incomes and better neonatal health outcomes (Hoynes et al. (2015)). Marriage itself is associated with improved pregnancy outcomes (Buckles and Price (2013)). Conversely, lower-income women face higher risks of severe adverse pregnancy outcomes (Kennedy-Moulton et al. (2022)), and being a single mother can negatively impact mental health (DeKlyen et al. (2006)).

Second, securing a higher-quality partner—whether wealthier, healthier, or more educated—can enhance health outcomes. Higher-income spouses are linked to improved women's health (Skalická and Kunst (2008)); healthier partners produce positive spillover effects on spousal health, employment, and income (Fletcher (2009); Jeon and Pohl (2017); Du and Zaremba (2024)); and partners with higher education are associated with better personal health, even after accounting for selection (Monden et al. (2003); Guo et al. (2020)).

Third, increased bargaining power and matching with higher-quality partners can reduce domestic violence and stress (Rao (1997); Panda and Agarwal (2005); Banks (2011)). These reductions lower the risk of hypertension (Zhang et al. (2013); Mason et al. (2012)) and prevent adverse pregnancy outcomes associated with these factors (Currie (2013b); Currie et al. (2018); Aizer (2011)). Moreover, greater bargaining power leads to better nutrition and improved health (Li and Wu (2011)).

These mechanisms may have long-term implications for women's health. Prolonged exposure to a more favorable dating market could generate cumulative effects, as sustained competition among men for partners may influence health behaviors, fertility decisions, household composition, and the resources available to women. Over time, these changes could shape health outcomes across a broad spectrum, resulting in women reaching childbearing age in better overall health.

Sex composition can also influence short-term health outcomes, particularly those related to sexual health and the prevalence of certain sexually transmitted infections (STIs), by shaping sexual behaviors and network structures. A low supply of men leads women to engage in shorter, higher-risk partnerships (Dauria et al. (2015)). Male scarcity is associated with more sexual partners, especially among men (Adimora et al. (2002); Cornwell and Cunningham (2008); Pouget et al. (2010)). Consequently, communities with high male incarceration—and thus low sex ratios—suffer worse sexual health outcomes (Thomas et al. (2008); Johnson and Raphael (2009); Stoltey et al. (2015); Kang and Pongou (2020)). Preventing STIs during pregnancy is crucial, as such infections are linked to poor birth outcomes (Ryan et al. (1990); Elliott et al. (1990)).

Finally, changing dynamics within couples can significantly influence childbearing decisions. Empirical evidence indicates that women typically desire fewer children than men (Westoff, 2010; Ashraf et al., 2014; Doepke and Kindermann, 2019). When women possess greater bargaining power, they may insist on contraceptive use or choose to have children only within committed relationships with adequate resources. Consequently, in dating markets favorable to women, improvements across a broad range of pregnancy outcomes and infant health may arise from positive selection into motherhood.

Thus, multiple channels might link a favorable sex ratio to improved maternal health through the dating market. We need not assume that women have specific preferences for children's well-being; it suffices that they care about their own health, as neonatal outcomes depend on maternal health during pregnancy. This assumption explains the asymmetry: improvements in male health do not directly affect birth outcomes. Moreover, if mothers prioritize children's health, greater female bargaining power may lead men to allocate more resources to satisfy this desire. Therefore, I hypothesize that increasing the proportion of men in the dating market enhances women's decision power, maternal health, and consequently, neonatal health. While the dating market likely plays a significant role in this relationship, I also consider other potential mechanisms in Section 7.

3 Sample Construction and Data

3.1 Defining Dating Markets and Computing Sex Composition

I evaluate the extent to which dating markets favor women by measuring deviations from a balanced sex composition within a woman's dating market. The explanatory variable of interest is the proportion of the dating market that is male (*proportion male* henceforth), and I compute it from the 2010 Census which provides the exact population count. While I use the proportion rather than the sex ratio, the two measures have a one-to-one relationship, and I am using the words sex ratio and sex composition interchangeably when describing the imbalance in the dating markets. Moreover, all the results are robust to using the sex ratio instead of the proportion male (see table A5).

I define dating markets as the intersection of age group, race, and county. In other words, I assume that individuals within the same 5-year age cohort, of the same race, and residing in the same county participate in a single dating market. Naturally, alternative conceptualizations of the dating market exist, encompassing broader geographic regions such as states, varying age brackets by gender, and diverse racial compositions. For instance, an alternative definition could conceptualize the market to reflect age differences sometimes observed in couples, such as older men dating younger women. While each alternative definition can help to represent a different aspect of the market, my approach does not aim to capture the entire market. Even partial shifts in the market can significantly alter market power. In the context of new parents within the natality data, 42% of couples fall within my definition of the market [9]. While this approach does not encompass the entire population, it focuses on a segment substantial enough to influence dating dynamics and bargaining power across the market. Shifts in this segment should influence the decisions of most participants by altering their outside options. At the same time, my definition aims to preserve the validity of the research design and remain consistent with data constraints. Furthermore, as shown in Appendix C.10, allowing for relationships that cross the boundaries of my definition would make my current estimates conservative. Additionally, my research focuses on individuals of heterosexual orientation; a substantial portion of the population may prefer same-gender partners, for whom the sex ratio would not serve as a relevant measure of bargaining power, making my current methodology inapplicable. Finally, I include married individuals in the dating pool, as they can either divorce or engage in extramarital affairs, thereby remaining potentially available partners and relevant to the bargaining dynamics.

My definition of the market also follows previous literature such as Chiappori et al. (2002), Charles and Luoh (2010), Cornwell and Cunningham (2008), and Johnson and Raphael (2009), except that I reduce the geographic scope of the markets to the county. Two reasons

[9] Figures in the section A.1 demonstrate measures of shares of couples formed within the market by the market type.

motivate this choice. Firstly, search patterns are usually local. People typically find partners through friends, at local events, or online (Rosenfeld et al. (2019)). Friendship networks tend to be local (Backstrom et al. (2010), Laniado et al. (2018)). Even in the online dating apps, users tend to look for partners locally, with 2/3 of respondents of the survey by Kirkham (2019) setting their search radius to 30 miles or less. Moreover, dating usually requires physical proximity at a high frequency. Goldman et al. (2024) Shows that 70% of couples lived in the same county 5 years prior to marriage. Additionally, to assess the geographic scope of the market, I examine whether the marriage rate in a county is influenced by the sex composition (at birth) of the dating markets in neighboring counties. With a high level of confidence, I can rule out any significant effects of such cross-county spillovers (table A7). Importantly, I can accurately compute sex composition among non-incarcerated populations in a county by leveraging exact population counts on the census-block level. While the procedure requires substantial computing power, using this method based on the Census summary files helps to overcome limitations of traditionally used ACS or Census microdata samples, which provide information only on higher geographic level and contain substantial sampling variation[10].

Age is the second criterion that I use to define dating markets. People must be in the same age cohort to belong to one market. The cohorts are people aged 15-19, 20-24, 25-29, and 30-34 in 2010. These groups stem from the cells' definition in the Census Summary tables, but they reflect the age composition of partnerships relatively well. Figure A.1 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 group.

The final criterium is racial homophily. I use four racial groups: White, Black, Asian, and Native Americans[11]. People tend to date within their own race for either availability or

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

[11]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.

preference reasons. Evidence from a speed-dating experiment corroborates a racial preference among women (Fisman et al. (2008)). This pattern is clear in the natality data, especially for White and Black mothers (figure B.18 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[12]. Interracial parents are slightly more frequent in smaller locations (figure A.6 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)[13]. I expect my measure of the strength of one's position in the dating market to be less noisy in markets with fewer interracial relationships. Indeed the heterogeneity analysis (in the appendix figure: C.23) shows that the main results are stronger in more racially segregated locations. I find no evidence that people seek partners of a different age group or race when facing unfavorable markets (appendix section C.1). Similarly, Goldman et al. (2024) also finds minimal interracial substitution in partner choice within the marriage market.

It is important to acknowledge that, empirically, individuals tend to match on the educational attainment. However, the ability to form a relationship with a highly educated partner, often associated with higher income, can depend on how strong one's position is within the dating market. Consequently, education appears to be an endogenous variable, and thus, I do not use it to define the markets.

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

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

[13]I do not find evidence that individuals engage in more interracial relationships when facing a constrained market, though the results exhibit considerable noise.

county/race/cohort level [14].

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

3.2 Health Outcomes

I measure fertility, 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.

4 Descriptive Statistics: Sex Composition and Health Outcomes

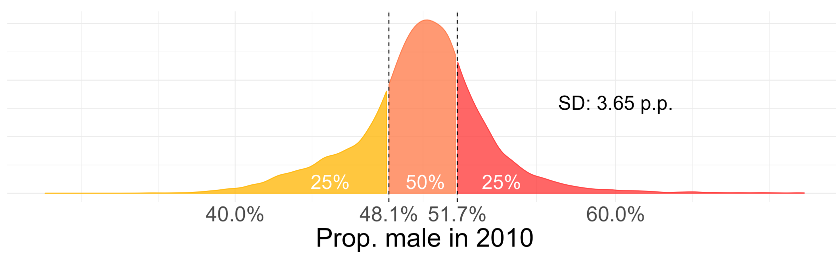
Sex composition in the US dating markets varies substantially. Notably, there are significant racial discrepancies in the sex ratio, which are largely policy driven. Moreover, the racial health inequalities coincide with racial differences in the sex ratios.

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

4.1 Variation in the sex composition of the dating markets

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

Figure I: Density of Proportion Male in 2010

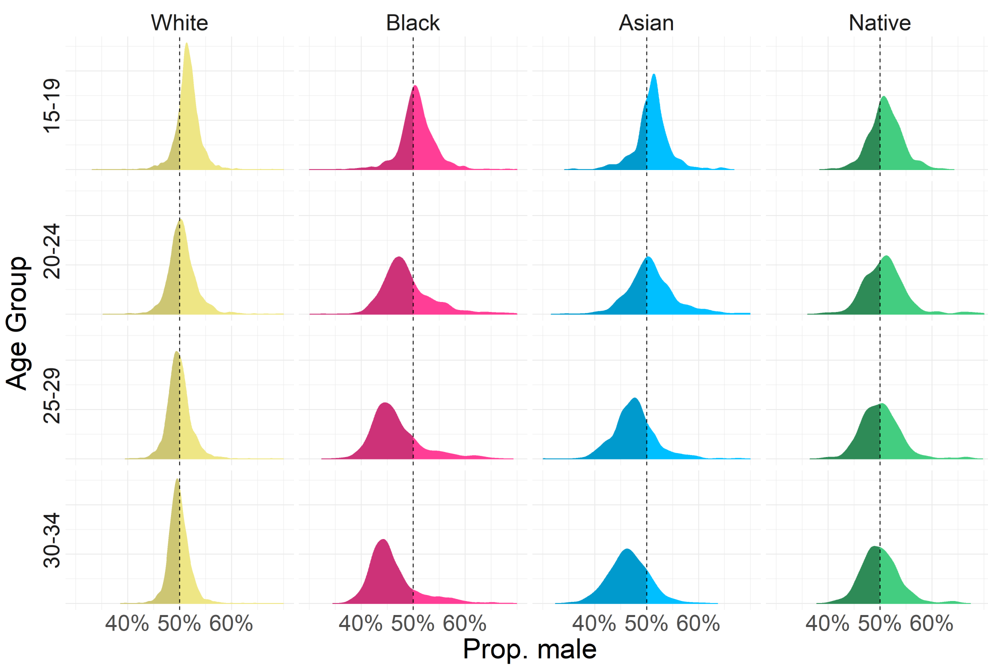


Notes: Figure shows the empirical distribution of the sex compositions. Each observation represents the proportion of men among agents on the dating market. The two vertical lines show the first and the third quartile. Standard deviation is noted on the side. Markets with fewer than 100 people are excluded.

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

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

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



Notes: Figure shows the empirical distribution of the sex composition. Each observation represents the proportion of men among agents on the dating market. The dashed line represents the balanced sex composition of 50%. Markets with fewer than 100 people are excluded. Hispanics are excluded due to the lack of relevant information in historical birth records used for the instrument.

4.2 Explaining racial differences in sex composition

To quantify how various factors contribute to racial disparities in the sex ratio, I analyze how the disparity changes when racial differences in each factor are eliminated. I construct a simple model where the number of available mates depends on parameters like incarceration rates, mortality rates, and immigration rates. By comparing the proportion of men in the actual situation to a hypothetical scenario where a chosen parameter equals that of White people (the reference group), I assess the impact of that specific factor. I present the main insights here; details on methodology, data, assumptions, and results are provided in Appendix A.2.

For Black people, the most critical driver by far is incarceration. Incarceration rates for Black males are significantly higher than for White males—10% of Black men aged 30–34 are imprisoned compared to 2% of their White counterparts. My results indicate that if Black individuals faced the same incarceration rates as White people, the difference in sex compositions would shrink by 45% (see Appendix Figure A.7a). Moreover, a substantial portion of missing Black men are incarcerated for non-violent offenses. Equalizing incarceration rates for non-violent crimes alone would reduce the racial gap in sex ratios by a quarter (see Appendix Figure A.7b). Another factor is mortality due to violence. If Black individuals had the same violent death rates as White individuals, the difference in sex compositions would decrease by approximately 5%. For Asians in the U.S., migration is the primary factor driving the scarcity of men, entirely explaining the observed gap. The difference in sex ratios between Native Americans and White Americans is minimal, at only 0.15%.

While policies like incarceration may influence outcomes through various channels beyond affecting the sex ratio, the goal of this paper is to isolate the pure effect of changes in dating market dynamics on outcomes. By doing so, it contributes to policy discussions by measuring the specific portion of the policy impact arising from the influence on the dating market.

The sex composition gap between Black and White individuals partly results from biases and policies. Black individuals are more likely than similar White individuals to be stopped and searched, arrested, prosecuted and held in pre-trial detention, and charged and sentenced more harshly [15]. Consequently, biases and policies in the criminal justice system

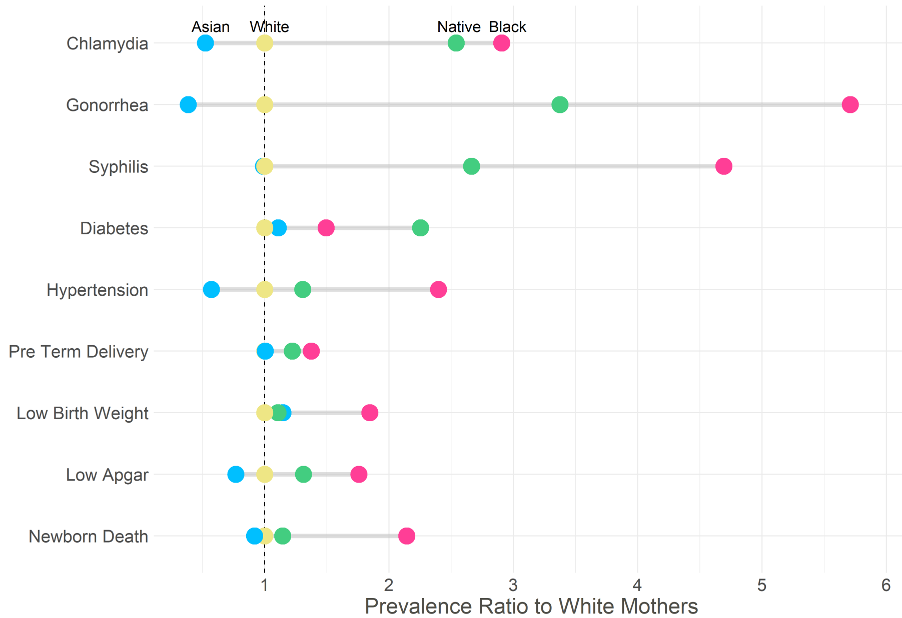
[15] See for instance: Gelman et al. (2007); Spohn (2009); Sutton (2013); Rehavi and Starr (2014); Kochel et al. (2011); VERA (2012); Mitchell and Caudy (2015); Arnold et al. (2018); Mastracci (2018)

have led to a disproportionate number of Black men being incarcerated. Section A.2 reviews the literature on the causes of disproportionate incarceration of Black men and criminal justice initiatives that could mitigate incarceration disparities without compromising public safety. Implementing these policies would not only narrow the sex ratio gap but also enhance marriage market prospects for Black women and, as argued in this paper, improve the health of Black infants. Indeed, racial differences in sex composition are closely associated with disparities in health outcomes.

4.3 Large racial disparities in maternal and neonatal health

Fertility rates are higher among Black women and their pregnancy outcomes are notably worse than those of White women. Between 2011 and 2019, the annual birth rate per 1,000 women averaged 57.4 for White women, 63.2 for Black women, 58.1 for Asian women, and 63.2 for Native American women. Additionally, over 60% of births to White and Asian women occur within marriage, compared to just 32% for Native American women and 28% for Black women (Figure A.5a). Figure III highlights the disparities in pregnancy outcomes. It sets the prevalence of an outcome among White mothers as a benchmark. Next, it shows how much larger is the prevalence among another racial group when compared to White mothers. Asian women have similar health outcomes as White women. Asian mothers are considerably more likely to be highly educated (see figure A.9 in the appendix) and education is strongly correlated with health outcomes (figures A.10, A.11). Such advantage likely compensates other drawbacks that may hamper health in this racial group. Native and Black women had a higher prevalence of negative outcomes for each measure, with much higher severity among Black mothers. Compared to White women, Black women are at 3 times higher risk of having chlamydia, 5.7 times higher risk of Gonorrhea, and 4.8 times higher risk of having Syphilis during pregnancy. Moreover, they are more likely than White women to have hypertension and Diabetes pre-pregnancy. Black infants are more often delivered too early, with low birth weight, and more frequently have too low APGAR scores. Finally, Black infants are twice as likely to die shortly after birth. Importantly, these inequalities cannot be explained by differences in socio-economic measures such as education: they persist at each education level, as the figure A.11 in the appendix shows. I also show that disparities in deaths cannot be explained by differential marital rates (figures A.5a and A.5b in the appendix).

Figure III: Racial Disparities in Pregnancy Outcomes

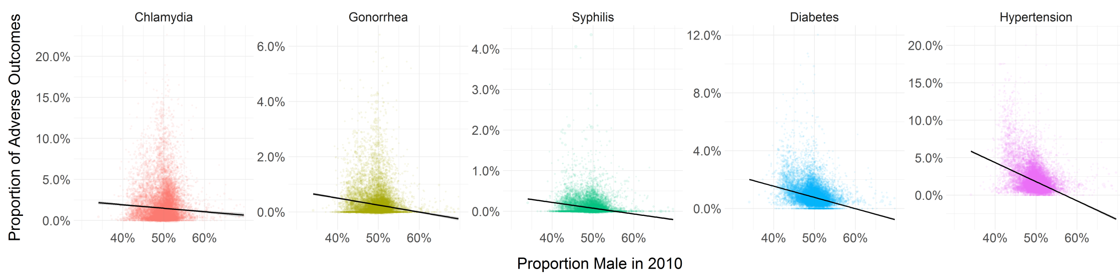


Notes: The light dots on the dashed line correspond to the baseline of the White mothers. Other dots represent the ratio of the average prevalence of a morbidity among a racial group to the average prevalence among White mothers.

