Deadbeat Dads*

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Abstract

Why do some men father children outside of marriage but not provide support? Why are some single women willing to have children outside of marriage when they receive little or no support from unmarried fathers? Why is this behavior especially common among blacks? To shed light on these questions, we develop and estimate a dynamic equilibrium model of marriage, employment, fertility, and child support. We consider the extent to which low earnings and a shortage of single men relative to single women among blacks can explain the prevalence of deadbeat dads and non-marital childbearing. We estimate the model by indirect inference using data from the National Longitudinal Survey of Youth 1979. We simulate three distinct counterfactual policy environments: perfect child support enforcement, eliminating the black-white earnings gap, and equalizing black-white population supplies (and therefore gender ratios). We find perfect enforcement reduces non-marital childbearing dramatically, particularly among blacks; over time it translates into many fewer couples living with children from past relationships, and therefore less deadbeat fatherhood . Eliminating the black-white earnings gap reduces the marriage rate difference between blacks and whites by 29 to 43 percent; black child poverty rates fall by nearly 40 percent. Finally equalizing gender ratios has little effect on racial differences in marriage and fertility.

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1 Introduction

""I came to understand the importance of fatherhood through its absence - both in my life and in the lives of others. I came to understand that the hole a man leaves when he abandons his responsibility to his children is one that no government can fill. We can do everything possible to provide good jobs and good schools and safe streets for our kids, but it will never be enough to fully make up the difference. - President Barack Obama, June 19, 2009

By 2006, the United States reached a "dubious milestone" as over half of all births to women under 30 were to single mothers.[1] As President Obama pointed out, many of these families suffer from a lack of resources: the 48 percent poverty rate for families in this circumstance are among the highest of any social group.[2] Such statistics likely reflect the reality that many single mothers are welfare recipients and have low, or no, labor market earnings. Although single motherhood has also been increasing in other developed nations, the problem of poverty among female-headed households with children is especially acute in the United States, because growing up in a single parent home has been associated with many unfavorable outcomes for children (McLanahan and Sandefur, 1994; Haveman and Wolfe, 1995; Carlson and Corcoran, 2001).[3]

This problem is exacerbated by the fact that single mothers also tend to receive little support from the fathers of their children. Several policy changes in recent years attempt to address the lack of financial support coming from so called 'deadbeat dads,' fathers that do not live with their children and do not pay child support. Most state-level policies focus on increased enforcement of child support payments and punitive measures such as withholding wages and tax refunds (Freeman and Waldfogel, 2001; Sorensen and Hill, 2004). However, success in boosting support rates has been limited, and some have argued this is because paying support is difficult for some: of men that did not pay support, between 16 and 33 percent had incomes below the poverty threshold for an individual in 1990 (Mincy and Sorensen, 1998). On a national level President Obama's recent budget proposals have included $500 million dollars to establish the Fatherhood, Marriage and Family Innovation Fund for community programs which facilitate responsible fatherhood, including involvement and financial support. The program comes on the heels of fatherhood initiatives which have become a staple of every recent presidential budget.[4] These social and policy trends raise

[1]See Robert Herbert's "A Dubious Milestone" in the *New York Times*, June 21, 2008.

[2]2013 Current Population Survey (CPS) data indicate the poverty rate among households headed by a female under age 30 with children was 48 percent. The CPS data from the 1980s show poverty rates were even higher—66 percent—among these families.

[3]Wong et al. (1993) attribute this to cross-national differences in demographics, labor force participation rates, and social program design. González (2007) notes the general differences in the structure of social programs between the US (means-tested and targeted) and Western Europe (universal and often not means-tested), and these differences may play a role as well.

[4]President Clinton put forward the "Fatherhood Initiative" 1995 and the "Fatherhood Counts Act" of 1999 which aimed at promoting marriage and child support payments among fathers; these were followed by President GW Bush's "Healthy Marriage Initiative," which allocated $500 million in federal funds toward improving couples' relationships.

important questions: Why do so many men father children outside of marriage and not provide support? Why are single women willing to have children outside of marriage when they receive little or no support from unmarried fathers?

The goal of this paper is to understand and quantify the economic incentives which surround decisions of deadbeat dads and single mothers. We develop and estimate a dynamic equilibrium model of marriage, employment, fertility, and child support that is designed to account for the following stylized facts, documented in the 1993 wave of the National Longitudinal Survey of Youth 1979 cohort (hereafter NLSY79) and in several previous studies (Bartfeld and Meyer, 1994; Clarke et al., 1998; Mincy and Sorensen, 1998; Freeman and Waldfogel, 2001; Cancian and Meyer, 2004):[5]

1. **The majority absent fathers do not pay financial support, have lower education levels, employment rates and earnings than other fathers.** About 30 percent of all fathers and almost 65 percent of all absent fathers do not pay child support. As documented in Table 1, deadbeat dads are 1.4 times (2.7 times) more likely to be high school drop-outs than absent fathers that pay support (present fathers) and have employment rates that are about 20 percentage points lower than other fathers. Deadbeat dads that are employed work fewer hours on average than all other men and receive lower earnings on average than other men.

2. **Single mothers that do not receive support tend to be less educated and have lower employment rates than other mothers.** Table 2 indicates that 41 percent of single mothers that do not receive support are high school drop-outs as compared to 30 percent for single mothers receiving support. Childless women tend to have higher levels of education than mothers: 30 percent of childless women have a college degree compared to 14 percent for married (or cohabiting) mothers. Less than 3 percent of single mothers, regardless of support status, have a college degree. Single mothers that do not receive child support have the lowest employment rates and the highest welfare participation rates compared to all other women.