The health gap between White and Black mothers has been attributed to various sources. Structural racism is an important factor explaining this phenomenon (Bailey et al. (2021)). Past policies affected housing and socioeconomics situation of Black people (Williams and Collins (2001)) and their access to healthcare (Alsan and Wanamaker (2018), Hoffman et al. (2016), Ly (2021)). As the consequences of racist policies are persistent, they co-determine the population's current health. For instance, black people are still more likely to live in neighborhoods exposed to pollution (Lane et al. (2022)), which damages infant health (Currie et al. (2009); Currie (2013a)). In addition, Black people are insured at lower rates (Buchmueller et al. (2016), Lillie-Blanton and Hoffman (2005)).

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

Figure IV: Relationship between Sex Composition and Health Outcomes



(a) Maternal Outcomes

(b) Infant Outcomes

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

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

5 Relationship Between Health and Sex Composition: Empirical Framework

5.1 Basic approach

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

$$y_{i,cra} = \beta PM_{cra} + \gamma X_i + \epsilon_i \tag{1}$$

The left-hand side variable is an outcome $y_{i,cra}$ of a mother i who resides in a county c, is of race r, and is from cohort a. The main independent variable of interest is PM_{cra}, which measures the proportion of men in the mother's dating market identified by county c, race r, and the cohort a.

The number of observations allows to include a large set of controls and fixed effects that could potentially alleviate the issue of the endogeneity. The X_i includes control variables and fixed effects. In particular, I control for the cohort size as measured in 2010. I also include *County-Age at birth* fixed effects , *Race-Age at birth* fixed effects $\delta_{r,y-b}$ and *Race-Single Age Cohort*. These variables aim to capture the variation that may produce a spurious correlation between the proportion of males and health outcomes. County economic characteristics may impact both migration of young people and health outcomes; hence I control for the county fixed effects and allow them to be age specific. Furthermore, there exist substantial racial differences in sex composition and health which may be caused due to third factors. To ensure that my results are not driven by these cross-racial differences, I include interactions between race and age, as well as race and cohort, to flexibly account for these variations. Controlling for single years of age helps to reduce the variance of the residuals as pregnancy outcomes vary considerably and non-linearly with age. Moreover, it is crucial to compare women of the same age, as cohort differences may influence the timing of the observed childbearing. Mother's age at birth does not appear to be moved by market imbalance as documented in the table A11. Results are qualitatively unchanged when excluding mother's age from controls. Hence, I effectively compare women of the same race giving birth at the same age, while accounting for cohort-specific and county-specific factors. The remaining standard deviation in the proportion male after accounting for all the fixed effects and covariates is 2 percentage points. Results are qualitatively unchanged when including alternative sets of fixed effects in the model. While other maternal and paternal characteristics, such as parents' education, are available in the data set, controlling for them in the regression could lead to a bias, as they might be affected by the treatment (sex ratio), and hence they are bad controls (Angrist and Pischke (2009)).

5.2 Endogeneity Concerns

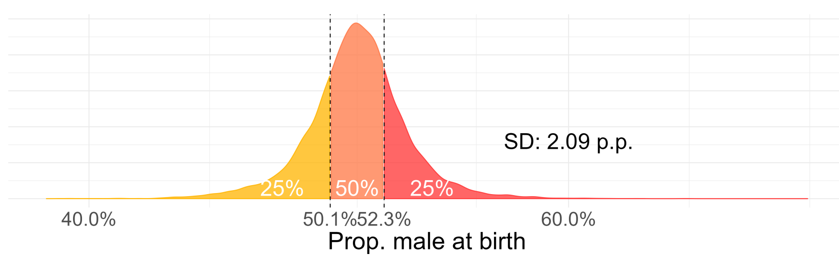
The parameter β captures the treatment effect if the variable PM_{cra} is uncorrelated to residuals when conditioning on controls. This assumption presumes that within race-age and county-age variation in sex composition is not related to other factors that could determine health outcomes. Nonetheless,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

5.3 Instrumental Variables Approach

Hence, to isolate the exogenous variation in sex composition, I leverage randomness in the sex ratio at birth. The instrument for PM_{cra} is the proportion of male births or race r 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 1975-1995. This dataset permits to calculate number of boys and girls born in each county, race, and month-year. Figure V shows the distribution of the instrument together with its standard deviation and the first, and the third quartile. Figure A.12 in the appendix shows the distribution of the sex composition at birth by race and cohort.

Figure V: Density of Proportion Male at Birth



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

The primary motivation behind this instrument relies on three assertions. First, the instrument is relevant because a substantial amount of people live close to their childhood homes. The demographic structure of the generation tends to be locally persistent and, consequently, the sex composition at birth helps to predict the proportion of men in the future. Second, the exogeneity plausibly holds because sex at birth is predominantly random. Hence, it might be reasonable to assume that it is exogenous to pregnancy outcomes observed

20–30 years later, when women in this cohort reach childbearing age. Third, while various potential mechanisms could mediate the direct relationship between the sex ratio and health outcomes, my findings suggest that the dating market is a particularly important channel.

5.4 Relevance

The first assertion can be corroborated using *Opportunity Insights* data. Chetty et al. (2018), using various administrative sources, followed the cohort born between 1978 and 1983 until their adulthood. While there is no direct answer to how many people still live in their childhood county, data provides information on the share of adults who live in the same commuting zone (CZ) and the same census tract (CT). CZ is larger than a county and CT is smaller than a county, so they provide upper and lower bounds on the share of adults living in their childhood county. Figure A.13 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 100 miles. Hence, one may expect a non-negligible amount of persistence in the sex composition of local cohorts.

5.5 Exogeneity

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

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

Figure VI illustrates this pattern empirically. The sex composition is nearly balanced in all the largest markets[16]. However, significant variation in the proportion of male births is observed in smaller markets. This variation can be attributed to chance, where some cohorts happen to have more male or female births. Since these cohorts are small, they remain unbalanced. Ashlagi et al. (2017) demonstrate theoretically that even small imbalances can significantly influence matching markets. The variation becomes negligible only in cohorts with more than 5000 births, representing less than 20% of the markets. Hence, I exclude them from the main analysis[17]. Nonetheless, choosing a different thresholds (2000 or 10000) 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.

The sample restricted in this way covers around 27% of all Americans in these cohorts and 33% of births during the study period. For illustration purposes, some counties with the smallest cohorts are Polk County, Florida, for its Asian population, and Cheyenne County in Kansas, for White people. Conversely, some counties with the largest cohorts are Middlesex County, New Jersey, for its Asian population, and Escambia County, Florida, for Black people. Hence the sample can include markets in large urban counties with populations in the millions, and as shown in Appendix section B.2, the urban markets play a significant role in driving the results. Focusing on small markets may have implications for the estimated treatment effect, a topic I address when discussing the first stage.

[16] The sex ratio at birth slightly skews toward men.

[17] In over 80% of county-race pairs, all four cohorts enter the sample. Although applying the 5,000 threshold leads to the exclusion of some cohorts in specific county-race pairs that exceed this cutoff, increasing the threshold reincorporates these cohorts, and the results unchanged remain.

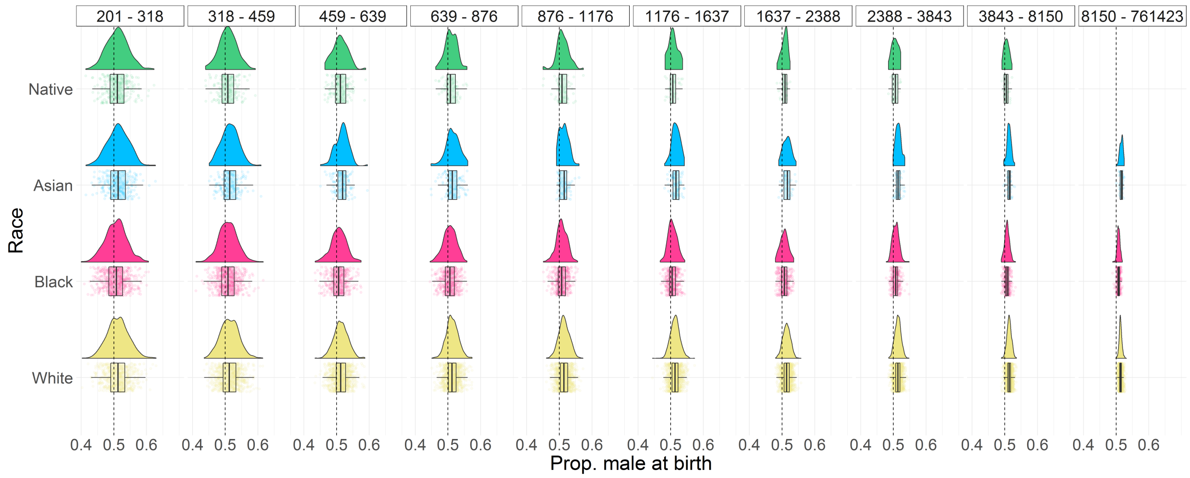


Figure VI: Density of Proportion Male at Birth by Cohort Size

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

I further provide a series of robustness checks to show that sex ratio at birth is not affected by a range of potential confounders. A potential issue arises if the sex ratio at birth is influenced by socioeconomic factors, as these factors could also affect health outcomes in subsequent generations. Likewise, it would be problematic if healthier women are more likely to give birth to male children and if health is transmitted intergenerationally. A particular concern stems from Trivers-Willard hypothesis stating that good conditions tend to favor male offspring, which found some evidence in societies with son-preference (Lee and Orsini (2017, 2018)). However, I conduct detailed examination in the appendix section C.7 to show that, in my sample, the sex ratio at birth is not predicted by the mother's education, age, relationship status, or local economic conditions during pregnancy. I also provide evidence that pollution is not influencing the sex ratio at birth. Moreover, in the same section, I demonstrate that even severe health conditions such as syphilis, which are associated with high rates of stillbirths and neonatal mortality, do not predict the sex of the child in my sample, challenging the Trivers-Willard hypothesis. Finally, as a placebo test, I regress the probability of male birth on the instrumented proportion of men in the market. The absence of a substantial relationship helps rule out the hypothesis that healthier women are more likely to produce male offspring across generations as a significant driver of the results. In interpreting the null result in this and the following section, it is important to note that the coefficient value represents a change in the proportion of men from 0 to 1—an unrealistic scenario. A more meaningful approach is to consider the effect of a one-standard-deviation change in the proportion of men, approximately 0.0365, to construct a plausible range of effects. Confidence intervals based on this approach are provided in the appendix to illustrate the precision of the null results.

Moreover, a sex selective abortion could endanger this identification strategy if son preference also impacts maternal health in the next generation. While existent, sex selective abortion in the US is of small magnitude. Abrevaya (2009) finds evidence of sex selective abortion only among Chinese and Indian mothers in the US. He computes that around 2000 Chinese and Indian female births were missing in the US between 1992 and 2004, which correspond to 0.04% of Asian births. If the same rate of missingness held for my period of interest, it would change the sex composition in the Asian category by only 0.09 percentage points, which correspond to 3% of a standard deviation. Moreover, the potential effect of sex selective abortion would likely go against my hypothesis. Girls suffer worse health outcomes in communities with son preference, both in their native countries (Ganatra and Hirve (1994); Borooah (2004); Bharadwaj and Lakdawala (2013); Barcellos et al. (2014)) and in the US (Almond and Cheng (2020); Blau et al. (2020)). Consequently, one would expect worse female and maternal health in areas with a higher proportion of men induced by sex selective abortion. Overall, due to small magnitude and likely opposite effect, sex selective abortion is unlikely to drive my results. Similarly, as documented in subsection C.3, there is little evidence that stopping rules have influenced the sex composition at birth in the U.S. during the period of interest. While parity might be associated with the sex ratio at birth (Almond and Edlund, 2008), it cannot account for the observed variation. For parity to act as a confounder, it would need to vary non-randomly across markets, such that some markets have significantly higher or lower average parity, conditional on cohort, race, county, and their interactions. Additionally, to explain the observed variation in the sex ratio at birth, the standard deviation of county-level parity would need to be implausibly large—on the order of 33—given that increasing parity by one decreases the probability of a male birth by only 0.06 percentage point (appendix table A8).

Even assuming the exogeneity of the instrument, it is essential to consider the channels through which it affects health. While this paper focuses on the impact of sex composition via the dating market, other mechanisms may also play a role. I defer the discussion of the channels to the mechanisms section 7 after presenting the results. Based on the findings, I argue that the dating market is an important channel, while other mechanisms, though potentially relevant, may play a more limited role.

5.6 Specification and Outcomes

If the above mentioned assumptions hold, the instrument eliminates problems present in the OLS estimation. Firstly, it isolates the variation in the sex composition unrelated to endogenous factors such as migration, economic conditions, or crime. Hence, it improves the measurement of women's position in the dating market. Moreover, it focuses on changes in the strength of that position while keeping factors affecting household specialization constant. Consequently, it addresses a different mechanism than the one analysed by Autor et al. (2019), who investigate the gendered impact of economic shocks on household outcomes. Secondly, it guards against measurement error. As the sex ratio at birth is a persistent predictor of the sex composition in the future, it reduces the worry that 2010 measurement is no longer relevant for births in later years. In particular, it indicates that markets with high proportion male at birth will have relatively high proportion male for the next 15-35 years. This persistence also helps capture the cumulative effects of exposure to a skewed sex ratio. I proceed with the IV framework by estimating the following equations:

$$P\hat{M}_{i,cra} = \zeta PMB_{i,cra} + \theta X_i \tag{2}$$

$$y_{i,cra} = \beta P\hat{M}_{crfa} + \gamma X_i + \epsilon_i \tag{3}$$

The estimation proceeds as the usual TSLS. That is, it first predicts the value of the proportion male in 2010 given the proportion male at birth and the covariates and fixed effects X_i (the same as in equation 2). The first stage hence isolates the variation in 2010 sex composition, which is only due to randomness in sex at birth. Next, I use the predicted values in the second stage (equation 3) to estimate the treatment effect β.

I analyze four sets of outcomes, starting with fertility, which is a natural first step given that my primary data is derived from natality records. Fertility decisions are closely tied to the proportion of men in the dating market, reflecting two contrasting dynamics. On one hand, a larger pool of potential partners may increase childbearing by improving partner availability. On the other hand, greater female bargaining power can lead to more selective fertility decisions. Figure **??**, based on survey data from the US, highlights this pattern: women are consistently less willing than men to have another child at any parity. Women with limited resources or poor health may opt out of pregnancies they might otherwise carry to term if influenced by a partner with stronger bargaining power. The net effect of these dynamics, however, remains an empirical question. To address this, I measure fertility as the total number of births per 1,000 women in each market over the period 2011–2019. Each market is treated as a single observation, and I regress this fertility measure on the instrumented proportion of men, controlling for race, county, and cohort fixed effects.

Second, I analyze the marriage market dynamics. If the proportion of males is a valid distribution factor and affects dating markets, 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 [18], whether the mother is married and the difference in mother's and father's education years. I expect that a 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

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

higher quality partner. Movement in these outcomes would not only corroborate that the sex ratio affects dating market, consistent with other findings in the literature (Angrist (2002); Abramitzky et al. (2011)), but also provide evidence that changes in health are linked to dynamics within the dating market.

The third 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 pre-pregnancy diabetes or pre-pregnancy hypertension. 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. Given this, it is helpful to examine pre-determined health variables that take longer to develop, such as diabetes, as they can help indicate whether health improvements emerge specifically around pregnancy or are instead shaped by selection effects or the cumulative impact of more favorable dating markets. Additionally, to avoid the issues related to multiple-hypothesis testing, and to gain statistical power, I aggregate the main outcomes to an index which I call Adverse Maternal Health Index. I follow Hoynes et al. (2016) by taking a simple average of z-scores of all the outcomes mentioned above. The lower the index, the fewer adverse health events.

The last set of outcomes contains variables relevant to neonatal health. In particular, I examine whether birth was pre-term (gestation < 37 weeks), weather brithweight was low (weight < 2500g), whether the APGAR score is below 7, whether the newborn was put on assisted ventilation, and whether it was alive at the time of writing the birth certificate. The APGAR score is particularly interesting 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)). 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. Analogous to maternal health, I also construct and utilize the Adverse Neonatal Health Index.

6 Relationship Between Health and Sex Composition: Results

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

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, the instrument seems relevant. However, the magnitude is substantially lower than one, which can partially be explained by incarceration and migration patterns balancing highly uneven sex ratios.

While the first stage estimation is sufficiently strong overall, understanding who this

Table I: First Stage

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

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

instrument affects—and thus which population the effect arises from—requires considering a broader empirical strategy. The primary interest lies in the impact of dating market imbalances on health outcomes. Therefore, it is important to consider whose dating markets are most affected by this instrument, focusing on three key aspects: sample inclusion (1), the strength of the first stage (2), and the heterogeneous relevance of markets measured in this way (3).

Firstly, regarding sample inclusion, the only criterion used is birth cohort size. Given that the impact of imbalance and bargaining power might vary with cohort size, it is important to note that the estimated effect is local to the population of compliers in small markets. Despite the label, "small markets" encompass a wide range of demographics, from isolated counties to urban minority segments, as well as cohorts emerging during demographic downturns. Focusing on smaller markets involves a trade-off. While I gain variation in sex composition, individuals in smaller markets may be more inclined to seek partners outside their county, race, or age group. This suggests that the bounding exercise in Appendix section C.10 would apply with a higher $\alpha_{c,c'}$, making the estimates conservative compared to changing the full market. Additionally, it is worth noting that the instrument's variation is driven by the U.S.-born population, as foreign-born migrants are not in the US natality data.

Secondly, understanding where the first stage is strongest is key to identifying the source of the effect. The instrument tends to be more potent in less geographically mobile cohorts. Evidence presented in Appendix Table A2 indicates that the first-stage relationship is more pronounced for younger cohorts, who have had less time to experience displacement. Similarly, the first stage is stronger for Native and Black Americans, who are less mobile compared to White or Asian populations (table A2). Furthermore, the first stage is larger in urban markets (table A6), which also exhibit stronger results. When considering the size of the county where the market is located, the first stage appears stronger in small and mid-sized counties and weaker in the largest counties (figure A.16).