3. **Deadbeat fathers and single mothers are more prevalent among blacks than whites.** Table 3 indicates that single motherhood is concentrated especially in the black population. Black women are 3.6 times more likely to be single mothers than white women. Roughly 70 percent of black single mothers do not receive financial support from fathers compared to 56 percent for whites in 1993. Black men are about 3 times more likely to be absent fathers than white men.

We formulate a dynamic discrete choice model in which men and women decide whether to work and men decide whether to provide child support for children from prior relationships. Individuals are assumed to match in marriage markets segmented by age, region, and race. The rate at which men and women meet in the marriage market is driven by the ratio of single men to single women, and the probability of meeting a partner with certain characteristics, such as educational attainment

[5] All dollar amounts are expressed in constant 2000 dollars.

and children from past relationships, depends on the population distribution of these characteristics within each marriage market. If an individual makes a contact in the marriage market, the matched man and woman make work and support decisions jointly and must also jointly decide whether to have a birth and whether to marry. As a result, both the number of singles and their characteristics distributions evolve endogenously in the model.

We estimate the parameters of the dynamic model by efficient method of moments, a type of indirect inference, using a sample of men and women from the NLSY79. We use the estimated model to conduct several counterfactual experiments to examine the extent to which low earnings and the supply of men and women in the marriage market can account for the prevalence of non-marital childbearing and deadbeat fathers, as well as racial differences in outcomes. In the first experiment, the black-white gap in labor earnings is eliminated. In the second experiment, we assume the stocks of black men and women by age, education, and year are the same as they are for whites. Our results show that closing the racial gap in labor earnings explains a substantial portion of the differences in outcomes across races: black marriage rates rise by 27 percent, non-marital childbearing rates fall by 25 percent, and deadbeat fatherhood rates fall by 8 percent. Differences in population supplies are, on the other hand, not able to explain racial differences in these behaviors, but do explain the black-white female employment gap.

The model includes a number of mechanisms to account for the prevalence of deadbeat dads and non-marital childbearing as well as differences in the prevalence of these outcomes across races, including low earnings, a shortage of single men relative to single women, and the interaction between family structure and support of children from prior relationships, which is the key dynamic channel. The basic intuition is the following in a given period: men and women may both prefer to have children within marriage, but if faced with a shortage of suitable (i.e. high-income) husbands, it may be optimal for women to have children with low-income men outside of marriage right now. In turn, if women are willing to have children outside of marriage, some low-income men may have incentives to have children outside of marriage but not support them when faced with the tradeoff between own consumption and providing child support. Finally, across time incentives to delay or forego marriage (for instance, in hopes of finding a different partner), can further incentivize deadbeat fatherhood and single motherhood.

We also analyze a counterfactual policy experiment in which there is perfect child support enforcement. We find perfect enforcement leads to substantial reductions in births outside of marriage, and the declines are especially strong among black women, who see 65 percent reduction. The vast majority of women experience welfare gains from perfect enforcement, and surprisingly many men benefit as well, with the majority of black men also experiencing welfare gains. Finally, we compare child poverty rates across the counterfactuals, and find the elimination of the racial gap in earnings is most effective in reducing poverty rates among black children. The decline in child poverty comes about in part from the increase in marriage as well as the increase in child support provision by absent fathers when the racial earnings gap is eliminated. This suggests policies directed toward boosting employment and earnings among absent fathers are a particularly effective means of fighting poverty.

This paper builds on several related literatures, including the theoretical literature that studies the rise in non-marital childbearing. Akerlof et al. (1996) and Willis (1999) establish conditions under which women may choose to have children outside of marriage. In Willis (1999), men in populations that have low absolute levels of income and low levels of income relative to women will tend to have children outside of marriage. This occurs because absent fatherhood may require a lower financial commitment than present fatherhood and because higher earning women can produce quality children without the support of fathers. We extend Willis (1999) by quantifying the effects of low earnings and the scarcity of spouses on patterns of employment, fertility, and marriage rates.

This paper also contributes to the literature explaining racial differences in marriage behavior. Wood (1995) and Brien (1997) test Wilson's (1987) hypothesis that a shortage of marriageable men is behind racial differences in marriage. Moffitt (1998) confirms that the availability of support programs for single women also contributes to the differences in marriage rates across races. Blau et al. (2000) find differences in marriage rates across races, education groups, and over time can be related to declining low-skill male labor markets. Our paper contributes to this literature by identifying how fertility and support decisions interact with the marriage decision across races.

The paper is also related to work that estimates structural models of work and marriage. van der Klaauw (1996) estimates a dynamic structural model of both marriage and employment for women but does not endogenize the fertility decision. Sheran (2007) estimates a dynamic model of women's marriage, fertility, employment, and education decisions. Keane and Wolpin (2010) estimate a dynamic model of school attendance, marriage, work, fertility, and welfare use. They use the model to provide quantitative estimates of the relative importance of labor market opportunities, marriage market opportunities, and preference heterogeneity in explaining minority-majority differences in outcomes. These papers focus only on women in a partial equilibrium setting. Tartari (2014) formulates and estimates a dynamic model of couples' behavior starting from marriage onward in a partial equilibrium context. She endogenizes child support transfers in the event of divorce, and studies how better enforcement of child support affects children's cognitive achievement, among other counterfactuals. Del Boca and Flinn (2012, 2014) study marriage and household time allocation decisions and focus on determining whether household decision making is efficient or inefficient. Our paper builds on Seitz (2009), which develops and estimates a dynamic equilibrium model of marriage and employment. She analyzes the extent to which population supplies and wages can account for black-white differences in marriage and employment rates for men and women. We extend Seitz (2009) by introducing both fertility and child support decisions.