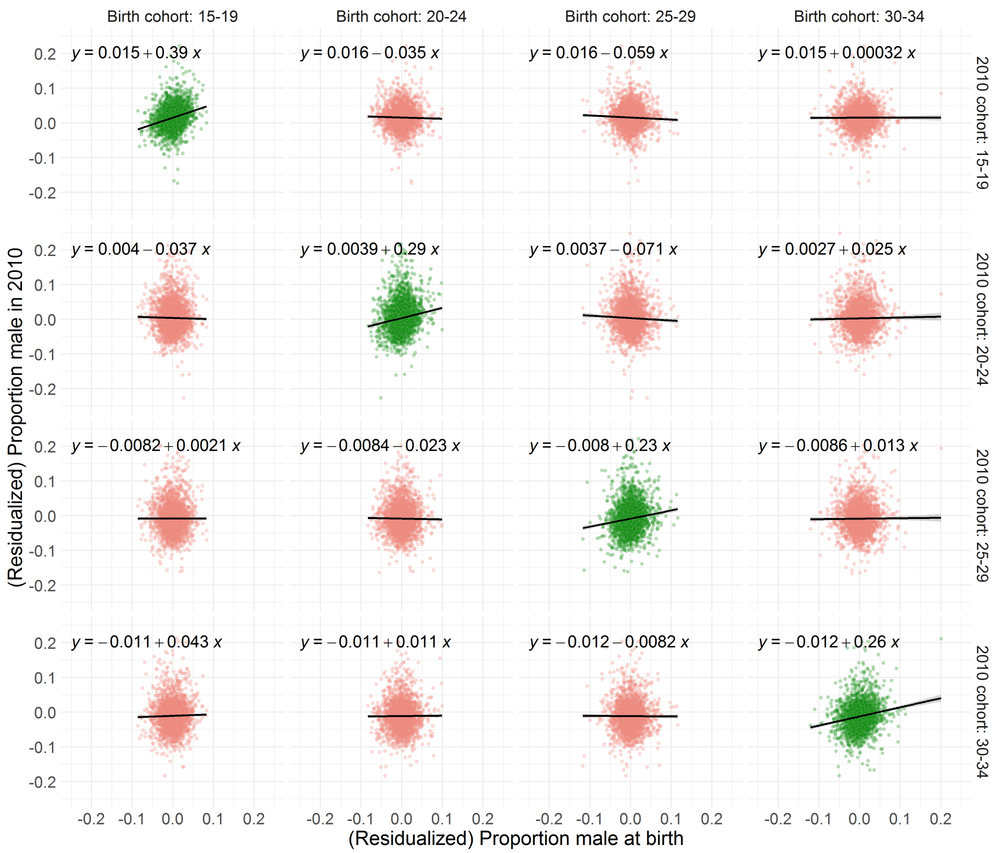
Thirdly, the impact of the instrument is also closely tied to the importance of the market segment defined by my criteria within the population. Analyzing the percentage of couples that meet this definition, it appears that the relevance is most pronounced for cohorts over 19 in 2010 (figure A.1), who already represent the majority of births. This market definition is also more pertinent for White and Black populations, who are more inclined to seek partners within their race (figure B.18), and for mid-sized markets where racially homogeneous relationships are more prevalent (figure A.6). Furthermore, as demonstrated through the model (section C.12), market imbalances influence the bargaining power of everyone, including those already in relationships and at high end of the market, as they experience the most significant changes in their outside options. If the dating market is the primary channel, the impact should also be strongest in areas where my definition of the market (race by cohort by county) is most precise.

These considerations will shape how I interpret and apply the coefficients when predicting the effects of changes in the sex ratio. In Section 8, I focus on the impact of these changes on health outcomes within the Black population, where the instrument is likely more effective. This is due to a lower likelihood of exclusion from the sample compared to Whites, as Black dating markets tend to be smaller. Additionally, the first stage is stronger for this racial group, and 91% of Black births occur in urban markets, where the first stage is also stronger. The relevance of my market definition is also amplified by higher rates of racially homogeneous partnerships within this group.

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

To further corroborate the instrument's validity, I show that the instrument is related to the future sex composition in its own cohort, but it cannot predict sex composition in other cohorts in the same county and race. Because of this cohort specific effect, it is highly unlikely that the first stage relationship could be explained by omitted factors related to county of residence. Figure VII illustrates this placebo exercise. It shows the relationship between prop. male at birth PMB_{cra} on the x-axis and proportion male in 2010 PM_{crs} on y-axis. Proportions are residualized with respect to race. The diagonal panels represent the first stage where the sex composition at birth correlates with the future sex composition in the same cohort, that is a=s. The off-diagonal panels are placebos that plot sex composition at birth in one cohort against the future sex composition of another cohort from the same county and of the same race, that is $a \neq s$. The linear relationships are represented visually and through the estimated coefficients. All diagonal relationships, as expected, are positive and highly significant. The correlation is stronger in young cohorts with less time to get incarcerated or engage in migration. The off-diagonal placebo relationships are close to null. Most p-values are above traditional thresholds, and the magnitudes are low. Thus, the relationship between the instrument and the endogenous variable is likely to stem from persistence in cohorts' demographics rather than from other nuisance factors. In particular, it challenges hypotheses suggesting that certain areas are characterized by specific types of mothers who consistently have higher probabilities of giving birth to boys. This placebo increases the confidence in the instrument; hence I proceed with the second stage estimation. The results of the IV estimation are presented in Table II, while the OLS results for the full sample (Table A3) and the IV estimation sample (Table A4) are provided in the appendix.

Figure VII: First Stage Placebo



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

Firstly, I observe that fertility declines in markets with a higher proportion of men. In this sample, an average of 414 children were born per 1,000 women during the analysis period,

Table II: IV Results

Fertility Outcomes Dependent Variables:	Birth Rate	Birth Rate (marital)	Birth Rate (non-marital)
Prop. male 2010	-804.2*	-277.4	-495.4***
	(466.8)	(364.2)	(186.5)
Dep. var. mean	414.05	242.51	168.71
Observations	14,203	14,203	14,203
Sig. at 5% (Lee et al. 2022)	No	No	Yes
Wald KP (1st stage)	119.89	119.89	119.89

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

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

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

Notes: Birth Rate is the total number of births given between 2011-2019 in a given dating market divided by the number women in that market and multiplied by 1000. Both marital and non-marital births use the same denominator. Fertility regressions are at the market level and contain controls for for cohort size in 2010 and at birth, and interactions of cohort and race and county and race. Negative *Diff. in Edu.* means that the father is more educated than the mother. In the Panel B, the proportion of men in 2010 is instrumented with proportion of men at birth of the cohort. Each regression at the individual level (Marriage Market, and Health Outcomes) contains controls for cohort size in 2010 and at birth, County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample of markets between 200-5000 people. Standard errors clustered at the County-Race level in all regressions. Wald statistic (Kleibergen-Paap) for the first stage is presented together with an information whether the coefficient is significant at 5% according to tF statistic (Lee et al. 2022).

including 242 births to married couples and 168 to unmarried parents.[19] A one standard deviation increase in the male proportion of the market reduces the number of births by 28.14 per 1,000 women. This decline is most pronounced in non-marital births, which decrease by

[19] The Census does not provide marital status-specific population counts at such a granular level, so the denominator reflects the total number of women in the market regardless of marital status.

17.4 per 1,000 women, representing a reduction of approximately 10% relative to the mean. Such reduction is unlikely to be driven solely by the change in the marital composition.[20]

These results may help explain recent declines in fertility rates, driven in part by improvements in women's bargaining power. Furthermore, there is evidence suggesting that in more favorable dating markets, women are more likely to pursue pregnancy only when the conditions are suitable. In Appendix B.1, I show that in markets with a higher proportion of men, mothers tend to have higher levels of education, are less likely to be overweight, and have more educated partners (Table A11). It is important to consider that subsequent changes in outcomes may result from this selection into motherhood, which could reflect averted births among less advantaged women or broader improvements in health and socioeconomic conditions.

Secondly, a higher proportion of men significantly influences the *Marriage Market Outcomes* and strengthens women's positions within relationships. Women are considerably less likely to give birth to an unknown father and more likely to be married during delivery. The magnitudes are twice as large as in the case of the OLS estimate (table A3). Changing the proportion of men from the 25th percentile to the 75th percentile decreases the chance of birth without a father by 1.6 percentage points, and it increases the share of married mothers by 2.9 percentage points. Both coefficients are significant according to tF standard errors. The coefficient on the difference in education is small and not statistically significant. Importantly, the positive effect on female marriage extends to the general female population and is not limited to the subset giving birth. As documented in the appendix (Section

[20]The reductions in out-of-wedlock births are larger than what would be expected solely from the shift of women from unmarried to married status. While married women tend to have more children on average, the effect of higher marriage rates alone can be quantified using the estimated effect on marriage and the average fertility rates within and outside of marriage. A back-of-the-envelope calculation suggests that a one-standard-deviation increase in sex ratios would reduce non-marital births by 11.2 per thousand women. At the same time, it would increase births within marriage by about 20 per thousand women. However, the estimated decline in births to unmarried women (-17.4 per thousand) is even larger, indicating that unmarried women are also less likely to give birth when there is more men around. For married women, while a positive effect on fertility cannot be ruled out with reasonable confidence, an increase larger than 15 births per thousand can be excluded at the 95% confidence level. This suggests that even married women are likely having fewer children.

B.3), women in more favorable dating markets are more likely to be married, with this effect already evident at age 24 and persisting as they age. Overall, the higher proportion of men on the market has a favorable causal impact on the mother's situation in the marriage market. The results regarding marital outcomes are overall consistent with empirical literature (Angrist (2002); Charles and Luoh (2010); Abramitzky et al. (2011); Brainerd (2016)) showing that the scarcity of women improves their marital prospects and decreases the rate of out-of-wedlock births.

The set of results regarding *Maternal Health Outcomes* provides evidence that women giving birth are healthier in the markets with a higher proportion of men. While in the OLS results (table A3) all coefficients are statistically significant, albeit small, and go in the expected direction, only two IV coefficients are statistically significant. Increasing the share of men on the market results in fewer mothers having chlamydia and hypertension. The magnitudes are three times as large as the OLS estimates, which suggests that a simple OLS largely underestimates the impact of dating markets on health. IV results imply that moving from the 25th percentile (0.4836) to 75th percentile (0.5225) of the proportion male decreases the share of mothers with chlamydia by 0.26 percentage points (compared to the mean of 1.9%) and hypertension by 0.37 percentage points (mean of 2.2%). Gonorrhea, Syphilis, and Diabetes, relatively rare conditions, have coefficients that are not statistically significant but align with the expected direction. The coefficient on the index is negative and strongly significant. Regarding the magnitude, closing the gap in sex compositions between Black and White people would reduce the gap in the index by 6%.

Finally, an increase in men's share of the dating market results in healthier newborns. OLS results in the appendix table A3 show small, but statistically significant correlation between all the outcomes and the proportion of men on the market. IV results (in *Intant Health Outcomes*) demonstrate that increasing the supply of men on the market relative to women causally lowers the percentage of infants born with a low APGAR score. For example, children born to mothers in the 75th percentile of prop. male are 0.2 percentage points less likely to have an APGAR score below seven compared to children of mothers at the 25th percentile. This is a sizeable difference given that only 2.43% of infants have APGAR lower than 7. To give additional context, expansion of EITC reduced share of children with low APGAR score by 0.185 percentage points Hoynes et al. (2015). While other coefficients are of the hypothesized sign, they are not statistically significant at the traditional thresholds[21]. The negative and significant coefficient on the index indicates that increasing the number of men on the market would result in fewer births with adverse outcomes. These effects are slightly stronger for the male newborns (see appendix figure C.20), but the gender differences are not statistically significant.

7 Mechanisms

The findings above indicate that sex composition affects birth outcomes. Sex ratios can potentially influence multiple factors that shape health. Among these potential mechanisms, I find that changes in the dating market constitute a particularly important and theoretically well-grounded channel.

First, as discussed in the section 2 and supported by theory and prior literature, sex ratios play a pivotal role in shaping the dating market. The present findings on women's marital status and partner characteristics provide additional empirical evidence that imbalances in sex composition meaningfully influence dating and partnership dynamics.

The observed response in the dating market—reflected in higher marriage rates and fewer births with unknown fathers—likely accounts for part of the improvements in health outcomes. Married women tend to exhibit better health on average, including maternal health (Currie and Moretti, 2003). Improvements associated with marriage are consistent with the notion that it provides sexual exclusivity, greater financial stability, and protection from stressors such as divorce or domestic violence. These factors can determine both short-

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

and long-run health. While not causal, OLS regressions of health outcomes on marital status and controls—estimated on the full sample of 26 million births and presented in Table A10—illustrate the strength of these associations. For example, married women are 1.26 percentage points less likely to test positive for chlamydia, relative to a mean of 1.9 percentage points. They are also more likely to have healthier children in general. In contrast, adverse outcomes are more common when the father is unknown. While these descriptive results do not capture a causal effect of marriage—reflecting selection and other factors—they suggest that marriage outcomes may be an important channel through which sex composition affects health.

Beyond changes in observed marital status, shifts in unobserved sexual networks likely play a role as well. Kang and Pongou (2020) show that a one-unit increase in the sex ratio reduces the number of sexual partners over the past five years by 2.0 for women and 2.4 for men, and is associated with fewer concurrent partnerships and lower rates of unprotected sex. These changes plausibly contribute to the observed declines in sexually transmitted infections, reinforcing the role of the dating market as a key channel through which sex composition affects these outcomes.

Additionally, a stronger position in the dating market may influence selection into motherhood, as reflected in the fertility results. Women may insist on contraceptive use when they do not wish to conceive (as in Kang and Pongou (2020)). If those who do choose to become mothers are positively selected on health and socioeconomic characteristics, this could contribute to the observed improvements in birth outcomes. In Appendix Section B.1, I examine the relationship between sex composition and the decision to become a mother. The decline in fertility is indeed associated with positive selection into motherhood: women who give birth are more likely to be higher educated, to have more educated partners, and to be less likely to be overweight prior to pregnancy. These characteristics are all associated with better long-term health outcomes for both mothers and children, including reduced risks of hypertension and diabetes (as documented descriptively in table A10). Maternal age at birth does not appear to vary systematically with the sex composition of the cohort, suggesting that delayed childbearing is not a key margin of adjustment. Overall, as the supply of men increases, the composition of women entering motherhood improves rather than deteriorates. This supports the view that dating market imbalances reduce fertility while simultaneously leading to positive selection into motherhood, thereby potentially averting births with poorer health outcomes.

Third, in more favorable markets—consistent with theoretical predictions—women may secure a more advantageous allocation of household resources within couples, contributing to better health outcomes. This could manifest through greater spending on healthcare and nutrition, or through an increased ability to influence partner behavior, such as enforcing fidelity. My empirical analysis suggests that the observed health improvements are not primarily driven by increased healthcare utilization around childbirth. For instance, as shown in Appendix Table A10, a more favorable market position does not significantly affect prenatal care use. Instead, the gains appear to stem from women being healthier at the time of conception, with lower rates of diabetes, hypertension (Table II), and overweight status (Table A11). It is worth noting that sex ratios tend to be persistent, suggesting that women may be exposed to more favorable or unfavorable dating markets over an extended period. This prolonged exposure could shape attitudes, behaviors, and relationship dynamics well before pregnancy. In this sense, stronger female positioning in the dating market may yield cumulative benefits over the life course, ultimately resulting in better maternal health at the time of childbirth.

Results consistent with theoretical predictions from dating market models—together with substantial shifts in the marriage market—point to a central role for dating dynamics. In addition, evidence of positive selection into fertility and enhanced female bargaining power further suggests that the dating market is an important driver of the observed relationship between sex composition and health.

Moreover, heterogeneity analyses provide additional suggestive evidence that the dating market is a relevant mechanism. These tests focus on dimensions that should matter only if dating dynamics are central to the observed effects. Consistent with this, results are stronger in contexts where dating constraints are more binding. For instance, effects are more pronounced in racially segregated markets, where race-specific sex composition is more consequential for partner matching (Figure C.23). Similarly, women with longer exposure to the dating market conditions—particularly older women—experience larger effects (Figure C.24).

While the marriage market provides a compelling channel linking sex ratios to health outcomes, it may not be the sole mechanism. I also consider other potential pathways that might help explain the link between early-life sex composition and later health.

One such mechanism might be peer effects. A body of work suggests that the gender composition of social environments, particularly in school settings, can influence educational outcomes. For instance, Hoxby (2002) leverages variation in classroom gender ratios to show that student performance improves when there are more female classmates. Consistent with this, related studies find that a higher proportion of female peers positively affects academic achievement (Lavy and Schlosser, 2011; Sacerdote, 2011; Lu and Anderson, 2015). However, the magnitude of these effects tends to be modest.Lavy and Schlosser (2011), for example, finds that a 10 percentage point increase in the share of female peers raises matriculation rates by about 1 percentage point, but does not affect dropout rates at any level. In the context of my study, where the standard deviation of the sex ratio shift is around 3.65 p.p., this would translate into an estimated change in matriculation probability of merely 0.35 percentage points. Anelli and Peri (2019) examine the impact of female peer share in high school on college completion and find that male students are slightly more likely to graduate from college when the proportion of female classmates exceeds 90 percent. However, no effect is observed when the female share is around 80 percent or below, and the study finds no significant impact on subsequent labor market outcomes. In my setting, the sex composition never reaches 90%. To further assess this channel in my context, I conduct an additional robustness check using data from Opportunity Insights. As reported in Table A17, I can exclude with high confidence economically significant effect of plausible variation in the sex ratio at birth on long-term educational attainment. Moreover, even if peer effects were relevant, the direction of influence would go against the main findings of this paper. The literature generally finds that a higher share of females improves outcomes for both genders in educational settings. In contrast, my results show that a higher female-to-male ratio at birth worsens women's health outcomes later in life. Thus, while shifts in sex composition could shape peer dynamics, this mechanism is unlikely to explain the observed patterns.

A related mechanism—often discussed in conjunction with peer effects—is the influence of gender composition on antisocial behavior and violence. Since females are generally less prone to violence, one might expect that a higher proportion of girls in a cohort would reduce the incidence of violent or antisocial behaviors. In line with this intuition, Edlund et al. (2008) document that regions in China with a surplus of males tend to experience higher crime rates. To investigate whether shifts in sex composition in my setting could similarly affect criminal behavior, I utilize Opportunity Insights data to examine incarceration outcomes. The results suggests that being part of a cohort with a skewed sex ratio at birth has no significant impact on the likelihood of incarceration [22]. Moreover, while violence is definitely relevant for birth and early-life outcomes (Currie et al., 2018), the direction of this relationship also runs counter to my findings. If antisocial behavior were an important channel driving my results, a higher female-to-male ratio should lead to improved health outcomes. Instead, I find the opposite: more females in the cohort are associated with worse outcomes for women.

Another potential mechanism is migration. An unfavorable sex ratio at birth may induce individuals to relocate to areas with a more favorable dating market. In this sense, migration can be viewed as an endogenous response to dating market imbalances and thus an extension of that channel. If this migration is not selective, it poses no threat to identification beyond potentially weakening the first-stage relationship. However, if migration is selective—for

[22] While the auxiliary data are more aggregated and sample sizes are smaller, the inference remains robust, with standard errors clustered at the same level as in the main analysis.

instance, if higher-quality individuals are more likely to move—it could affect the estimated effects. In Section B.4, I use census migration data to document that women are indeed more likely to move away from areas with unfavorable sex ratios and toward those with more favorable ones. Nonetheless, additional evidence suggests that migration is not strongly selective, at least along observable dimensions such as income. [23] While the evidence is somewhat reassuring, it does not fully rule out selective migration as a potential channel. However, any selection appears modest and likely reflects a broader behavioral response to dating market conditions, rather than a distinct mechanism.

Previous research has also documented that having daughters may be associated with a higher likelihood of family dissolution (Dahl and Moretti, 2008; Kabátek and Ribar, 2021), which in turn could affect child development outcomes. (Dahl and Moretti, 2008), for instance, find that parents with a first-born daughter are 2.2 percentage points more likely to divorce. According to this magnitude, and conservatively assuming that each additional girl causally increases the probability of divorce, a one standard deviation increase in the proportion of girls would imply an increase in the divorce rate of just 0.077 percentage points. This needs to be multiplied by the effect of divorce on potential birth outcomes. For example, Frimmel et al. (2024) document that parental divorce raises the probability of giving birth before age 20 by approximately 0.7 percentage points. Multiplying this by the 0.077 figure yields an effect of roughly 0.05 percentage points—a magnitude too small to plausibly drive the main results. To further assess the empirical relevance of this mechanism in my setting, I examine whether divorce rates are higher in areas with a greater proportion of female births. The regression results in Section C.6 reveal no evidence of such an association among the likely parent cohort. While this channel would predict outcomes in the same direction as the main findings, both prior estimates and the evidence presented here suggest that its

[23] I assume that individuals do not "overshoot" in their migratory response—i.e., those originating from areas with highly skewed sex ratios do not relocate to such an extent that these areas end up with more balanced or even reversed sex ratios compared to those with initially less skewed ratios. This assumption is consistent with migration acting to equilibrate supply and demand in the dating market and is necessary for the monotonicity condition underlying the instrumental variable strategy.

quantitative contribution is minor.