The rest of the paper proceeds as follows. Section 2 discusses the panel data from the NLSY used for estimation. Section 3 outlines the dynamic equilibrium model while Section 4 discusses identification of the structural parameters. Sections 5 and 6 cover the estimation procedure and results, respectively. In Section 7 we conduct three counterfactual experiments and examine child poverty rates, and in Section 8 we offer some final thoughts on child support policy, marriage, and childbearing.

2 Data

Data is collected from the NLSY79 for the years 1979 to 1993. The NLSY79 is ideal for our purposes for several reasons. In addition to standard demographic information, the NLSY79 contains detailed relationship and birth histories for a large cohort of young individuals. It also contains information on the payment and receipt of child support, allowing us to identify whether absent fathers are providing financial support to children. Finally, it contains information on an individual's employment, earnings, and non-labor income across time.

Annual information on marital status and cohabitation is used to construct an individual's marital status for every year in the data. An individual is defined as married if they are currently married or if they list an opposite sex adult as partner on the household roster. For simplicity and to avoid an exceedingly large choice set in the model, cohabitors are treated as married couples in our estimation. Consecutive periods of cohabitation or marriage are treated as a single marriage spell as are transitions from cohabitation to marriage.[6] We make these assumptions to maintain consistency in our definition of marital status and our measurement of marriage spells across years.[7]

To determine whether an individual has children within their current marriage or children from past relationships, information on the number of children ever born is collected from the Fertility and Relationship History section of the NLSY79. Children from current relationships are those whose conception falls within the current marriage spell.[8] All remaining children, including children from dissolved relationships, are included in the stock of children from past relationships.[9]

We create an indicator for deadbeat fathers, equal to one if the father has children from past relationships and did not pay at least one dollar of child support in that calendar year.[10] If the

[6]It is possible an individual reports consecutive periods of marriage or cohabitation and was in two distinct relationships which we treat as one relationship. We find only 172 person-year observations reported more than one spouse or partner in two consecutive periods of marriage or cohabitation, which is less than 0.3 percent of our sample. We may also miss relationships when an individual reports being single in consecutive periods but was married or cohabited between interviews.

[7]We do not use the start and end dates of marriage to construct marital status or marital histories because we do not have this information for all years for cohabitors. Information on the start and end dates of cohabitation is not available until 1990, while information on current cohabitation status is available in all years.

[8]Given the annual nature of the data and the model, we date conception (and the decision to have a birth) as occurring the year prior to the child's birth.

[9]If we infer that an individual became pregnant while single but is married at the following interview date (i.e. the next year), it is assumed the child is part of the current relationship. For these "shotgun marriages," we define the whole relationship as a marriage in order to be consistent with the evolution of the state space outlined below and to not overstate deadbeat fatherhood.

[10]During our sample period we do not observe whether a male respondent (or a female respondent's prior partner) is under an explicit court order to pay child support. Thus, a deadbeat father in our model is any absent father who does not provide any financial support, regardless of whether a formal support award has been established. A potential concern is that we overstate deadbeat fatherhood among never-married men who are less likely to have court-ordered child support payments (since paternity is less likely to be established). However, descriptive statistics from the sample period show that women who were ever married to (or cohabited with) the father were only 5 to 6 percentage points more likely to receive support than women who were never married to the father. Similarly, we find men who were ever married to (or cohabited with) the mother were only 6 to 7 percentage points more likely to

individual is female, we generate a deadbeat indicator equal to one if she has children from a past relationship but did not receive support. Child support receipt information for women is available in the data for all years, and is aggregated with alimony receipt for calendar years 1979 and 1980. After 1980, alimony and child support receipt are separate, and we only consider child support receipt.[11] Child support provision information for men is unavailable for calendar years 1979 and 1980, available for years 1981 to 1987, unavailable for years 1988 to 1992, and available again in 1993.[12] Our non-likelihood-based estimation strategy allows us to still use male observations in years which data on child support provision is unavailable.

An individual is defined as employed if they work more than 775 hours during the calendar year. Labor income is defined as total earnings from wages and salary and income from a farm or business in the calender year for which hours are recorded. Non-labor income is composed of unemployment insurance, welfare, food stamps, income from other sources, workman's compensation, disability, and veteran's compensation. While this is a broad definition of non-labor income, it is necessary given the model's inclusion of both men and women. Sorensen and Zibman (2001) show that low-income women tend to get much of their non-labor income from welfare and food stamps while low-income men tend to receive non-labor income from workman's compensation, disability insurance, or veteran's compensation.

Indicators for whether an individual's highest level of education is a high school diploma or a college degree are constructed from several measures of educational attainment. The indicator for high school is equal to one if the individual completed 12 years of school or obtained a GED. The indicator for college is equal to one if the individual obtained a Bachelor's degree or higher.

As in Seitz (2009), to construct the sex ratios, an individual's marriage market is assumed to be limited to same-race individuals that live in the same region and are in the same age cohort.[13]

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provide support than men who were never married to the mother.

[11]We do not include alimony receipt in the years alimony and child support receipt are reported separately due to the different nature and purpose of those sources of income. In 1981, conditional on receiving alimony or child support, we find on average alimony makes up less than 1.6 percent of combined alimony and support receipt for women (and 0 percent for the median woman), which should alleviate concerns about using the combined alimony and child support receipt variable in 1979 and 1980.

[12]It is possible males make (or females receive) child support in the form of informal payments, whether cash or in-kind. To the extent these transfers are not captured in our data, the number of deadbeat dads may be overstated.

[13]It would have been possible to allow blacks and whites to participate in the same marriage market and have preferences over the race of their spouse. However, Wong (2003) finds that interracial marriage rates are generally

Regarding race, individuals are identified as black or white based on self-reported data collected during the first interview with the NLSY. Data from the 1990 Census indicate that interracial marriage is relatively uncommon: approximately 97 percent of whites and 93 percent of blacks have same-race spouses.[14] Given the low rates of interracial marriage, and the fact that data on the race of the spouse is not available in the NLSY79, we segment the marriage market by race.[15] Region indicators for the Northeast, South, West, and North Central are created using the regional groupings in the NLSY. The age cohort we consider is limited to women ages 15 to 19 in 1979 and men ages 17 to 21 in 1979, which allows us to follow the behavior of a single cohort over time.[16] We treat completed schooling as exogenous and assume individuals enter the marriage market in the first period they leave full-time school.[17] The original NLSY sample in 1979 consists of 6,403 males and 6,283 females. We remove individuals serving in the military, and as mentioned above, we restrict the sample to women ages 15 to 19 years and men ages 17 to 21 years in 1979. The end sample consists of 3,203 women and 2,811 men in 1979, and 69,280 person-year observations.

Since our NLSY sample may not be representative of the population in terms of age, sex, race, and marital status, when we construct the stocks of single and married individuals in each marriage market we follow Seitz (2009) and re-weight the NLSY using the Current Population Survey (CPS). More specifically, as described above, we define the marriage market by age, region, and race. We then create sampling weights such that the stocks of single and married men and women in each marriage market in each year in our NLSY sample match the corresponding stocks in the CPS. The stocks of single men and women in each marriage market as well as the sex ratios are then

unresponsive to improvements in black male human capital endowments as well as increases in the rate at which black males meet white females. Thus, allowing interracial marriage seems unlikely to substantively alter the qualitative implications of our model.

[14]Source: http://www.census.gov/population/socdemo/race/interractab2.txt

[15]Hispanics are eliminated from the sample because they have much higher inter-ethnic marriage rates: roughly one-third of Hispanics marry non-Hispanics. See http://www.census.gov/population/socdemo/race/interractab3.txt.

[16]We choose the age cohort in this way since the data suggests men tend be older than their spouses by 2 to 3 years on average, with about 90 percent marrying women who are less than 3 years older and 7 years younger (Seitz, 2009). In our data, 70 percent of respondents who are married have a spouse whose age falls exactly in the age cohort or one year outside the age cohort.

[17]In the empirical specification, time is measured in terms of the number of years the age cohort has been eligible to be in the marriage market (i.e. the number of years since 1978). Since we only follow a single cohort over time, time and age are used interchangeably throughout the paper.

created using the NLSY data and these constructed weights.[18,19] Figure 1 shows the sex ratios for each marriage market. In early periods, for both blacks and whites, the sex ratios are more favorable for females which reflects the fact that women who are not in school are relatively scarce at the beginning of the sample period (since we assume individuals enrolled in school are not in the marriage market). However, after a few periods, sex ratios become much less favorable for black women, which reflects in part differences in mortality and incarceration rates across black and white men and women.

3 Model

The model described below is designed to account for the stylized facts outlined in Section 1. Two important mechanisms are incorporated in the model to capture the above-mentioned behavior. The first is that labor earnings and non-labor income faced by agents are assumed to differ depending on characteristics such as education, gender, and race. Different earnings and non-labor income in turn determine the desirability of current and future marriage and fertility, and the extent to which fathers are likely to support their children. Second, the supply of men and women in the marriage market differs by gender, education, and race. One of the goals of the empirical analysis will be to determine the extent to which these mechanisms can account for the aforementioned outcomes.

3.1 Contact Rates

In every period, single agents of gender $g \in \{m, f\}$, where $g = m$ for male and $g = f$ for female, meet potential spouses with a probability that varies by gender, race, region, and time. All

[18] To maintain consistency between the CPS data and our NLSY data, we exclude individuals in the CPS who serve in the military, who are Hispanic, and who are enrolled in school when constructing the weights. In addition, as in Seitz (2009), since data on cohabitation is not available in the CPS for the time period we consider, individuals who cohabit in the NLSY are treated as single individuals for assigning CPS weights, but are treated as married individuals when we construct the stocks with the reweighted NLSY. Cohabiting individuals make up only 7.5 percent of our NLSY sample.

[19] We cannot use the CPS to directly calculate the stocks because the individual-level transitions in and out of marriage observed in the NLSY79 are used to measure sex ratio changes over time. The marriage transitions (the flows) must be completely consistent with the sex ratio (the stocks) in equilibrium. Thus, the stocks must be calculated directly from the NLSY79.

meetings occur within marriage markets segmented by race and region, which we suppress here for convenience. Let e denote the race-region marriage markets, $e \in \{1, 2, ...E\}$. The contact rate is composed of two parts. First is the probability an individual of gender g is contacted by a potential spouse, $\gamma^g(S_t^e)$, which is market specific and depends on the ratio of single men to single women in the cohort range we consider at time t, S_t^e.[20] The second part is denoted $\Phi_e^g(N^{g'}, K_t^{pg'}, t)$ which is the probability conditional on making a contact that the potential spouse has characteristics $\{N^{g'}, K^{pg'}\}$ in period t, where N^g is education and K^{pg} is the number of children from prior relationships.[21] In other words, this is the fraction of potential spouses with education N^g and past children K^{pg} in marriage market e in period t.