There may also be broader, harder-to-measure channels through which sex composition at birth influences outcomes, particularly in areas with limited prior research. One such possibility is the development of soft skills or pro-social attitudes. Growing up in a sex-imbalanced cohort could affect interpersonal dynamics and shape social competencies. To explain the observed effects through this mechanism, one would need to assume that a higher presence of boys promotes the development of traits beneficial for women's health. Although these traits are difficult to observe directly, they may manifest in social behaviors such as network structure or participation in pro-social activities. In Section C.5, using Opportunity Insights data, I find no evidence that variation in sex composition at birth significantly affects these proxies. Still, other dimensions of soft skill development may not be captured by these measures. Another possibility is that unbalanced sex ratios influence social norms, which in turn shape behavior. For this to explain the observed outcomes, male-skewed cohorts would need to develop norms that benefit women. While this is a plausible mechanism, it is worth noting that sex ratios vary independently across cohorts. Hence, any such norm shifts due to market imbalance would likely be confined to the cohort itself and unlikely to affect older individuals—such as parents, teachers, or healthcare providers—who play a significant role in shaping women's health outcomes. It remains reasonable that prolonged exposure to an unbalanced dating market from early childhood could shape attitudes, relationships, or behavioral patterns in ways that influence health. To the extent such long-run adaptations exist, they could represent an additional pathway through which the sex composition exerts influence. While they might be considered part of a longer-term response to dating market conditions, their precise role remains difficult to isolate.

While multiple mechanisms may be involved, the evidence points to dating market exposure as an important channel, supported by theory and consistent empirical patterns. Pinpointing the exact mechanisms is valuable, especially for designing targeted policy interventions. However, the central finding—a robust relationship between cohort sex composition and early-life health—remains informative. The results shed light on underlying determinants of birth outcomes, offer new perspectives on racial disparities, and help illuminate the broader consequences of sex ratio imbalances.

Even if selection or alternative mechanisms partly explain the observed relationship, efforts to address sex ratio imbalances may still improve child health and reduce adverse birth outcomes. Whether such strategies align with broader policy objectives will depend on contextual trade-offs, but these findings shows the importance of incorporating dating market dynamics into the design of health and demographic policy.

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

8 Counterfactual scenarios

Implementing a policy addressing the dating market disadvantage faced by Black women can help narrow the gap in health outcomes between them and White women. In this section, I use my causal estimates and simulations to quantify what share of the racial gap in health outcomes could be attributed to the racial disparity in the dating markets. I focus on Black mothers because Section 6 documents that this group exhibits strong compliance with respect to the instrument, and Section 4.2 shows that their sex ratio is largely driven by policy factors. A policy—though politically challenging—that reverses differences in sex compositions could potentially reduce health disparities. While these counterfactual scenarios lack direct causal interpretation due to using different sources of variation than those leveraged for identification, they provide an order of magnitude of the effects of dating markets on health at the national scale.

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

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

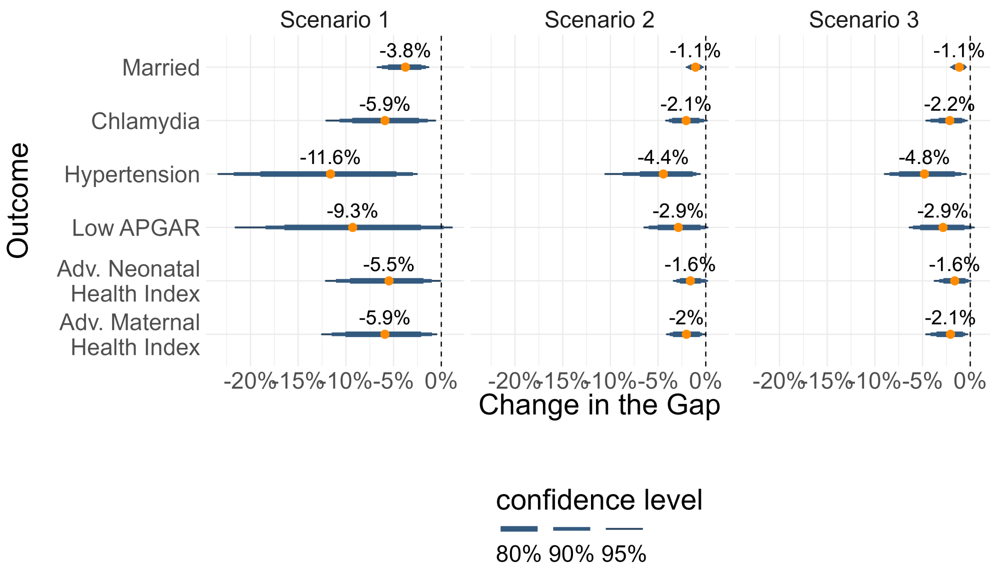
The second scenario focuses on a particular policy driving the sex ratios: incarceration rates for non-violent crimes. The counterfactual assumes that Black men and women are incarcerated for non-violent offenses at the same rate as their White counterparts in the same county and age group. The consequence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

One may still be concerned that incarcerated individuals have lower potential income, and therefore are not an attractive partners for the majority of women. Nonetheless, a dating market model implies that adding even low income individuals to the dating pool improves outcomes for all women. In the appendix section C.12, I adapt the model from section C.11 to accommodate a variety of assumption on the potential income of the individuals fueling the dating pool. While the detailed results are in the section C.12, the two important implications are: (1) the magnitude of female welfare gains depends relatively little on the quality of men added to the pool and (2) that highest income women always benefit the most. These results are similar to findings by Chiappori and Oreffice (2008) who show that introducing more efficient birth control increases the welfare of all women, even those who do not use them. The intuition behind my findings is that low-income women, who were previously single, can now find a partner. As these women have now higher utility, outside option for all subsequent women improves. Hence, they obtain more favorable resource allocation in their partnerships.

As the model indicates that female welfare gains are relatively unaffected by the quality of men added to the pool, I use my IV estimates for this counterfactual scenario. Details on calculating counterfactual sex ratios are provided in Appendix C.8. While these measures address several concerns, caution is warranted in interpreting the counterfactuals causally. Instead, their purpose is to establish a benchmark for understanding the magnitude of the potential impact of narrowing the sex ratio gap to an extent comparable to that arising from racial disparities in incarceration rates.

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

Figure VIII: Simulations: Reduction in Racial Health Inequality



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

The simulations rely on bootstrapping the estimation and comparisons sample, with details of the procedure in the appendix section C.9. The simulations show that Black mothers' disadvantage in the dating market can produce a significant share of racial health disparities. Figure VIII illustrates the results. Equating the sex composition of Black and White women reduces the gap in the number of births to non-married women by 3.5%. Moreover, the gap in the prevalence of chlamydia and hypertension among pregnant women shrinks by respectively 5.4% and 10.5%. The racial disparity in the newborns who need medical assistance (low APGAR score) diminishes by 9.2%. Finally, the gap in adverse health indices declines as well: by 5.5% for neonatal and by 5.9% for maternal health.

Equating the incarceration rates for non-violent offenses also reduces the gap in health outcomes, although to a smaller extent. It reduces the gap in out-of-wedlock births by 1.1%, the gap in chlamydia and hypertension by 2.2% and 4.2% respectively, and the gap in Low

APGAR by 2.8%. The disparity in the neonatal health index decreases by 1.6% and in the maternal health index by 2%.

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

One could also ask whether a higher rate of inter-racial relationships could diminish the gap in the health outcomes. Bringing Black sex composition to the balanced level would require around 650 000 additional men. Since there is a surplus of White men, one could shift White men to Black women. This would require 2.2% of White men to enter relationships with Black women, and conversely 10.8% of Black women to consider White men [24]. While such transfer would decrease bargaining power of White women (decreasing their sex composition from 0.505 to 0.499), their loss would still be lower than the benefit to Black women.

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

9 Conclusion

In this study, I investigate how a sex composition of the dating market influences pregnancy outcomes. My empirical framework identifies the causal effect by leveraging a novel instrument: the cohort's sex composition at birth. The findings indicate that increased male availability reduces fertility and enhances maternal and neonatal health.

The observed health improvements stem from two primary mechanisms: (1) a positive

[24] 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

selection into fertility, where women opting for delivery in advantageous dating markets tend to be more educated and healthier, (2) and enhanced partner quality and resource allocation for women with greater bargaining power. Nonetheless, the study cannot precisely disentangle the individual contributions of these mechanisms, presenting a limitation and a direction for future research.

Finally, my findings highlight the impact of the dating market within the first 24 hours of a child's life. These effects may continue and accumulate throughout the child's life. Understanding the effects' persistence could help address the inter-generational transmission of health inequalities by improving outcomes for the most vulnerable populations.

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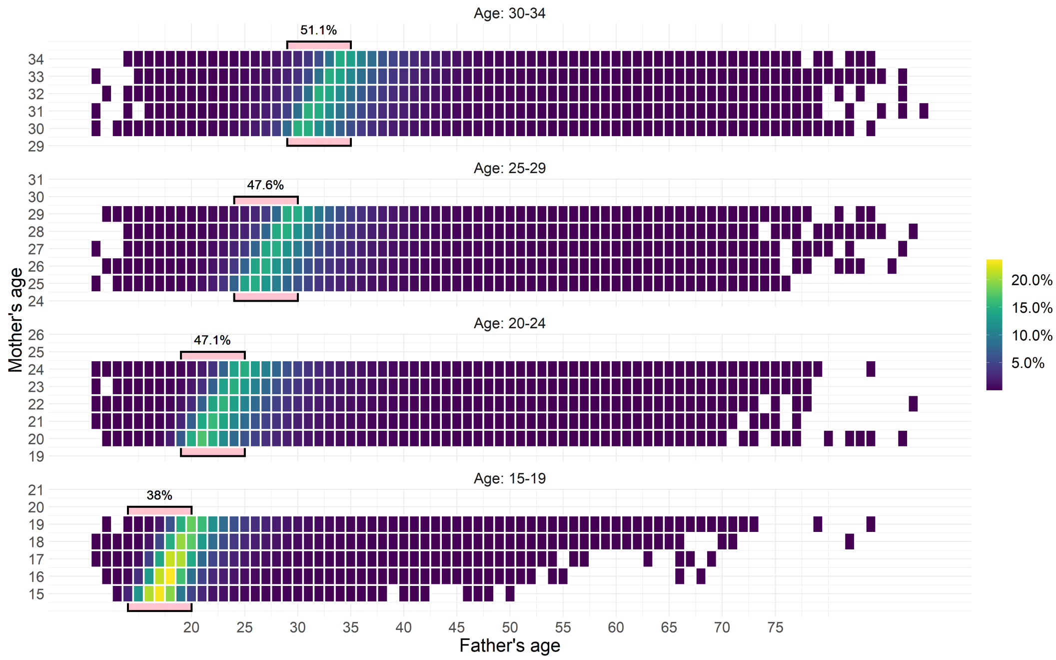
A Supplemental Appendix

A.1 Additional Figures

Figure A.1: Age Composition of Parents



Notes: Small rectangles show couples by father's age a_f and mother's age a_m. Colors indicate the share of mothers aged a_m with fathers aged a_f, with light colors on the diagonal showing most women have children with men of similar age. Larger boxes represent 5-year age groups, and the number above indicates the share of mothers in that age group with similarly aged fathers. Source: Natality data 2011-2019

Figure A.2: Racial Composition of Parents and Interracial Births

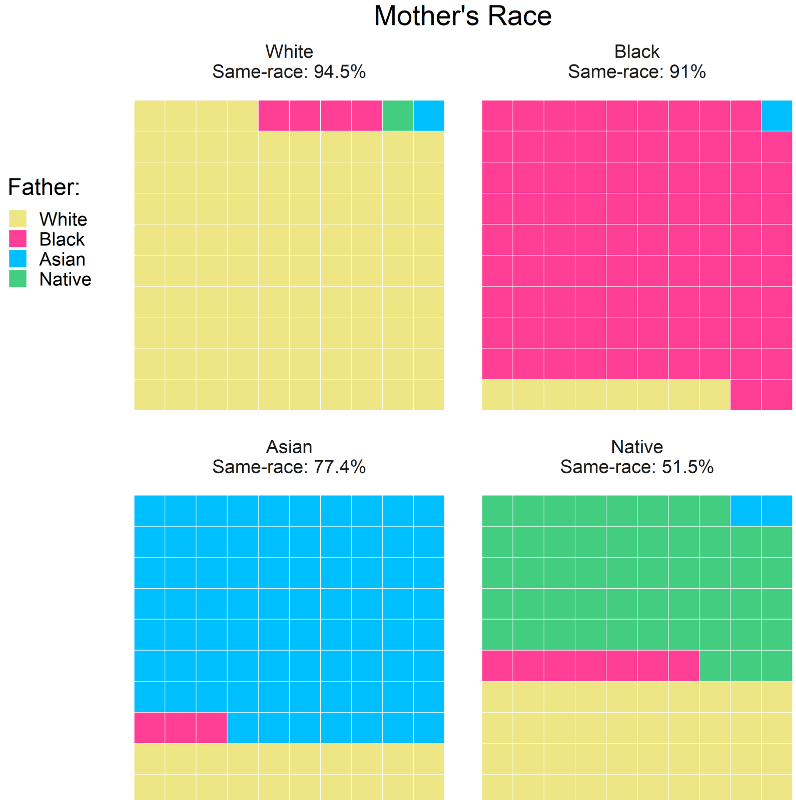


Figure A.3: Racial Composition of Parents

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

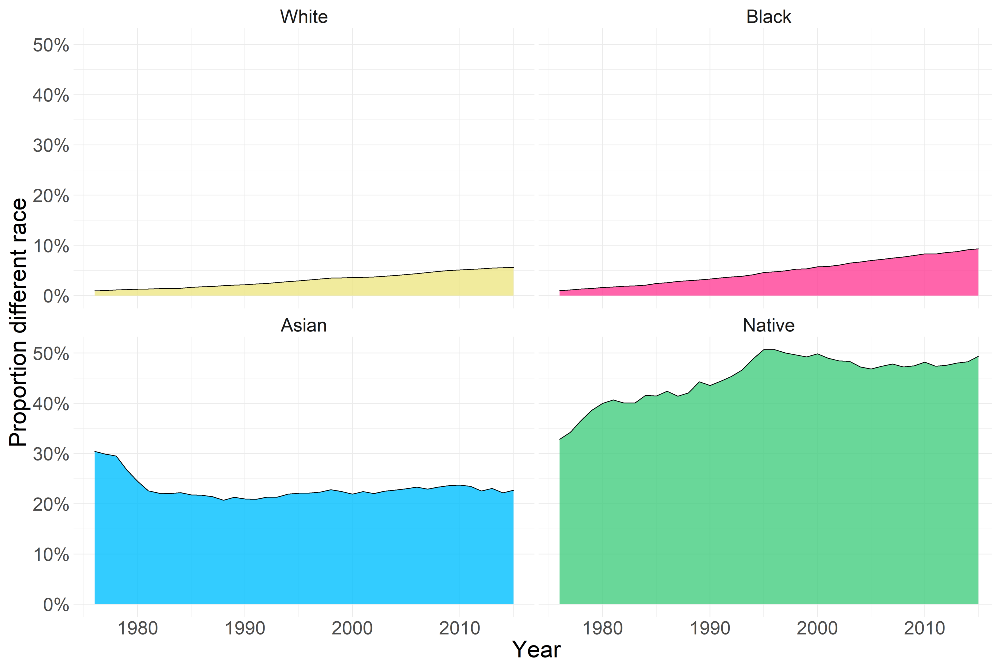
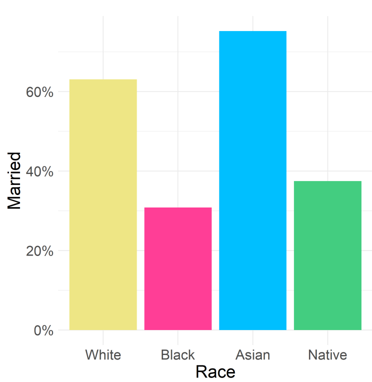


Figure A.4: Interracial Births

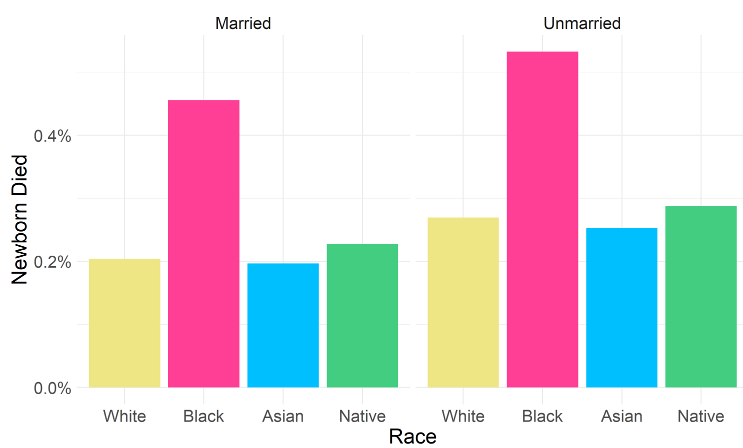
Notes: Each line represents the share of pregnancies such that the father is of a different race than the mother, conditional on mother's race. Source: Natality data 1976-2016

Figure A.5: Marital Rates and Neonatal Deaths by Race



(a) Marital Rates by Race

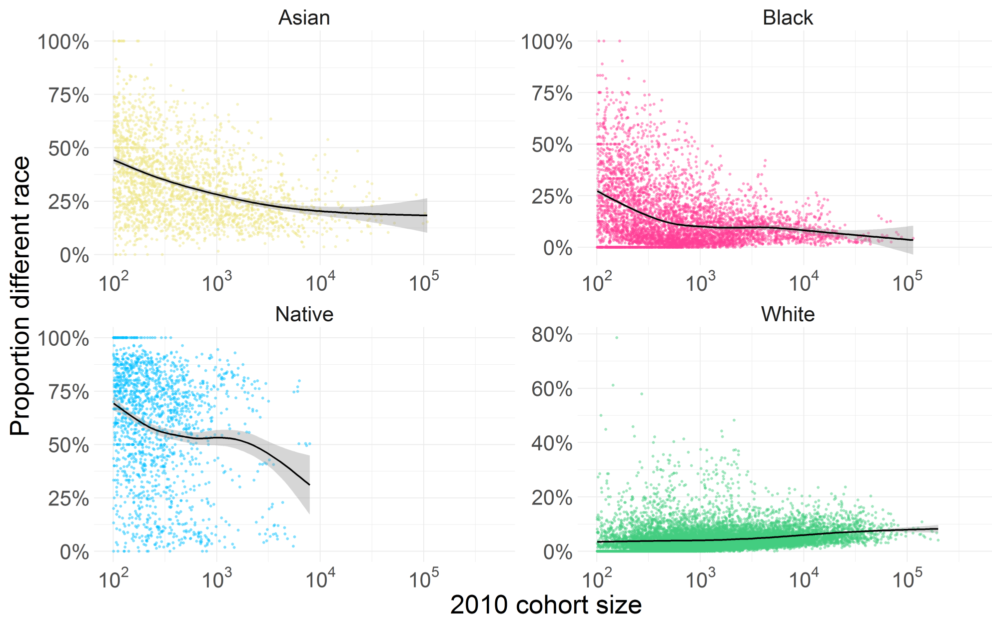
Notes: Each bar represents the share of married mothers by racial group. Source: Natality data 2011-2019



(b) Neonatal Deaths by Race and Marital Status

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

Figure A.6: 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.2 Details on the decomposition of racial differences in the sex composition

Below are the derivations for racial differences at the national level. This method can be further disaggregated, and I also present race- and cohort-specific results (figure A.8). This decomposition was inspired by Hall (2000)'s analysis of changes in the Black sex ratio in the late 20th century.

Consider incarceration as an example of a factor affecting Black-White sex composition differences. The number of Black men and women in dating markets is calculated by multiplying the total number of Black men and women by the complement of gender-specific incarceration rates[25]. To assess the impact, I replace Black incarceration rates with White ones while holding other factors constant, then calculate the proportion of Black men under these conditions. Comparing the actual and counterfactual sex compositions reveals incarceration's contribution to the Black-White sex composition gap Formally, let N_{rs} be the number of people of race r and sex s. This number can be decomposed in the part born in

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

the US (B_{rs}) and foreign born (IM_{rs}): $N_{rs} = \underbrace{B_{rs}}_{\text{US Born}} + \underbrace{IM_{rs}}_{\text{Foreign Born}}$.

I model the number of domestically born individuals of race r and sex s on the dating market in 2010 as follows. First, I multiply a hypothetical base population by the share born in the US $(1 - w_r)$, where w_r is the share of race r born abroad. This gives all domestic births for race r. Then, I multiply it by the probability pb_{rs} that a birth is of sex s, yielding the total domestic births of sex s and race r. Next, I apply the survival rate $(1 - m_{rs})$, where m_{rs} is the mortality rate, to get those still alive in 2010. Finally, I multiply by the probability they are not incarcerated $(1 - i_{rs})$, where i_{rs} is the incarceration rate for race r and sex s. Incarceration and mortality can also be disaggregated by cause or offense.

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

The term for the foreign-born population is similar, with two modifications. The product $BP_r * w_r$ represents the baseline immigrant population of race r arriving before 2010. This is then multiplied by pi_{rs}, the proportion of sex s among immigrants of race r. Thus, Im_{rs} represents all foreign-born individuals of race r and sex s who are alive and not incarcerated 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 below. In the next step, I calculate the value of the residual X_r which represents all unaccounted factors affecting sex composition. It is fitted through equating the empirical sex composition Pm_r to the predicted sex composition $\frac{N_{rm}}{N_{rm}+N_{rf}}$ multiplied by X_r: $Pm_r = \frac{N_{rm}}{N_{rm}+N_{rf}} * X_r$. Note that this last fraction is a function of parameters and can be used to predict counterfactual sex compositions under different parameter values. I substitute the male and female parameters for race r with those of White males and females in the same age group to obtain a counterfactual sex composition without racial differences in that parameter. For example, to calculate the impact of incarceration on Black-White sex composition differences: (1) Replace Black incarceration rates with those of Whites; (2) Compute the counterfactual proportion of Black males using the new incarceration rates while keeping other parameters fixed; (3) Calculate the counterfactual sex composition disparity. The difference between the counterfactual and empirical results gives the contribution of incarceration.

Parameters computations The incarceration rate i_{rs} is calculated from the 2010 Census as the ratio of the population aged 15-34 of race r and sex s living on prison census blocks to the total population of the same group. Offense-specific rates are obtained by multiplying i_{rs} by the share of prisoners of race r and sex s sentenced for specific offenses, sourced from the BJS CSAT tool[26]. The mortality rate m_{rs} is derived from vital statistics by counting deaths of individuals of race r and sex s born between 1976 and 1996, up to 2009. I calculate death rates by dividing total deaths by the sum of those alive in 2010 and deaths. Cause-specific mortality (natural, violent, external) is classified per ICD9/ICD10. The probability of a birth being sex s in race r is derived from 1976-1996 natality data as the ratio of births of sex s to total births of race r. The share of the foreign-born population is calculated from 2010 census microdata, as is the probability that an immigrant of race r is of sex s.

Parameters computations Several simplifying assumptions are necessary due to data limitations. First, death and incarceration rates are assumed the same for both local-born and immigrant populations, as I cannot differentiate them in mortality data. Second, Hispanics are included for all races, since I can only distinguish them in the mortality dataset starting from 1989, while my first cohort was born in 1976. Third, the proportion of foreign-born is based on 2010 data, which already reflects mortality, though I assume it does not. The

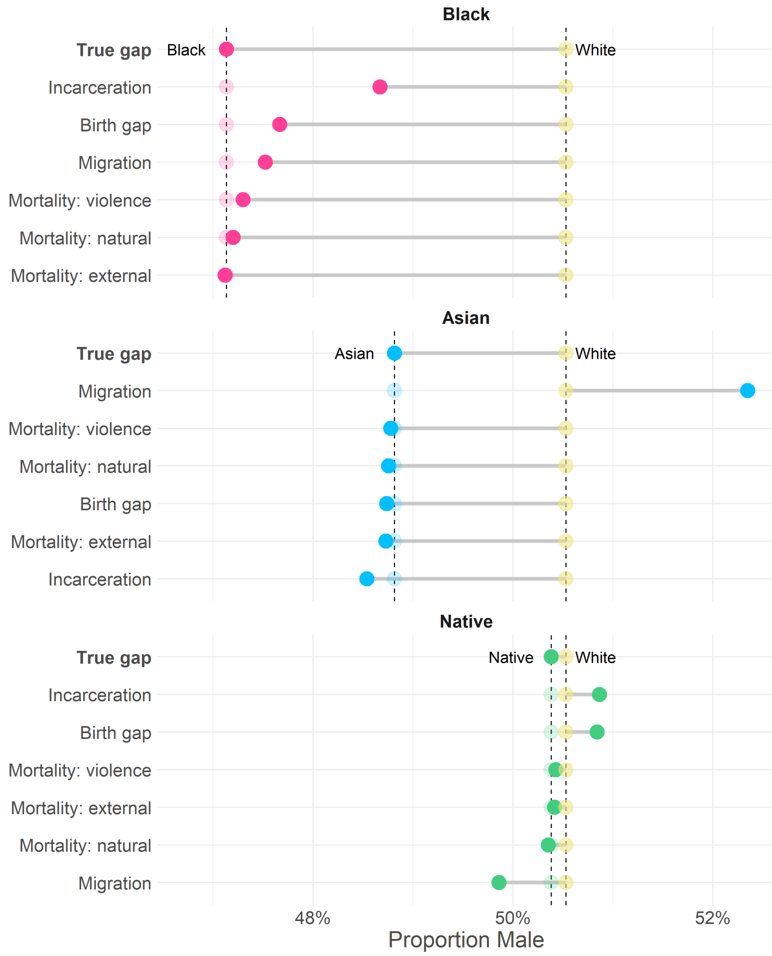
[26]https://csat.bjs.ojp.gov/advanced-query

same applies to the male proportion among immigrants, but I adjust using mortality data. Fourth, I do not manipulate the relative shares of US-born and foreign-born populations. Lastly, I do not account for interactions between multiple parameters.

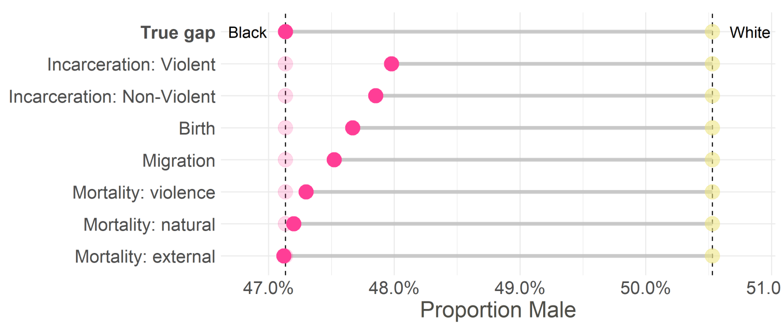
Main results Figure A.7a demonstrates the primary factors driving the racial differences in sex composition. The x axis represents the proportion of men under each scenario, and y axis shows the parameters, ordered by their importance for each race. The first row in each panel illustrates the actual values of the sex compositions.

For Black people, incarceration is the largest factor, explaining 45% of the gap. A 15% contribution comes from the lower proportion of male births among Black people globally. Violent deaths account for 5%. Among Asians, migration is the key driver of male scarcity. Differences between Native and White Americans are mostly negligible. The desegregation by cohort shows that these gaps mostly arise above the age 20 for Black people and above the age 26 for Asian people.

Figure A.7: Counterfactual Gaps in the Sex Composition



(a) All Racial Groups



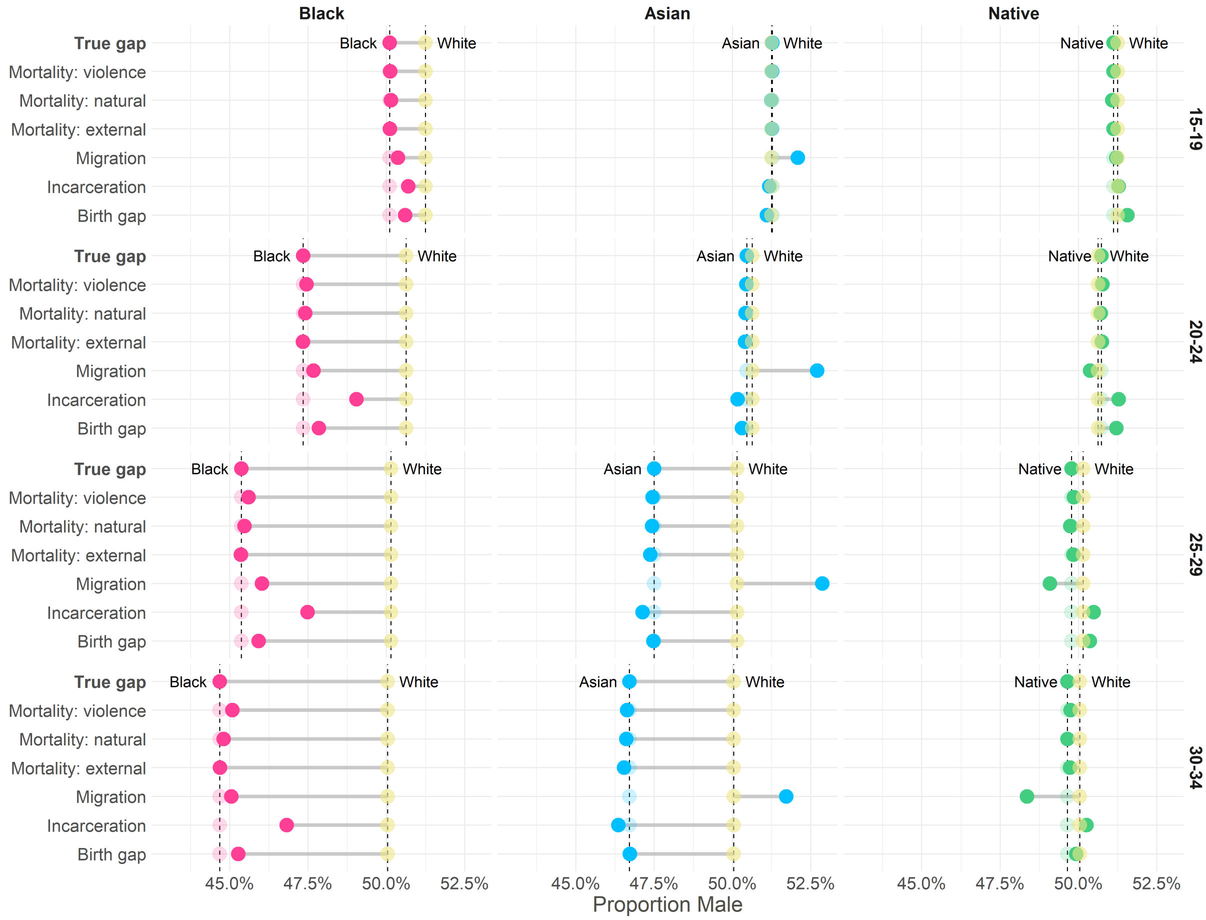
(b) Desegregated by Crime Type

Notes: Lines show the counterfactual gap (for the cohort 15-34 in 2010) that would arise if rates for a given factor were equalized to the value of White people. The dashed lines represent the true sex compositions.

Differences in sex ratios between Black and White people are policy sensitive. They come from biases interacting with legislation which prescribe harsher sentences for habitual offenders or particular drugs. An example in case was 100:1 sentencing disparity between crack cocaine, used disproportionately by Black people, and powder cocaine, consumed by White people[27]. Even race-neutral reforms, like changes to probation violations, can disproportionately impact minorities (Rose (2021)). Policies that reduce over-reliance on incarceration and address biases in the justice system could close the incarceration gap. Raphael and Stoll (2014) suggest eliminating mandatory minimums and reducing "truth in sentencing" laws to lower incarceration rates without risking public safety. Other reforms include expanding bail and sentencing options, increasing diversity in the legal profession, diverting drug offenders to treatment, and mandating racial impact analyses of legislation (Sentencing (2008), Ghandnoosh (2015)).

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

Figure A.8: Counterfactual Gaps in the Sex Composition: by Cohort



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

Figure A.9: Education of Mothers by Race

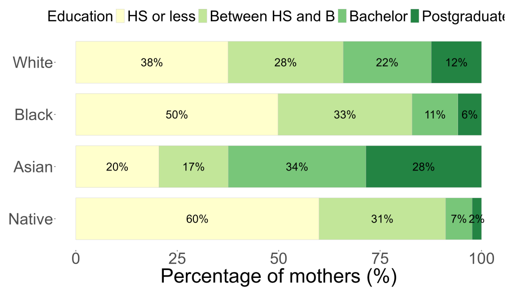
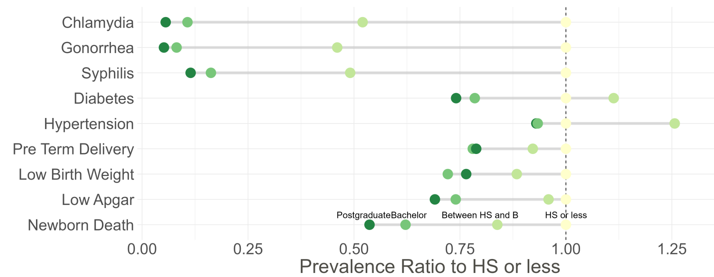
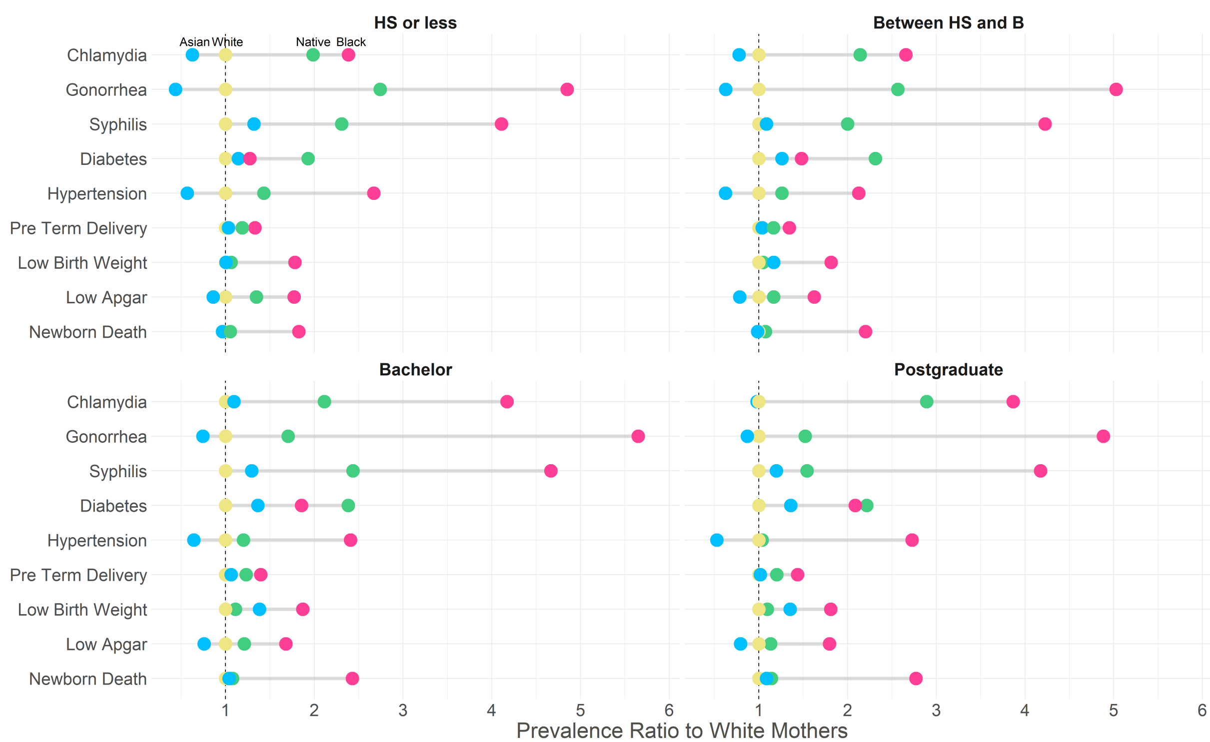


Figure A.10: Educational Disparities by Health Outcomes



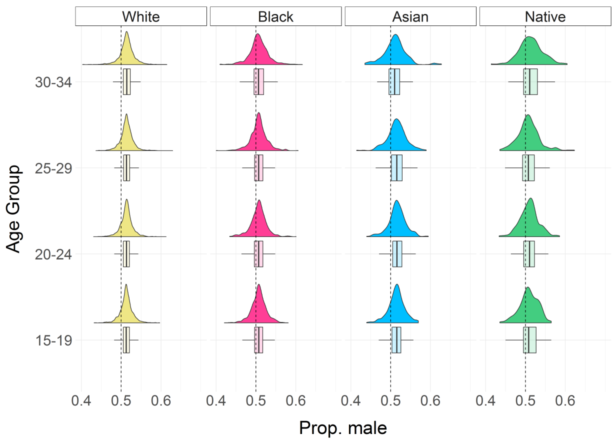
Notes: The left figure shows the share of mothers with a given education level in each racial group. The right figure shows the outcomes by education. The lightest dots correspond to the benchmark of mothers with less than high school education. Other dots represent the ratio of the average prevalence among an education group to the average prevalence among less than high school mothers. Darker color means higher, with the same legend as in the left graph.

Figure A.11: Racial Disparities in Health Outcomes by Education



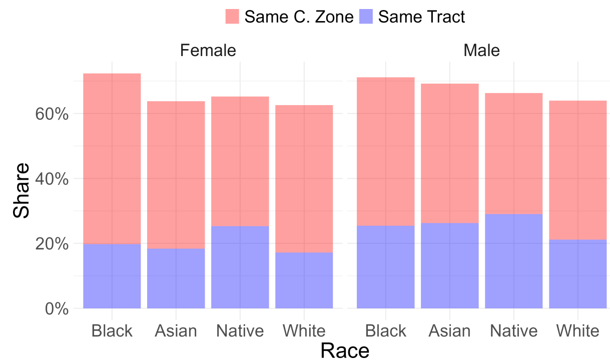
Notes: The light dots on the dashed line correspond to the baseline of the White mothers. Other dots represent the ratio of the average prevalence of a morbidity among a racial group to the average prevalence among White mothers. Blue, green and violet colors represent respectively Asians, Native Americans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

Figure A.12: Density of Proportion Male at Birth



Notes: Figure shows the empirical distribution of the sex composition. Each observation represents the proportion of male births in a dating market.