3.2 Choice Set

If a contact is made, the matched man and woman jointly decide whether to have a birth, b_t,[22] whether to marry, r_t, and whether the man and woman will work, $(1 - l_t^m)$ and $(1 - l_t^f)$, respectively. If they decide to marry, the couple jointly decides whether to remain married or to divorce in the following period. If a couple decides to remain single but have a child or if a married couple decides to divorce, men also decide whether to support the child, $(1 - d_t^m)$, in the subsequent period, where d_t^m is an indicator equal to one if the father does not provide support (i.e. is a deadbeat dad). Agents that do not make a contact in the marriage market make employment decisions. The choice set for unmatched men is denoted A_t^m. There are four elements in A_t^m, corresponding to each combination of l_t^m and d_t^m. There are two elements in the choice set for unmatched women, denoted A_t^f, as unmatched women only choose their employment status. The choice set for matched couples, denoted A_t^{mf}, includes the marriage choice, the pregnancy choice, whether the male provides support (if he has children from a past relationship), and the employment decisions of both partners. Thus, there are up to 32 elements in A_t^{mf}.[23,24] Denote each element of

[20] The gender in excess demand makes a contact in the marriage market with certainty. For example, the probability a woman makes a contact with a single man is $\gamma^f(S_t^e) = \min(1, S_t^e)$, and the probability a man makes a contact with a single woman is $\gamma^m(S_t^e) = \min(1, \frac{1}{S_t^e})$.

[21] $\sum_{N^{g'}, K^{pg'}} \Phi_e^g(N^{g'}, K_t^{pg'}, t) = 1$.

[22] The decision to have a birth in period t results in a new child in period $t + 1$.

[23] We treat cohabiting couples as married to avoid an even larger choice set.

[24] If the male does not have children from a prior relationship, then d_t^m is 0 and there are only 16 elements in A_t^{mf}.

the choice set a.

3.3 Children and Child Support

We assume agents care about children from their current marriage, K_t^c, and their past relationships, K_t^{pg}. All children born to single individuals and children from a dissolved marriage are treated as children from a past relationship, and they are assumed to reside with their mother.[25] The stock of children from previous and current relationships entering period $t+1$ evolves according to

$$K_{t+1}^{pg} = \begin{cases} K_t^{pg} & \text{if } \ r_t = 1 \\ K_t^{pg} + K_t^c + b_t & \text{if } \ r_t = 0 \end{cases} \tag{1}$$

and

$$K_{t+1}^{c} = \begin{cases} K_t^{c} + b_t & \text{if } \ r_t = 1 \\ 0 & \text{if } \ r_t = 0. \end{cases} \tag{2}$$

Note that if an individual divorces in period t, the children from that marriage become part of the stock of past children when entering period $t+1$. In addition, if a birth decision is made in period t and the individual is single, that child is part of the past children stock upon entering period $t+1$.

As mentioned above, we assume fathers have the choice to financially support children from past relationships, K_t^{pm}.[26] Similarly, we assume that women can receive support, $(1 - d_t^f)$, for children from past relationships, K_t^{pf}. Women treat the probability of child support receipt as given.[27] In other words, once a child arrives, the decision to transfer money to the mother is completely under the control of the father.[28] The probability of receiving support is a function of the female's

[25]During our sample period, about 85 percent of all custodial parents were mothers (Scoon-Rogers and Lester, 1995; Scoon-Rogers, 1999).

[26]We do not observe and therefore cannot explicitly model support that may occur through savings such as a college fund or other indirect non-monetary and in-kind transfers.

[27]It is possible that the number of past relationships that produced children, and thus eligibility to pay or receive support, differs across the mother and father. We cannot identify such cases in the data and ignore this possibility in the model, treating all children from past relationships the same, even if they have different fathers (or mothers). We do this because data on the sources of support from all fathers (or support to all mothers) is not available in the NLSY and the state space becomes exceedingly large if agents treat children from each possible past relationship differently.

[28]If we did not impose this assumption, it would be necessary for females to track all of her previous partners' state variables which are not available in the data and which would be very computationally demanding.

stock of prior children, education, race, region, and age. We estimate this probability outside the structural model.[29]

Annual child support transfers are denoted $\tau^g(\cdot)$. Child support transfers received by the woman, τ^f, are modeled separately from transfers provided by the man, τ^m, since we do not keep track of the characteristics of an individual's past matches.[30] Thus, transfers received by a woman are a function of her state variables and transfers given by a man are a function of his state variables. Since child support award amounts typically depend on the number of children owed support and the income of the father (and sometimes the mother), we allow support to depend on the stock of children from past relationships, education, race, region, and a quadratic in the parent's age. Finally, transfers depend on an idiosyncratic shock, ε^g_τ, to capture unobservable factors which affect award amounts such as variation in judicial discretion and variation in guidelines across states.[31] Child support transfers received by the woman are given by

$$\ln \tau^f_t = \tau^f_0 + \tau^f_N N^f + \tau^f_{Bl} Bl^f + \tau^f_{Reg} Reg^f + \tau^f_t t + \tau^f_{t^2} t^2 + \tau^f_p K^{pf}_t + \varepsilon^f_{\tau t}, \tag{3}$$

where N^g is a set of educational attainment indicators, Bl^g is an indicator for being black, and Reg^g is a set of region indicators.[32] Child support transfers to be paid by the man are given by

$$\ln \tau^m_t = \tau^m_0 + \tau^m_N N^m + \tau^m_{Bl} Bl^m + \tau^m_{Reg} Reg^m + \tau^m_t t + \tau^m_{t^2} t^2 + \tau^m_p K^{pm}_t + \varepsilon^m_{\tau t}. \tag{4}$$

Child support to be paid by the father is estimated within the structural model. However, support received by women is estimated outside the structural model since women's receipt of support from

[29] Estimates of this probability can be found in Table 10.