Figure A.13: Geographic Mobility since Childhood



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

A.3 Simulated Distribution of Sex Composition at Birth

I conduct an exercise showing that empirical and simulated distributions of sex compositions at birth are identical, as visualized in Figure A.14. First, I calculate the mean proportion of male births (p_r) for each race, assuming randomness in sex ratio conditional on race. Then, for each market, I simulate n_{cra} "coin tosses" with probability p_r, where n_{cra} is the number of births, repeating the process 100 times. If sex at birth is truly a random "coin toss", the empirical and simulated distribution should be similar[28]. The resulting simulated distribution mirrors the empirical one, as sex at birth seems to follow a Bernoulli process. Both distributions are visually identical, and Kolmogorov-Smirnov tests confirm no significant differences (table A1), with p-values above traditional significance levels, though close to 0.13-0.15 for Black and White populations.

[28] Note that they mechanically have the same mean

Figure A.14: Actual vs Simulated Density of Proportion of Male Births

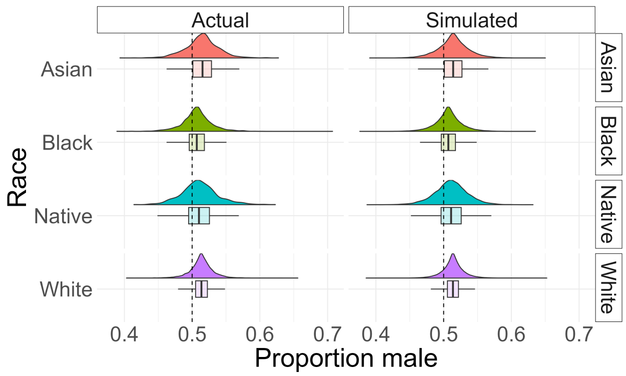


Table A1: Kolmogorov-Smirnov Test

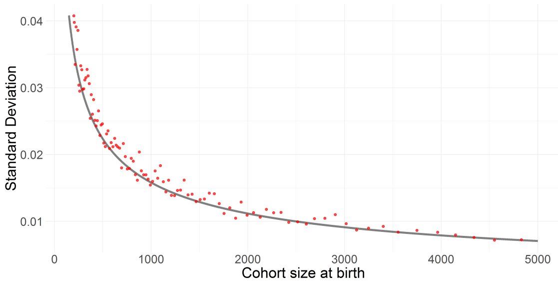
Race	**P-value**
Asian	0.728
Black	0.155
White	0.1303
Native	0.921

Notes: In the left figure, the left panel shows the empirical distribution of sex compositions where each observation represents the proportion of male births at a dating market when the cohort was born. The right panel shows the simulated distribution. Simulations are draws from the binomial distribution with parameters p_r and n_{cra}, and divided by n_{cra}. The table on the right shows p-values from Kolmogorov-Smirnov tests for the hypothesis that the empirical and simulated distributions in the figure A.14 are equal.

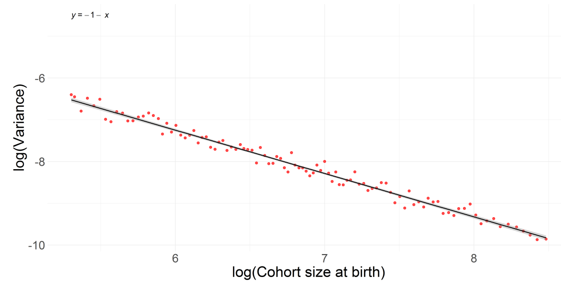
A.4 Relationship between Cohort Size and Variation in Sex Composition

Deviations from a balanced sex ratio are expected to be small in large cohorts but substantial in small ones, and this pattern holds in the data. Panel a of Figure A.15 shows the theoretical standard deviation by cohort size (n) using $p = 0.5$ and $\sqrt{\frac{p(1-p)}{n}}$, alongside empirical values. Markets are divided by birth cohort size percentiles, and the standard deviation of proportion male is plotted against average size. The close match between theoretical and empirical values suggests that observed variation is largely due to randomness in sex at birth. I also test this relationship formally. Taking logs of the theoretical variance gives $log(var) = log(p(1-p)) - log(n)$, so regressing the log of empirical variance on log cohort size should yield a coefficient of -1, as shown in panel b. A bootstrap regression with 10,000 samples produces a mean coefficient of -1.025 with a 95% confidence interval of (-1.052, -0.998).

Figure A.15: Variation in the Sex Composition



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



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

Notes: The curve in figure A.15a shows the theoretical standard deviation by sample size n using p=0.5 and $\sqrt{\frac{p(1-p)}{n}}$. The dots represent the standard deviation in the data. Specifically, markets were divided by the percentiles of the size of the birth cohort. Each dot represents a group of markets in a percentile. Standard deviation and average size are calculated in each percentile. Figure A.15b shows the relationship between log of the variance in the centiles of data and the average cohort size of the centile, and a fitted regression line.

A.5 Additional Tables

Table A2: First Stage by Cohort and Racial Group

Dependent Variable:	Prop. male 2010						
h1	Full sample	15-19	20-24	25-29	30-34	White & Asian	Black & Native
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Prop. male at birth	0.2329***	0.4267***	0.3281***	0.0511	0.2040***	0.1950***	0.3269***
	(0.0236)	(0.0336)	(0.0489)	(0.0645)	(0.0655)	(0.0242)	(0.0459)
Wald Kleibergen-Paap (IV only)	97.3	160.9	45.0	0.628	9.70	64.8	50.7
Dependent variable mean	0.496	0.511	0.498	0.486	0.482	0.501	0.481
Observations	7,138,182	1,966,817	2,486,046	2,033,986	991,687	5,673,531	1,805,005

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

Table A3: OLS Results in the Entire Sample

Marriage Market Outcomes						
Dependent Variables:	*Unknown Father*	*Married*	*Diff. in Edu. (years)*			
Prop. male 2010	-0.1912***	0.3055***	-0.6211***			
	(0.0208)	(0.0329)	(0.0788)			
Dependent variable mean	0.113	0.650	0.306			
Observations	23,299,377	23,818,474	20,174,436			
Maternal Health Outcomes						
Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*	*Adverse Maternal Health Index*
Prop. male 2010	-0.0189***	-0.0072***	-0.0022***	-0.0067***	-0.0326***	-0.137***
	(0.0033)	(0.0012)	(0.0007)	(0.0015)	(0.0045)	(0.019)
Dependent variable mean	0.015	0.003	0.0008	0.008	0.019	0
Observations	23,224,271	23,224,271	23,224,271	23,257,824	23,257,824	23,224,271
Infant Health Outcomes						
Dependent Variables:	*Preterm Birth*	*Low BW*	*Low APGAR*	*Assisted Ventilation*	*Death*	*Adverse Neonatal Health Index*
Prop. male 2010	-0.0472***	-0.0486***	-0.0085***	-0.0092*	-0.0022***	-0.093***
	(0.0053)	(0.0046)	(0.0021)	(0.0054)	(0.0007)	(0.011)
Dependent variable mean	0.113	0.082	0.021	0.041	0.003	0
Observations	24,467,061	24,461,432	24,385,422	23,246,802	23,266,090	23,142,465

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

Table A4: OLS Results in IV sample

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

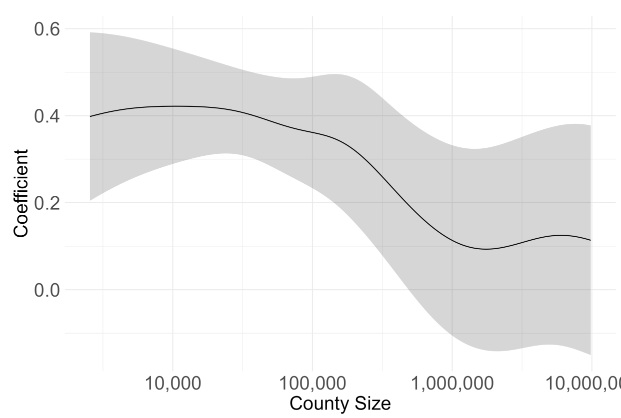
Notes: Negative *Diff. in Edu.* means that the father is more educated than the mother. Each regression contains controls for cohort size in 2010, County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects. The coefficient on *Prop. male 2010* correspond to β in equation 3. Sample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

Table A6: First Stage by Rural-Urban Status

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

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

Figure A.16: First Stage by County Size



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

Table A5: IV Results: Sex Ratio

First Stage and Marriage Market					
Dependent Variables:	*Sex Ratio in 2010*		*Unknown Father*	*Married*	*Diff. in Edu. (years)*
Sex ratio at birth	0.2280***	**Sex ratio in 2010**	-0.0903***	0.1850***	-0.1516
	(0.0228)		(0.0320)	(0.0446)	(0.1214)
Dependent variable mean			0.127	0.621	0.360
Observations	7,138,182		7,166,343	7,478,536	6,105,173
Wald Kleibergen-Paap (IV only)	99.602		111.11	116.37	95.634
Sig. at 5% (Lee et al. 2022)			Yes	Yes	No
Maternal Health Outcomes					
Dependent Variables:	*Chlamydia*	*Gonorrhea*	*Syphilis*	*Diabetes*	*Hypertension*
Sex ratio in 2010	-0.0191***	-0.0010	0.0002	-0.0070*	-0.0209**
	(0.0066)	(0.0023)	(0.0011)	(0.0040)	(0.0083)
Dependent variable mean	0.019	0.003	0.0008	0.010	0.022
Observations	7,138,182	7,138,182	7,138,182	7,151,592	7,151,592
Sig. at 5% (Lee et al. 2022)	Yes	No	No	No	Yes
Wald KP (1st stage), Sex ratio in 2010	112.35	112.35	112.35	111.54	111.54
Infant Health Outcomes					
Dependent Variables:	*Gestation*	*Birthweight*	*Low APGAR*	*Assisted Ventilation*	*Death*
Sex ratio in 2010	0.2002**	22.33	-0.0136**	-0.0165*	-0.0010
	(0.1021)	(27.86)	(0.0058)	(0.0097)	(0.0020)
Dependent variable mean	38.586	3,260.0	0.02361	0.04517	0.003
Observations	7,540,450	7,539,221	7,515,076	7,149,031	7,155,905
Sig. at 5% (Lee et al. 2022)	No	No	Yes	No	No
Wald KP (1st stage), Sex ratio in 2010	115.81	116.07	115.71	111.55	110.93
Marriage Market Outcomes					

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

Table A7: Cross-County Marriage Effects

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

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

Table A8: Parity

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

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

Table A9: Prenatal Care IV

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

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

Table A10: Maternal and Neonatal health as function of parents Charactersitics

Variables	Married	Unknown Father	Mother's Edu.	Father's Edu.	Overweight
Chlamydia	-0.0126***	0.0070***	-0.0005***	-0.0005***	-0.0004**
	(0.0009)	(0.0009)	(5.47×10^{-5})	(4.61×10^{-5})	(0.0001)
Gonorrhea	-0.0016***	0.0014***	-9.73×10^{-5}***	-5.24×10^{-5}***	-2.41×10^{-5}
	(0.0001)	(0.0003)	(1.5×10^{-5})	(7.86×10^{-6})	(2.54×10^{-5})
Syphilis	-0.0005***	9.83×10^{-5}	-0.0001***	-3.24×10^{-5}***	2.1×10^{-5}
	(3.06×10^{-5})	(0.0002)	(1.23×10^{-5})	(3.38×10^{-6})	(1.3×10^{-5})
Diabetes	-0.0003**	-0.0002	-0.0005***	-0.0007***	0.0079***
	(0.0001)	(0.0004)	(5.11×10^{-5})	(5.05×10^{-5})	(0.0005)
Hypertension	-0.0015***	-0.0002	0.0003***	-0.0009***	0.0182***
	(0.0004)	(0.0005)	(3.1×10^{-5})	(8.13×10^{-5})	(0.0010)
MH Index	-0.0308***	0.0155***	-0.0024***	-0.0039***	0.0447***
	(0.0016)	(0.0022)	(0.0002)	(0.0002)	(0.0025)
Preterm Birth	-0.0143***	0.0073***	-0.0026***	-0.0027***	0.0067***
	(0.0007)	(0.0020)	(9.37×10^{-5})	(9.33×10^{-5})	(0.0010)
Low Birthweight	-0.0131***	0.0153***	-0.0008***	-0.0017***	-0.0062***
	(0.0008)	(0.0016)	(0.0001)	(8.59×10^{-5})	(0.0008)
Low APGAR	-0.0009***	0.0058***	1.6×10^{-5}	-0.0002***	0.0040***
	(0.0002)	(0.0007)	(3.23×10^{-5})	(3.16×10^{-5})	(0.0002)
Assist. Vent.	-0.0018***	0.0041***	0.0005***	-0.0002***	0.0083***
	(0.0002)	(0.0007)	(5.15×10^{-5})	(5.77×10^{-5})	(0.0004)
Death	0.0003***	0.0040***	-7.52×10^{-5}***	-7.12×10^{-5}***	0.0006***
	(2.6×10^{-5})	(0.0004)	(7.67×10^{-6})	(6.03×10^{-6})	(4.44×10^{-5})
NH Index	-0.0206***	0.0370***	-0.0019***	-0.0036***	0.0155***
	(0.0013)	(0.0037)	(0.0001)	(0.0002)	(0.0017)

This table presents estimates from ordinary least squares (OLS) regressions using data on all births from 2011 to 2019 (n = 26,579,202). Each row corresponds to a specific health outcome, and columns indicate different regressors. The regressions include fixed effects at the mother's age-by-race level, with standard errors clustered accordingly. The variable "Overweight" refers specifically to the mother's overweight status

B Extensions

B.1 Change in Composition of Mothers

Conditions in the dating market may affect maternal health through the changes in the composition of mothers. Building on the changes in fertility, I next examine whether the birth rate effect is linked to changes in mothers' characteristics. Table A11 shows that women in more favorable markets tend to be healthier and more educated, with less likelihood of being overweight and having more educated partners. This suggests that empowered women pursue pregnancy only when household resources are sufficient. In contrast, women with less bargaining power may agree to childbearing as a concession to their partner. This also indicates that the average quality of couples having children does not decline as the supply of men increases.

Table A11: Effect on Composition

Dep. Var.: Model:	Overweight (1)	Age at birth (2)	Mother's Edu. (3)	Fathers's Edu. (4)
Prop. male 2010	-0.2729**	-0.1546	3.246**	3.585**
	(0.1109)	(0.7672)	(1.286)	(1.464)
Dep. var. mean	0.544	28.3	13.9	13.7
Observations	6,973,738	6,973,738	7,119,580	6,116,977
Wald KP (1st stage)	112.3	113.5	99.7	78.9

Notes The table shows IV regressions with mother's and father's characteristics on instrumented proportion of men on the dating market and covariates. Covariates include County×Age at birth, Race×Single age cohort, and Race×Age at birth fixed effects.

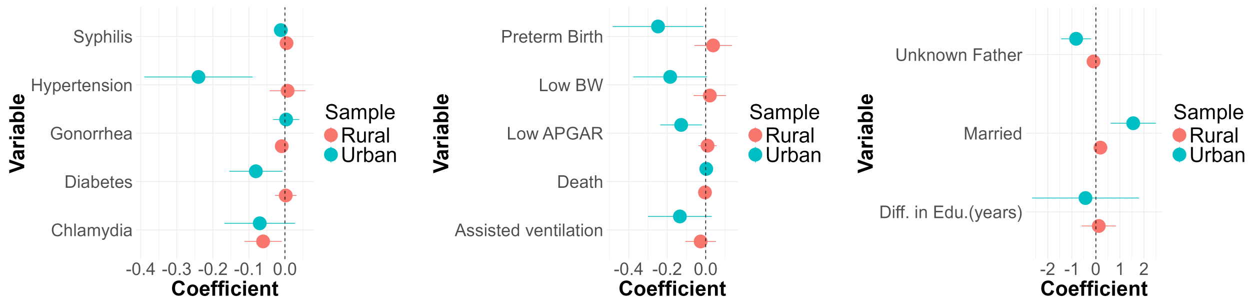
B.2 Heterogeneity analysis

To evaluate the impact of market definition and sample selection, I examine heterogeneity in bargaining effects. The strongest effects are seen in urban markets and among racial minorities, suggesting the findings are generalizable to the excluded parts of the sample.

The impact of sex composition on maternal and neonatal outcomes is primarily driven by urban markets[29] , as shown in Figure B.17. The effects on unknown father status and marital status are significantly stronger in urban areas. Maternal health outcomes, like diabetes and hypertension, are also more influenced by bargaining in urban settings, while chlamydia shows similar coefficients in both. Neonatal health outcomes, such as preterm birth, low birth-weight, and low APGAR scores, exhibit larger negative coefficients in urban areas, though not statistically significant at 5% due to smaller sample size.

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

Figure B.17: Heterogeneity: Urban vs Rural Markets

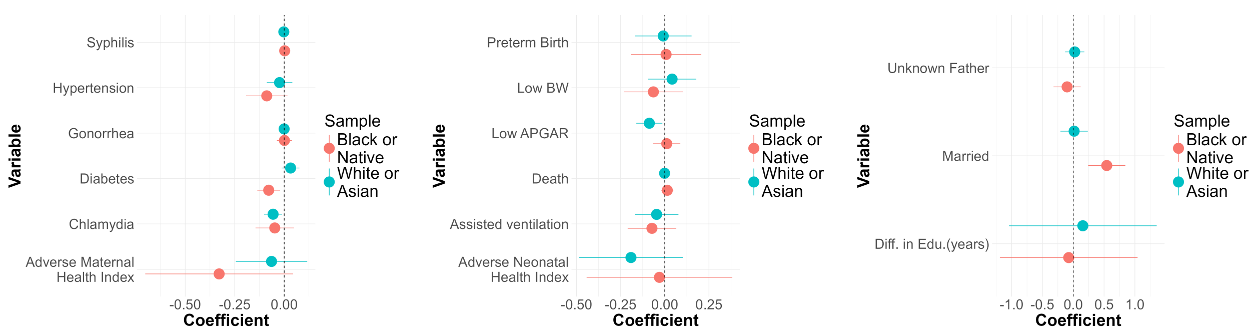


(a) Maternal Health Outcomes (b) Neonatal Health Outcomes (c) Marriage Market Outcomes

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

When split by race (Figure B.18), the dating market effects are more pronounced for racial minorities, with larger absolute coefficients in most outcomes. In the below analysis I divide the sample into two groups: (1) Black and Native, (2) White and Asian [30]. Larger effects for minorities may be due to minorities' higher poverty rates or differences in healthcare treatment, making them more sensitive to bargaining-related factors like domestic violence. Future research could explore how poverty and discrimination mediate the impact of household bargaining.

Figure B.18: Heterogeneity: Racial Group



(a) Maternal Health Outcomes (b) Neonatal Health Outcomes (c) Marriage Market Outcomes

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

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

Table A12: 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)
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)
Observations	3,945	3,947	3,945	3,947	3,945	3,947	3,945	3,947
R^2	0.96513	0.95193	0.97390	0.96073	0.97854	0.97017	0.98036	0.97232

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

B.3 Effect on population marriage rates

Dating market favorable to women increases the marriage rate in the female population. Table A12, 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:

$$Married^{a}_{crg} = \beta^{ag}\text{Prop. male at birth}_{cr} + \gamma^{ag}X_{cr} + \lambda^{ag}_{c} + \delta^{ag}_{r} + \epsilon^{a}_{crg} \tag{4}$$

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 is only one cohort in the outcome data. Controls include cohort sizes and fixed effects for race and county. 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.

Results (columns 1,3,5,7) show women are more likely to be married when the proportion of men is high, with the largest effect at age 32 (significant at 5%). Women in the 75th percentile of male proportion are 3.6 p.p. more likely to be married than those in the 25th percentile. This suggests the increase in married mothers (Table II) is not solely due to fertility selection. For men (columns 2,4,6,8), the effect is smaller and consistent with Angrist (2002), who found a positive effect for women but no significant effect for men.

B.4 Migratory Response to Unfavorable Dating Market

Using census data on migration flows (2011-2015), I show that women are more likely to leave counties with a scarcity of men and move to places where men are relatively plentiful. I construct yearly arrival and departure rates for both genders and regress them on the proportion of male births in two cohorts (ages 15-24 and 25-34 in 2010). The data are not desegregated by race or age, so I restrict the sample to racially homogeneous counties. I estimate the following equation:

$$y_c^g = \alpha + \beta_{15-24}^g \text{Prop. male at birth: 15-24}_c + \beta_{25-34}^g \text{Prop. male at birth: 25-34}_c + \gamma^g X_i + \epsilon_c \tag{5}$$

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. I control for the cohort size in 2010. The parameters β_{cohort}^g identify the migratory response to the instrument for gender g. Tables A14 and A13 presents the estimation results.

Table A14 indicates that women are less likely to leave counties with a favorable sex composition in cohort 25-34 (column 2), while the effect for men is smaller and not significant (column 1). Table A13 shows that female arrival rates increase with the proportion of men in cohort 15-24 (column 2), with no significant effect for men (column 1).

Table A13: In Migration

Dependent Variables: Model:	Male arrival rate (1)	Female arrival rate (2)
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)
Dependent variable mean	0.06990	0.05890
Observations	1,727	1,727

Table A14: Out Migration

Dependent Variables: Model:	Male departure rate (1)	Female departure rate (2)
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)
Dependent variable mean	0.06889	0.06248
Observations	1,735	1,735

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

This migratory response helps explain why the first-stage magnitude in Table I is less than one: women leave counties with unfavorable sex ratios, evening out the sex composition. Xiong (2022) observes a similar pattern in China. While migration could affect population composition and bias health estimates, I show in Section C.2 that it likely does not drive the main results.

C Robustness Checks

C.1 Effect on partners' characteristics

While my framework assumes people date within a *race* × *county* × *cohort* cell, women might explore other markets if their own has an unfavorable sex ratio. If this occurs, my estimates would be biased toward zero since the market I analyze is only a part of the actual market women face (see Section C.10 for derivation). To investigate, I use the IV framework from equations 2 and 3 to estimate the impact of *Proportion male* on two variables: the age difference between parents and whether the parents are of different races (Table A15). Column (1) shows that the age difference between parents does not change with sex composition. The coefficient on *Prop. male 2010* is small and insignificant—one standard deviation in the male proportion changes the age difference by just 0.06 years, suggesting women do not seek partners in different age groups when faced with an unfavorable sex ratio. Column (2) shows a slight increase in interracial partnerships when the proportion of men is high, though the estimate is noisy. This result contradicts the expectation that women would seek partners outside their race when men of their race are scarce and may instead reflect men's greater tendency to look outside their race in competitive markets. However, given the noisy estimate, I remain cautious about interpreting this coefficient, as it is not significant at the 5% level.

Table A15: Effect on Market

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

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

Table A16: RF: Income Rank of Stayers

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

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

C.2 Effects of migration on market's composition

The migratory response is unlikely to threaten the identification strategy, as this would only occur if women leaving due to a scarcity of men had better potential outcomes than those staying. Although direct comparison data is unavailable, I use income rank data from the Opportunity Insights dataset to assess this. If women with better outcomes (proxied by income rank) are more likely to leave when the sex ratio is unfavorable, the average income rank of women who stay should decrease as the sex ratio decreases. To test this, I run the following regression:

$$rank.stayed_{crg} = \beta^g \text{Prop. male at birth}_{cr} + \gamma^g X_{cr} + \lambda_c^g + \delta_r^g + \epsilon_{crg} \tag{6}$$

Where $rank.stayed_{crg}$ represents the average income rank of stayers in county c, race r, and of gender g. The main independent variable is the proportion of male births in county c and race r at the time of cohort's birth. Controls include cohort size and race/county fixed effects. Table A16 shows that the income rank of stayers is not related to the instrument. The coefficients β for both men and women are small and statistically insignificant. A one standard deviation change in the proportion of male births has an effect of 0.0067 for women and 0.0038 for men. This suggests that migration in response to the dating market does not alter the composition of stayers.

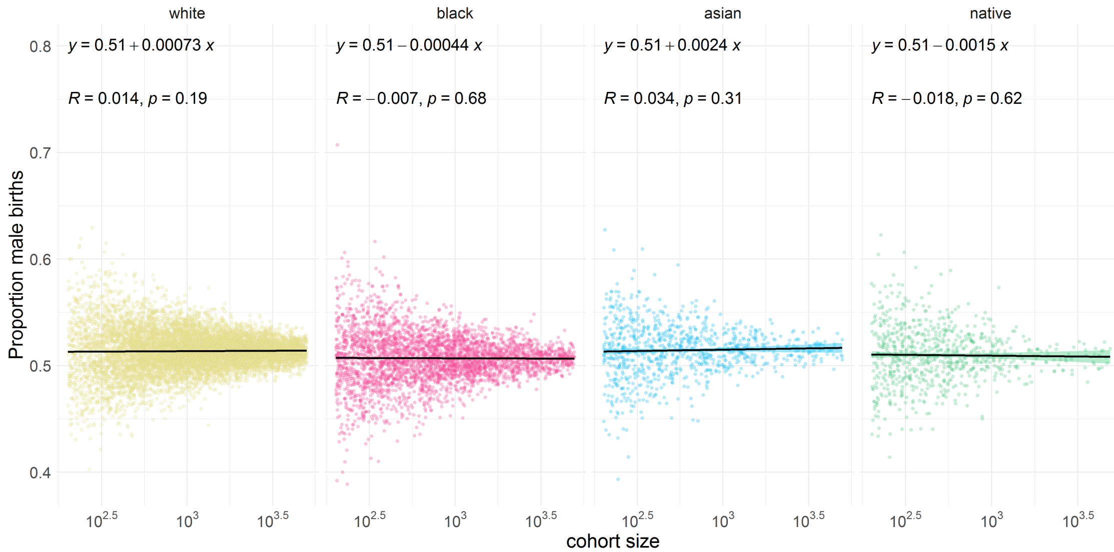
C.3 Stopping rules

Stopping rule does not seem to play a role in shaping sex ratio at birth in my sample. The concern stems from the fact that son preference and a stopping rule would result in more boys in smaller cohorts. Smaller cohorts may also benefit from more intensive human capital investments. Nonetheless, figure C.19 shows that there is no relationship between birth cohort size and proportion of male births in none of the racial group.

C.4 Effects Education and Incarceration

One may be concerned that growing up in a location with unbalanced sex composition may impact behaviors through channels unrelated to the dating market. Suppose that boys in mostly female cohorts could have different attitudes toward women than boys in mostly male cohorts. As I lack data for attitudes, this problem has to be acknowledged as a limitation of the study. Nonetheless, I attempt to partially address this issue by showing that outcomes not directly related to the dating market do not differ across locations with high versus low

Figure C.19: Birth Cohort Size vs Proportion Male at Birth



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

share of men. I focus on two plausible candidates which could be affected by upbringing in an uneven sex ratio setting. Firstly, I analyze whether sex composition at birth affects the share of people who are incarcerated. One would expect such relationship if, for instance, men growing up in cohorts dominated by male were more violent. Secondly, I look at the share of individuals who finished a 4 years college. Relationship between sex composition of a cohort and education could arise through peer effects, as women are more likely to attend college. Note that both outcomes to some extend measure human capital and hence address the previous scenario as well. I test the above mentioned hypothesis by estimating the following equation:

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

Where y_{crg} represents either the share of incarcerated or college educated in county c, race r, and gender g. Estimation results (in table A17) show no relationship between outcomes unrelated to the dating market and the sex composition at birth. Columns (1) and (2) indicate no significant effect on adult incarceration rates, ruling out changes larger than

0.02 percentage points for women and 0.1p.p. for men with 95% confidence. This null effect provides reassurance that growing up in an unbalanced sex ratio is not associated with violence. Furthermore, there is no evidence that educational achievements are shaped by the sex composition at birth, as estimates of β in columns (3) and (4) are not statistically significant. With 95% confidence, it is possible to discount any effects of a one standard deviation shift in the sex ratio on college completion rates that are larger than 0.5 percentage points for both genders. These findings lessen the concern that the main results are driven by the effect of growing up in unbalanced sex composition.

C.5 Effects on Social Networks

An unbalanced sex ratio might influence the development of soft skills, which in turn could affect health. While soft skills are difficult to measure, they may be reflected in social behaviors like forming social networks or engaging in volunteer activities. Using data from Opportunity Insights on social capital (based on Facebook), I examine the reduced-form impact of the sex ratio at birth on social behavior later in life. I focus on two measures: (1) the clustering of high school friendships, which reflects the cohesion of social networks, and (2) civic engagement, which indicates the likelihood of participating in civic organizations or volunteering. I estimate:

$$y_c = \alpha + \beta \text{Prop. male at birth}_c + \gamma^g X_{cr} + \epsilon_{crg} \tag{8}$$

where y_c represents one of the social behavior outcomes in county c and β captures the effect of an imbalanced sex ratio at birth on these outcomes. As shown in the table A18, there is no significant relationship between the sex ratio at birth and these social behavior measures. The maximum impact of a standard deviation change in the sex ratio, according to the 95% confidence interval, would range from -0.0033 to 0.0036 for social networks clustering and from -0.00038 to 0.0016 for social networks volunteering—both negligible relative to their

Table A17: RF: Education and Incarceration

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

Notes: Regressions of education and incarceration outcomes on the proportion of males at birth and covariates. The sample includes individuals born in 1978-1983, assigned to their childhood county. Each observation represents race × county × gender. *Prop. male at birth* measures the male share of births (1978-1983). Incarcerated refers to the share of the cohort incarcerated (columns 1 and 2), and College refers to the share with a college degree by age 25+ (columns 3 and 4). Controls: cohort size, race fixed effects. Standard errors are heteroskedasticity-robust. Data: Opportunity Insights.

Table A18: Reduced Form: Social Networks

Dependent Variables:	Clustering	Volunteering Rate
Model:	(1)	(2)
Prop. male at birth	0.012	0.054
	(0.158)	(0.045)
R^2	0.03590	0.00032
Observations	4,124	4,113
Dependent variable mean	0.59015	0.05815

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

means. These findings suggest that an unbalanced sex ratio at birth does not significantly affect social network formation or civic engagement later in life.

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

A potential concern is whether the sex ratio at birth influences marital stability in the parents' generation, as Dahl and Moretti (2008) found that parents of first-born daughters are more likely to divorce, which could impact children's health. To investigate, I analyze the reduced-form effect of the sex ratio at birth on divorce probability in the older generation using county-level data from the 2010 American Community Survey (ACS).

The analysis covers cohorts aged 35-54 in 2010 to capture variations in divorce timing among potential parents of generations aged 15-34. The variable *Prop. male at birth* measures the proportion of male births in a given county and cohort. The outcome variable indicates share of divorced respondents at the time of the survey. I estimate the following regression model:

$$y_{c,a} = \sum_{a'} \beta^{a'} \text{Prop. male at birth}_{c,a'} + \gamma X_{c,a} + \epsilon_{c,a} \tag{9}$$

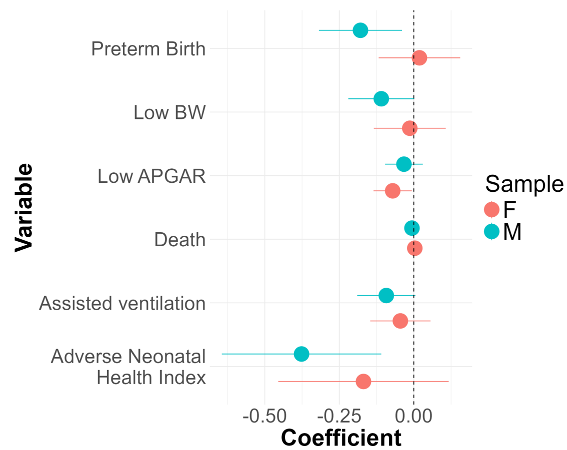
where $y_{c,a}$ represents the divorce probability in county c, cohort a, and $\beta^{a'}$ captures the effect of the sex ratio at birth in cohort a' on the likelihood of divorce in an older cohort.

Table A19: RF: Parent's Divorce

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

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

Figure C.20: Heterogeneity by Sex of the Child



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

The results (table A19) indicate that there is no significant relationship between the sex ratio at birth and the probability of divorce in parental generations. The maximum impact of a one standard deviation change in the sex ratio, according to the 95% confidence interval, ranges from -0.0037 to 0.0044. These findings imply that an unbalanced sex ratio at birth does not have a substantial impact on the likelihood of divorce among parents.

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

My main results rely on the assumption that no third variable drives the cohort's sex composition at birth and the pregnancy outcomes about 20 years later when the cohort enters the childbearing age. An example of such omitted variable could be a socio-economic environment, which according to the fragile-male hypothesis, can affect the sex of a newborn. This relationship would endanger the identification strategy if the socio-economic background at birth also influenced maternal health in adulthood. To address this concerns, I provide evidence that sex at birth in the US is not related to socio-economic variables. I examine several factors: the mother's education, marital status, age, and county unemployment during pregnancy.

A related concern arises if healthier women are more likely to give birth to male children and health is transmitted intergenerationally, potentially driving the observed relationship between sex ratio and health. In this scenario, markets with a higher proportion of male births would exhibit healthier women, who, in turn, would be more likely to produce male offspring, creating a correlation between the instrumented proportion of men (a linear function of birth proportions) and the probability of male births in the next generation. However, I demonstrate that the relationship between the instrumented sex composition and the probability of male births is, in fact, very weak. Furthermore, I also do not find any statistically significant relationship between some health indicators available for the mothers in the natality data and the sex of the child in the full sample of 19 millions mothers.

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. Education serves as a proxy for economic status, given its correlation with income. In each case, I regress the likelihood of a male newborn on these variables and fixed effects (columns 1-3 in Table A20, Panel A) and include all measures in a combined regression (column 4). Finally, in column 5, I add as a regressor the instrumented proportion of male births.

Table A20: Education and Sex at Birth

	Panel: A					Panel: B	
Dependent Variable:	Male birth						
Model:	(1)	(2)	(3)	(4)	(5)	Variable	(6)
High School	0.0010			0.0009	0.0010	Chlamydia	-0.0013 (0.0009)
	(0.0006)			(0.0006)	(0.0006)	Syphilis	0.0046 (0.0038)
Between HS and C	0.0010			0.0010	0.0010	Gonorrhea	0.0001 (0.0022)
	(0.0006)			(0.0006)	(0.0006)	Hepatitis B	0.0021 (0.0024)
College or more	0.0011			0.0011*	0.0010	Diabetes	-0.0000361 (0.0012)
	(0.0007)			(0.0007)	(0.0007)	Hypertension	0.0005 (0.0009)
Married		-0.0003		-0.0003	-0.0003		
		(0.0004)		(0.0005)	(0.0005)		
Age at birth			-4.64×10^{-5}	-8.65×10^{-5}			
			(7.46×10^{-5})	(7.92×10^{-5})			
Instr. prop male 2010					0.0419		
					(0.0638)		
Fixed-effects							
County-Age at birth	Yes	Yes			Yes		
Race-Single age cohort	Yes	Yes	Yes	Yes	Yes		
Race-Age at birth	Yes	Yes			Yes		
County and Race			Yes	Yes			
						Race	Yes
Dependent variable mean	0.512	0.512	0.512	0.512	0.512		0.51157
Observations	7,546,442	7,478,536	7,546,442	7,478,536	7,546,442		19,336,411

Notes: Outcome variable is a dummy equal to one if a male is born. Panel A is based on the sample for which instrument is available. Mother's education can have 4 levels: (excluded) less than high school, high school, between high school and college, and college or more. Standard errors are clustered at the County-Race level. Column (5) includes instrumented proportion of men on the market in 2010. The KP statistic for first stage is 97.252. Panel B is based on all mothers for whom the health information is available. The errors are heteroskedasticity-robust. Data source: Natality Data.

The variation in sex composition at birth is not related to a differential education, marital status or age among mothers. None of the coefficients are significant, and their magnitudes are small. For instance, 10 p.p. increase in mothers with College Education would only increase proportion male by. 0.01 p.p. Considering 95% confidence interval, the impact of having college or more on the probability of male birth would be between $(-0.000272, 0.002472)$ and that of being married $(-0.00128, 0.0006)$. Hence, socio-economic characteristics are unlikely to drive the relationship in the data. Similarly, regarding the effect of the proportion of men in the market, a 95% confidence interval for a one standard deviation change in the sex composition lies between -0.0030 and 0.0061. Consequently, the relationship is unlikely to be driven by a higher likelihood of male births from healthier mothers through the inter-generational transmission of health.

n Panel B of Table A20, I analyze the relationship between maternal health conditions and the sex of the child by regressing the probability of giving birth to a male child on indicators for maternal diseases available in the dataset: Chlamydia, Syphilis, Gonorrhea, Hepatitis B, pre-existing Diabetes, and pre-existing Hypertension. This regression leverages the full dataset where these health variables are recorded, encompassing approximately 19 million observations. The results reveal no statistically significant associations, and the estimated coefficients exhibit inconsistent signs. Notably, four coefficients are positive, suggesting a marginal tendency towards male births for mothers with these conditions, though the effects are small. A 95% confidence interval for these estimates rules out any impact greater than 0.5 percentage points in favor of male birth. While other health measures not captured here might influence male birth, the lack of consistent effects even for severe diseases like syphilis, which result in high mortality, challenges the hypothesis that male fetuses are more sensitive to maternal health and that this drives sex ratio patterns across generations.

Next, I demonstrate that economic conditions, proxied by unemployment during pregnancy, do not affect sex composition. I regress the sex composition of births on unemployment levels at the time of delivery and throughout pregnancy, allowing for differential effects based on exposure timing. Monthly county-level sex composition (2003-2020) comes from the Natality data, with unemployment data sourced from FRED. I estimate both an OLS and IV model using a Bartik-type instrument. The OLS follows this equation:

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

The outcome variable is the proportion of male births in county c during month-year t. The main independent variable, $Unemployment_{c,t-lag}$, represents the (lagged) unemployment level in county c at time $t-lag$. A lag of 0 refers to unemployment during the delivery month, while a lag of 10 refers to ten months prior. I include county γ_c and time fixed effects δ_t.

The IV framework uses a shift-share instrument to capture exogenous variation in unemployment based on county industry shares[31] and national industry-level monthly unemployment rates. Figure C.21 shows the results.