[30] Estimating one unified child support transfer process would require observing the characteristics, including the history of past children, of all the individual's past matches that produced children, which we do not observe in the NLSY or any dataset to our knowledge. In addition, in 1975, part D of the Social Security Act decreed that if a custodial parent received cash welfare benefits, she must assign her rights to child support to the government. The government then retains most of the child support payment that is collected to offset the cost of providing welfare benefits. Thus, child support paid by a father does not necessarily equal the amount received by the mother, which provides further support for modeling the two processes separately.

[31] Child support orders have traditionally been the responsibility of the courts, and in the past they were usually set on a case-by-case basis according to state family laws. In 1984, Congress mandated that states adopt advisory child support guidelines. In 1988, Congress required that state child support guidelines be binding on judges, unless a written justification was issued (Lerman and Sorensen, 2003).

[32] We assume there is no regional mobility. Thus, an individual's region of residence is fixed across time. Less than 3.5 percent of our sample experiences a change in region between periods.

past partners is treated as given.

3.4 Preferences

Individuals have preferences over whether they are married or single, r_t, leisure, l_t^g, the decision to have a birth, b_t, the decision to provide child support or not (men only), d_t^m, children from partnerships that produced children, K_t^{pg} and K_t^c, private consumption (which is a function of household consumption, c_t), and the stock of marital specific capital, M_t, which is measured as marriage duration entering period t. Marriage specific capital accumulates according to:

$$M_{t+1} = \begin{cases} M_t + 1 & \text{if } \; r_t = 1 \\ 0 & \text{if } \; r_t = 0. \end{cases} \tag{5}$$

Individuals split the joint surplus from a match via Nash bargaining which we discuss in more detail in Section 3.7. A matched individual's utility function includes a utility term for marital specific capital, utility costs from initiating a marriage which vary linearly with age, utility costs from dissolving a marriage, utility from children within the current marriage, utility from the decision to have a birth within or outside marriage which varies with race, and idiosyncratic shocks to the utility from marriage and birth, ε_r and ε_b, respectively.[33] We also allow the utility from marriage to differ for blacks. We allow preferences over marriage and the birth decision to vary by race since we found a model without such heterogeneity was not capable of matching racial differences in marriage rates as well as births within and outside of marriage.[34] We constrain the above-mentioned parameters to be the same for matched men and women.[35] Last, there are gender-specific shocks to the utility from leisure, ε_l^g, and a shock to the male's utility from providing support, ε_d^m. Preferences for men

[33] The shock to the utility from marriage can be thought of as a new draw of marriage match quality. Once married, new draws may lead to divorce.

[34] In addition, several studies have found that blacks enjoy lower utility from marriage than whites (Sheran, 2007; Seitz, 2009; Keane and Wolpin, 2010).

[35] It is not possible to separately identify different utilities from marital specific capital, marriage initiation, marriage separation, children within the current marriage, or the decision to have a birth for the husband and wife. We discuss this further in Section 4.

matched to a woman with K^{pf} prior children are

$$\begin{aligned}
&u^m(r_t, b_t, l_t^m, d_t^m, K_t^{pm}, K_t^{pf}, K_t^c, c_t, M_t) = \\
&\quad (\alpha_1 + \alpha_2 t)1(M_t = 0)r_t + \alpha_3 1(M_t \neq 0)(1 - r_t) + \alpha_4 M_t r_t + \alpha_5 Bl^m r_t \\
&\quad + \alpha_6(1 - Bl^m)b_t(1 - r_t) + \alpha_7(1 - Bl^m)b_t r_t + \alpha_8 Bl^m b_t(1 - r_t) + \alpha_9 Bl^m b_t r_t + \alpha_{10} K_t^c r_t \\
&\quad + \alpha_{11} l_t^m(1 - r_t) + \alpha_{12} l_t^m r_t + \alpha_{13} K_t^{pm} r_t + \alpha_{14} d_t^m 1(K_t^{pm} > 0)(1 - r_t) + \alpha_{15} d_t^m 1(K_t^{pm} > 0) r_t \\
&\quad + \ln\left(\frac{c_t}{\sqrt{1 + r_t + r_t(K_t^c + K_t^{pf})}}\right) + \varepsilon_l^m l_t^m + \varepsilon_d^m d_t^m + \varepsilon_b b_t + \varepsilon_r r_t
\end{aligned} \tag{6}$$

and preferences for matched women are described by

$$\begin{aligned}
&u^f(r_t, b_t, l_t^f, K_t^{pf}, K_t^c, c_t, M_t) = \\
&\quad (\alpha_1 + \alpha_2 t)1(M_t = 0)r_t + \alpha_3 1(M_t \neq 0)(1 - r_t) + \alpha_4 M_t r_t + \alpha_5 Bl^f r_t \\
&\quad + \alpha_6(1 - Bl^f)b_t(1 - r_t) + \alpha_7(1 - Bl^f)b_t r_t + \alpha_8 Bl^f b_t(1 - r_t) + \alpha_9 Bl^f b_t r_t + \alpha_{10} K_t^c r_t \\
&\quad + \alpha_{16} l_t^f(1 - r_t) + \alpha_{17} l_t^f r_t + \alpha_{18} K_t^{pf} r_t \\
&\quad + \ln\left(\frac{c_t}{\sqrt{1 + r_t + K_t^c + K_t^{pf}}}\right) + \varepsilon_l^f l_t^f + \varepsilon_b b_t + \varepsilon_r r_t
\end{aligned} \tag{7}$$

where the ε's are normally distributed and serially independent.[36] An individual's private consumption is adjusted for family size, and as mentioned above, we assume children born outside of marriage and children from dissolved marriages reside with their mother and receive an equal share of resources.