The regressions find no evidence that unemployment during pregnancy affects sex at birth. OLS coefficients are near zero with tight confidence intervals, and the IV results are similar. The instruments are strong, with Kleinberg-Paap Wald statistics between 24 and 44. Coefficients on all unemployment lags are insignificant. Hence, I conclude that the exposure to booms and recessions, as proxied by unemployment during pregnancy, does not influence sex at birth. Considering 95% confidence, the largest positive and negative impact (among all lags) of 1% change in unemployment on the probability of male birth would be {-0.0011, 0.0009}.

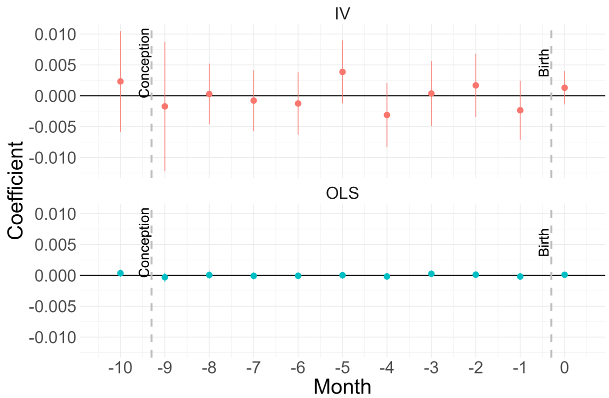
Similarly, one might argue that the relationship between pollution and the sex ratio at birth could be a confounder, as pollution is associated with a variety of other outcomes. However, I find no association between pollution levels during pregnancy and the sex ratio at birth in my sample. I regress the proportion of male births on the lagged Air Quality Index (AQI) for Ozone and PM2.5, following the specification in Equation 10:

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

Where β_P^{lag} captures the effect of AQI changes in the lag months before birth on the probability of a male birth. As shown in Figure C.22, there is no significant relationship between pollution and the sex ratio at birth. Considering 95% confidence interval, the largest positive and negative impact (among all lags) of 1 unit change in the AQI on the probability of male birth would be { -0.00133,0.00095}. These findings suggest that sex at birth in the US is not influenced by maternal economic status, aggregate economic fluctuations (proxied by unemployment), or pollution (proxied by AQI).

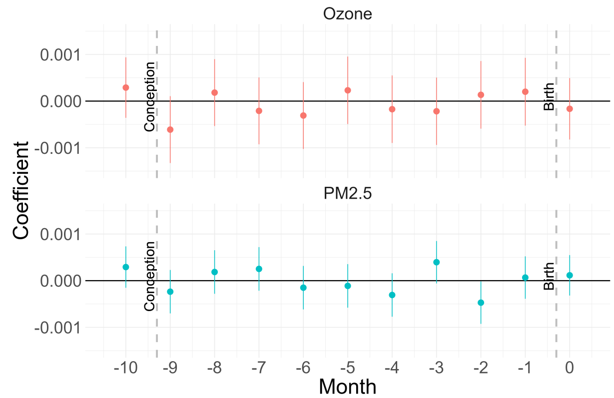
[31]Industry shares from 2000 Census summary file P049

Figure C.21: Unemployment and Sex at Birth



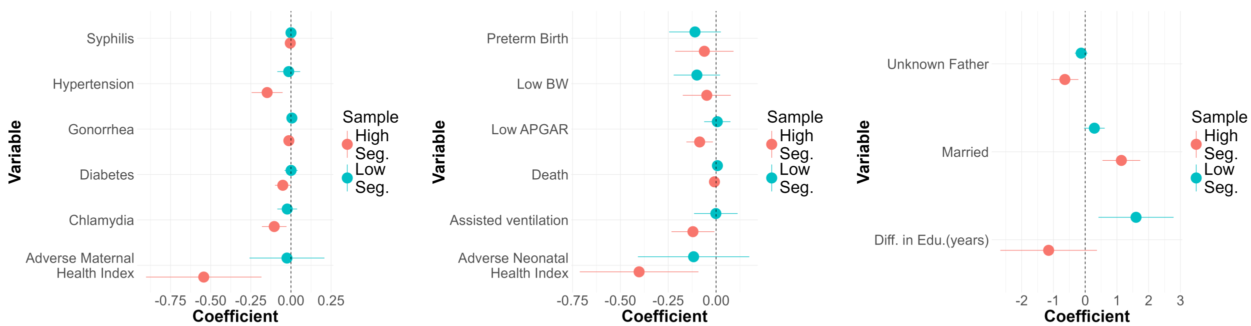
Notes: Each plot depicts coefficients from the regression 10. The IV is based on the Bartik-type instrument. Errors are clustered at the county level.

Figure C.22: Pollution and Sex at Birth



Notes: Each plot depicts coefficients from the regression 11. Estimated on the sample between years 2003 and 2020. Errors are clustered at the county level.

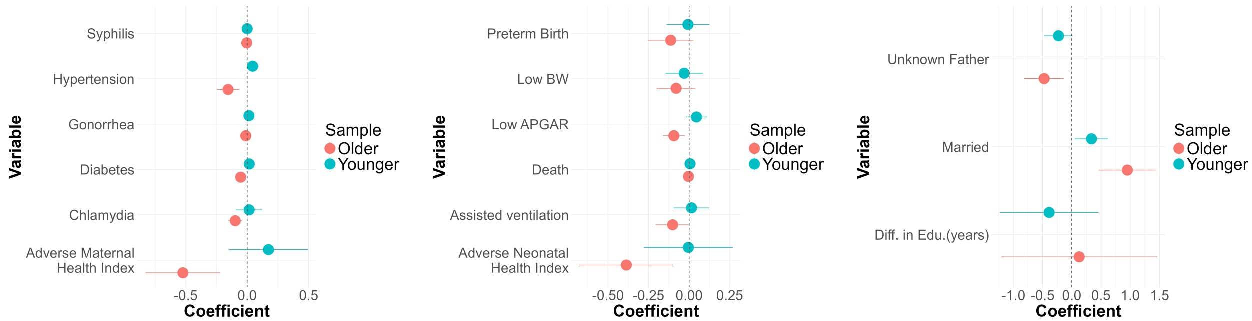
Figure C.23: Heterogeneity by Racial Segregation: Above Median Dissimilarity Index



(a) Maternal Health Outcomes (b) Neonatal Health Outcomes (c) Marriage Market Outcomes

Notes: Plots show coefficients on 'proportion male' from the IV framework for two subsamples: counties with above-median segregation (High Seg.) and below-median segregation (Low Seg.). Segregation is measured by the dissimilarity index (from FRED website), which quantifies the share of the non-Hispanic White population that would need to relocate for equal racial distribution within a county. A higher index indicates greater segregation.

Figure C.24: Heterogeneity: Young Mothers



(a) Maternal Health Outcomes (b) Neonatal Health Outcomes (c) Marriage Market Outcomes

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

C.8 Assigning Incarcerated Individuals to Their Communities

I first use census data on prison blocks to calculate the number of incarcerated individuals by state, race (Black and White), gender, and age group, denoted Inc_census_{srga}. I assume all individuals are incarcerated in their state of residence, though this may not hold for federal prisons, which house a small share of inmates. Next, I use Vera (2022) data, which provides inmate counts by year, race, and county of commitment. Let Inc_vera_{cr} represent the number of inmates of race r from county c. I average counts from 2008-2012 to address missing data and compute the share of inmates from each race contributing to the state's inmate population as $Share^s_{cr} = \frac{Inc\_vera_{cr}}{\sum_{c\in s} Inc\_vera_{cr}}$. I will use this to redistribute them to counties, assuming 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 equates incarceration rates for non-violent offenses between Black and White people. Since detailed geographic data isn't available, I use national race- and gender-specific shares of non-violent inmates ($Share_N V_{rg}$) from BJS CSAT. I calculate the number of non-violent inmates as $Inc\_census_N V_{crga} = Share_N V_{rg} * Inc\_census_{crga}$, which allows me to estimate the share of dating market participants incarcerated for non-violent crimes.

C.9 Bootstrap

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

C.10 Impact of the Market Misdefinition on the Coefficients

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

$$\begin{aligned}
\underbrace{PM^T_{cra}}_{\substack{\text{Proportion Male} \\ \text{At the True Market}}} &= \frac{\sum_{c' \in C} \alpha_{c,c'} n^m_{c'ra}}{\sum_{c' \in C} \alpha_{c,c'} n_{c'ra}} == \sum_{c' \in C} \underbrace{\frac{\alpha_{c,c'} n_{c'ra}}{\sum_{c' \in C} \alpha_{c,c'} n_{c'ra}}}_{\gamma_{c'}} \frac{n^m_{c'ra}}{n_{c'ra}} = \\
&= \gamma_c \frac{n^m_{cra}}{n_{cra}} + \sum_{c' \neq c} \gamma_{c'} \frac{n^m_{c'ra}}{n_{c'ra}} = \underbrace{\gamma_c}_{\gamma_c < 1} \frac{n^m_{cra}}{n_{cra}} + e_{cra} = \gamma_c \underbrace{PM_{cra}}_{\substack{\text{Proportion Male} \\ \text{At the Limited Market}}} + e_{cra}
\end{aligned} \tag{12}$$

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:

$$Y_{cra} = \beta PM^T_{cra} + \epsilon_{cra} = \beta\gamma_c PM_{cra} + \beta e_{cra} + \epsilon_{cra} = \hat{\beta} PM_{cra} + v_{cra} \tag{13}$$

Since γ_c is lower than one, $\hat{\beta}$ is lower than β. Note that IV strategy does not eliminate this bias. Now assume conversely that the measured market is too large. In this case a classical measurement error arises, which is eliminated by the IV.

C.11 Dating market model

I solve a dating market model which demonstrates the effect of sex ratio on the equilibrium female welfare. Suppose that there is a population of men and women. Each person i has a utility function composed of a private good q and a public good Q and it has the form: $u_i(q_i, Q) = q_i Q$. 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 a uniform distribution $y_g \sim U(1, 2)$, where g is gender and $g \in \{m, f\}$. Mass of women is normalized to 1 and mass of men is equal to S which reflects the sex ratio. Without loss of generality, let's assume that $S < 1$, i.e. there is surplus of women on the dating market. Men and women can form couples in which case they maximize joint utility $(q_m + q_f)Q$. The main benefit of being in a couple stems from sharing the public good Q. However, the allocation of resources toward private goods, and hence the final utility, is a result of matching and bargaining in equilibrium. The goal of each woman (man) is to find a partner who maximizes her utility. The natural constraint is that partners must accept each other. These two forces, together with the distribution of partners, drive the equilibrium outcomes. With this model, I aim to show how changes in the sex composition affect female utility in equilibrium. The equilibrium of the dating market is defined as the matching and resource allocation such that no man or woman would prefer a partner different than their match. To solve for the equilibrium I proceed in three steps:

1. **Within couple maximization** Couples maximize their joint surplus S subject to the budget constraint:

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

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

2. **Matching** As the surplus is supermodular, it is a well known property of the matching models that matching will be assortative in incomes. That is, the highest income man matches with the highest income woman, and so on. Let the match of woman y_f be $\theta(y_f)$. Given the uniform distribution of income, assortativity requires that the mass of women with income above y_f must equal the mass of men with income above $\theta(y_f)$. Hence, the match of women is $y_m = \theta(y_f) = 2 - \frac{2-y_f}{s}$. This equation shows the first channel through which the sex composition affects female outcomes. The higher relative abundance of men, the better partner a woman can secure.

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

(a) Marriage participation constraint: $U_m^m(y_m) + U_f^m(y_f) \geq S(y_m, y_f) \forall y_m, y_f$. For any pair of man and woman, their individual equilibrium utilities must be higher or equal to the surplus they would create as a couple. The inequality is strict for any couple not matched in the equilibrium, and it is an equality for couples matched in the equilibrium. This condition is related to the stability of matching: switching partners could never generate enough of surplus to make the new couple better off.

(b) No surplus for last woman in a relationship

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

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

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

Importantly, it can be shown that: $\frac{\partial U(y_f)}{\partial S} > 0$ That is, female utility in equilibrium increases with the sex ratio. There are two channels leading to this result. The first one is matching. As there are more men available on the market, woman can secure a higher quality partner. The second one is the resource allocation. As there is more competition among men, they need to provide women with higher private consumption to sustain the partnership.

C.12 Dating market model: restrictions on men available

The previous model assumes men are added across the entire income distribution when increasing the sex ratio. But would the effect differ if the increase comes only from the lower end of the income distribution, such as releasing incarcerated individuals, who likely have lower potential income? To explore this, I adapt the model to assume that the sex ratio adjustment occurs only among men with income below a threshold t. Solving for equilibrium utilities, I show that all women's utilities increase, even if only low-income men are added to the dating pool. In fact, women at the top of the income distribution benefit the most, regardless of the quality of men added.

The new assumption about male distribution is illustrated in Figure C.25a. The mass of men with income $y_m > t$ (blue rectangle) remains unchanged. Any change in S comes from adding or removing men with income $y_m < t$. The green rectangle represents men with income below t on the market, while the red rectangle shows the "missing" men. Increasing S reduces the red rectangle and expands the green one. Adjusting t allows us to model the potential income of men, such as incarcerated individuals. A lower t reflects lower potential income for men entering the market. When $t = 2$, we return to the baseline scenario from subsection C.11. Solving for equilibrium female utility using this new distribution, I obtain:

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

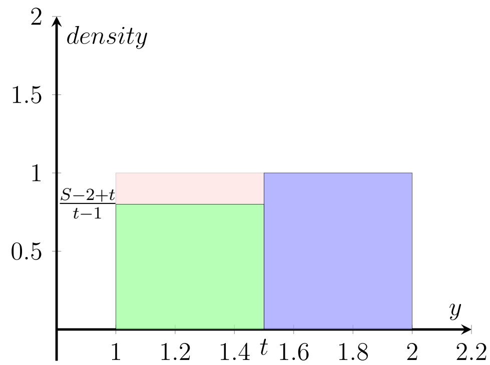
I now use this framework to explore the impact of changing the sex ratio under different assumptions about the men added to the dating pool. Specifically, I examine increasing the sex ratio from 0.9 to 0.95 (or from 47% to 49% male) under two values of $t \in 1.2, 1.8$[32]. The first, $t = 1.2$, represents adding only low-income men, while $t = 1.8$ includes both high- and low-income men.

For each t, I calculate the change in individual female utility (*individual treatment effect*) from the sex ratio increase. Figures C.25c and C.25d display the results.

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

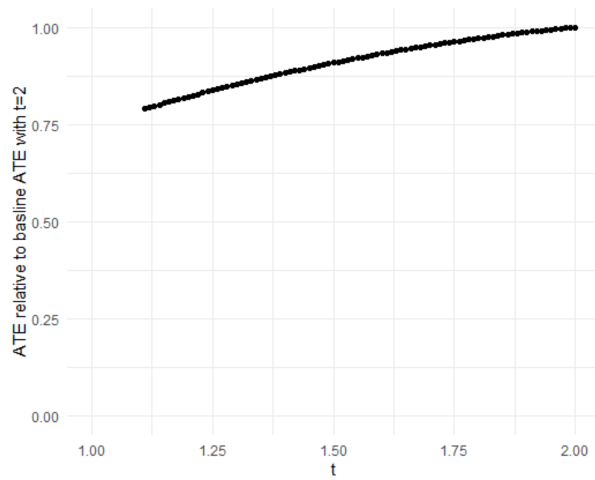
Figure C.25: Model

(a) Distribution of Men



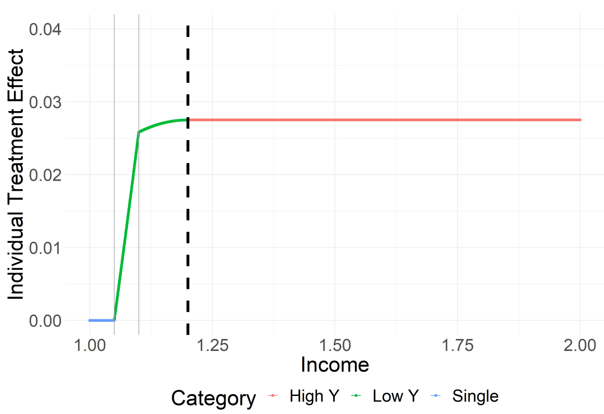
Notes: Plot shows the distribution of men on the dating market. The blue rectangle shows men with income above t, with mass equal to $2-t$. The green rectangle represents men with income below t on the market. The mass of men with $y_m < t$ is equal to $\frac{S-2+t}{t-1} * (t-1)$. The red rectangle corresponds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

(b) ATE(t) relative to ATE(2)

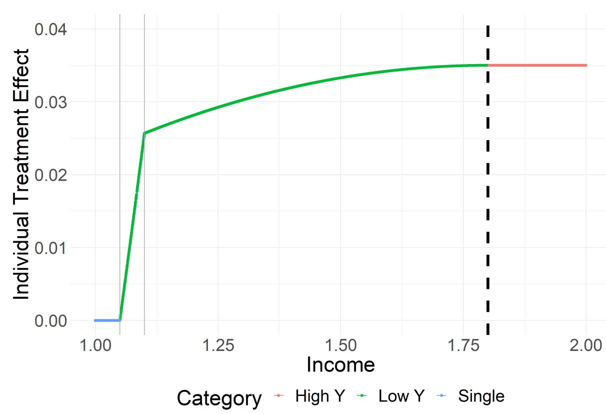


Notes: Plot shows the ratio of average treatment effect (ATE) for a given level of t compared to ATE at $t = 2$. The average treatment effect is the average change in the female utility across the income distribution for a change in the sex ratio from 0.9 to 0.95.

(c) Change in Female Utilities for t=1.2



(d) Change in Female Utilities for t=1.8



Notes: Plots show the changes in female utility as the result of an increase in the sex ratio from 0.9 to 0.95 when $t = 1.2$ and $t = 1.8$. 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 represents women below income t who have a partner. Women between two grey lines did not have a partner before and now have a partner. Red represents women who have income above t.

The impact of changing the sex ratio can be divided into four groups. First, women who were single and remain single (blue line), located at the bottom of the income distribution, experience no change in utility. Second, women with income below t who were previously single but now have a partner (between the grey lines) see an increase in utility from being in a relationship. Third, women with income below t who already had a partner benefit from both a slightly better partner and an improved outside option, enhancing their bargaining position and allowing them to negotiate more favorable resource allocations. Previously, the outside option of the last woman in this group was to be single. Now, her outside option is to be married to the man just below her current partner (previously such man was not on the market). As a result, her current partner needs to provide her with higher utility (more private good) to prevent her from switching to the outside option. Intuitively, her bargaining position improved and she can negotiate a more favorable allocation of resources. Lastly, women with income above t (red line) have the greatest utility increase, even though their partner doesn't change. Their improvement comes entirely from a better outside option. Women with $y_f > t$ can threaten their current partner to leave and date a man just below who now provides a higher utility to their partner. Hence, current partners of women with $y_f > t$ need to allocate more resources to female private good to maintain the relationship. Thus, increasing the pool of available men always benefits women at the top of the distribution.

Comparing the subplots C.25c and C.25d, the changes in utilities are not drastically different. The main utility increase comes from women who were single but are now married, improving the outside option for all subsequent women. In subplot C.25d, more women switch to higher-quality partners, but this contributes less to the utility gain than the effect of switching from singlehood to marriage.

I calculate the average increase in utility across the female income distribution (*Average Treatment Effect, ATE*) and compare them for different values of t. Figure C.25b shows the ratio of ATE for each t relative to the ATE at $t = 2$. Even at the lowest t, where only low-income men are added, the ATE is still more than 75% of the baseline ATE when men across the whole distribution are added to the pool.

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.