The utility functions for unmatched individuals include a subset of the preference parameters that govern matched individuals' utility. Preferences for unmatched men are described by

$$\begin{aligned}
u^m(r_t, b_t, l_t^m, d_t^m, K_t^{pm}, K_t^c, c_t, M_t) &= u^m(0, 0, l_t^m, d_t^m, K_t^{pm}, 0, c_t, 0) = \\
&\alpha_{11} l_t^m + \alpha_{14} d_t^m 1(K_t^{pm} > 0) + \ln c_t^m + \varepsilon_l^m l_t^m + \varepsilon_d^m d_t^m.
\end{aligned} \tag{8}$$

[36]We cannot separately identify utility from children from a prior relationship when single versus married. Thus, we normalize the utility from children from a prior relationship when single to zero for both men and women.

Preferences for unmatched women are described by

$$
\begin{aligned}
&u^f(r_t, b_t, l_t^f, K_t^{pf}, K_t^c, c_t, M_t) = u^f(0, 0, l_t^f, K_t^{pf}, 0, c_t, 0) = \\
&\alpha_{16} l_t^f + \ln\left(\frac{c_t}{\sqrt{1+K_t^{pf}}}\right) + \varepsilon_l^f l_t^f.
\end{aligned} \tag{9}
$$

Note that single unmatched men still have the choice to not support children from past relationships, while single unmatched women share their consumption with all of their past children.

3.5 Earnings and Non-Labor Income

Each period agents receive a job offer that is associated with an annual earnings amount. Annual earnings, w^g, are assumed to depend on the agent's human capital stock, which is a function of completed schooling and experience. Since we are missing information on experience for all spouses in the data, we instead include a quadratic in age. We also allow earnings to differ with an individual's race and region. Finally, earnings are a function of idiosyncratic shocks, ε_w^g, that are normally distributed and serially independent. Annual earnings associated with a job offer are given by

$$
\ln w_t^g = \kappa_0^g + \kappa_N^g N^g + \kappa_{Bl}^g Bl^g + \kappa_{Reg}^g Reg^g + \kappa_t^g t + \kappa_{t^2}^g t^2 + \varepsilon_{wt}^g. \tag{10}
$$

Annual non-labor income is denoted y_t^g and varies by gender and marital status and is a function of one's race, region, own education, spousal education (if married), the stock of children from current and past relationships, and a quadratic in age. We also allow non-labor income to vary with whether the individual works as well as interactions between some state variables to capture welfare and unemployment benefit receipt patterns. Non-labor income for singles is described by

$$
\begin{aligned}
y_t^g = {} & \zeta_0^g + \zeta_N^g N^g + \zeta_{Bl}^g Bl^g + \zeta_{Reg}^g Reg^g + \zeta_t^g t + \zeta_{t^2}^g t^2 \\
& + \zeta_p^g K_t^{pg} + \zeta_l^g (1 - l_t^g) + \zeta_{l,p}^g (1 - l_t^g) K_t^{pg} + \zeta_{Bl,p}^g K_t^{pg} Bl^g
\end{aligned} \tag{11}
$$

and non-labor income for married couples is

$$
\begin{aligned}
y_t^{mf} = {} & \zeta_0^{mf} + \zeta_{N^f}^{mf} N^f + \zeta_{N^m}^{mf} N^m + \zeta_{Bl}^{mf} Bl^m + \zeta_{Reg}^{mf} Reg^m + \zeta_t^{mf} t + \zeta_{t^2}^{mf} t^2 \\
& + \zeta_{pf}^{mf} K_t^{pf} + \zeta_{pm}^{mf} K_t^{pm} + \zeta_c^{mf} K_t^c + \zeta_{l^f}^{mf} (1 - l_t^f) + \zeta_{l^m}^{mf} (1 - l_t^m)
\end{aligned} \tag{12}
$$

recalling that individuals are assumed to match with individuals of the same race in their same region; thus, only the race and region of one partner is included in the non-labor income equation for married couples. The non-labor income equations are estimated outside the structural model by linear regression, and non-labor income is treated as deterministic within the structural model. In the event the non-labor income estimates imply negative non-labor income for an individual, we assign that individual zero non-labor income.

3.6 Household Budget Constraints

The household budget constraint for single women is[37]

$$c_t = w_t^f (1 - l_t^f) + y_t^f + \tau_t^f (1 - d_t^f). \tag{13}$$

The household budget constraint for single men is

$$c_t = w_t^m (1 - l_t^m) + y_t^m - \tau_t^m (1 - d_t^m). \tag{14}$$

The household budget constraint for married couples is

$$c_t = w_t^m (1 - l_t^m) + w_t^f (1 - l_t^f) + y_t^{mf} + \tau_t^f (1 - d_t^f) - \tau_t^m (1 - d_t^m). \tag{15}$$

[37]We do not include savings or asset holdings in the model. We are focused on decisions made early in the lifecycle and several studies show that young households hold little liquid wealth. Fernández-Villaverde and Krueger (2011) show that lifecycle wealth is hump-shaped, with young households holding very few liquid assets and only starting to accumulate significant amounts of financial assets later in life. Gourinchas and Parker (2002) find that households save relatively little and consume roughly their income on average early in the lifecycle. Further, data limitations prevent us from constructing accurate asset and savings measures, particularly in the early years of the NLSY. In addition, we do not allow for borrowing in the model.

3.7 Value Functions

In every period, agents maximize the present discounted value of expected lifetime utility. If a single individual meets a potential spouse, both partners jointly decide whether to become pregnant, whether to marry, and whether each spouse will work. If the male has children from previous relationships, he must also decide whether to provide child support. If they decide to remain single but have a child, men decide whether to support the child next period. We start by considering the value functions for unmatched men and women and then proceed to matched men and women.

The value function can be expressed as the maximum over the choice-specific value functions. Denote the choice-specific value function for men $V_t^m(a_t, \Omega_t)$ and likewise for women $V_t^f(a_t, \Omega_t)$ where Ω_t denotes the vector of state variables

$$\Omega_t = \{K_t^{pm}, K_t^{pf}, K_t^c, d_t^f, M_t, N^m, N^f, e, t, \boldsymbol{\epsilon_t}\} \tag{16}$$

and $\boldsymbol{\epsilon_t}$ contains the full set of preference, earnings, and child support shocks.[38] The state space vector conditions in the current sex ratio and the demographic composition of singles in an individual's marriage market, e, at time t.

The choice-specific value function for an unmatched man with choice set $A_t^m = (l_t^m, d_t^m)$ is

$$\begin{aligned} V_t^m(a_t, \Omega_t) &= u^m(a_t, \Omega_t) \\ &+ \beta \mathbb{E}_\epsilon \Big[\gamma^m(S_{t+1}^e) \sum_{i=0}^{1} \sum_{N^f, K_{t+1}^{pf}} \Phi_e^m(N^f, K_{t+1}^{pf}, t+1) Pr(d_{t+1}^f = i | K_{t+1}^{pf}, N^f, e, t+1) \\ &\cdot \max_{a_{t+1} \in A^{mf}} V_{t+1}^m(a_{t+1}, \Omega_{t+1} | a_t \in A_t^m) \\ &+ \Big(1 - \gamma^m(S_{t+1}^e)\Big) \max_{a_{t+1} \in A^m} V_{t+1}^m(a_{t+1}, \Omega_{t+1} | a_t \in A_t^m) \Big] \end{aligned} \tag{17}$$

where β is the discount factor and the expectation is taken with respect to the stochastic components

[38] Note that if an individual is unmatched, several of these state variables are zero or irrelevant to the individual's decisions.

of utility and income processes.[39] Notice, the discounted expected value for a single individual depends on his prospects in the marriage market. The second line of equation 17 shows that a man faces a probability in $t+1$ of matching with a woman, $\gamma^m(S^e_{t+1})$, and there is a probability that woman has a certain level of education as well as children from prior relationships given by $\Phi^m_e(N^f, K^{pf}_{t+1}, t+1)$. Further, the value of marriage depends in part on whether she receives support for those previous children, $Pr(d^f_{t+1}=0|K^{pf}_{t+1}, N^f, e, t+1)$. The fourth line of equation 17 shows that this man also faces a probability of not matching in $t+1$, $(1-\gamma^m(S^e_{t+1}))$. He takes into account how his choice set will differ in $t+1$ depending on whether he is matched or not.

The choice-specific value function for an unmatched woman with choice set $A^f_t = (l^f_t)$ is

$$
\begin{aligned}
V^f_t(a_t, \Omega_t) &= u^f(a_t, \Omega_t) \\
&+ \beta \mathbb{E}_\epsilon \sum_{i=0}^{1} Pr(d^f_{t+1} = i | K^{pf}_{t+1}, N^f, e, t+1) \Big[\gamma^f(S^e_{t+1}) \sum_{N^m, K^{pm}_{t+1}} \Phi^f_e(N^m, K^{pm}_{t+1}, t+1) \\
&\cdot \max_{a_{t+1} \in A^{mf}} V^f_{t+1}(a_{t+1}, \Omega_{t+1} | a_t \in A^f_t) \\
&+ \Big(1 - \gamma^f(S^e_{t+1})\Big) \max_{a_{t+1} \in A^f} V^f_{t+1}(a_{t+1}, \Omega_{t+1} | a_t \in A^f_t) \Big].
\end{aligned}
\tag{18}
$$

Unmatched women take into account that if they have children from prior relationships, there is a probability that they receive child support for those children, $Pr(d^f_{t+1}=0|K^{pf}_{t+1}, N^f, e, t+1)$. Similar to unmatched men, the discounted expected value depends on her prospects in the marriage market and she considers there is a probability in $t+1$ she is matched, $\gamma^f(S^e_{t+1})$, and the potential characteristics of that match, $\Phi^f_e(N^m, K^{pm}_{t+1}, t+1)$, as well as a probability she goes unmatched in $t+1$, $(1-\gamma^f(S^e_{t+1}))$. The woman also takes into account that she faces different choice sets depending on whether she is matched or not.

We assume that matched couples split the joint surplus generated by the match using symmetric Nash bargaining.[40] Joint surplus is defined as the additional discounted expected lifetime utility the matched man and woman enjoy from a particular choice relative to what they would enjoy from

[39] We set the discount factor equal to 0.96.

[40] The assumption of symmetric Nash bargaining is consistent with other empirical analyses of household decision-making. For recent examples of empirical analyses that assume symmetric Nash bargaining, see Bronson and Mazzocco (2013) and Del Boca and Flinn (2014).

the optimal choices they would each make if unmatched.[41] The choice-specific value function for a matched man with choice set $A_t^{mf} = (r_t, b_t, l_t^m, l_t^f, d_t^m)$ is

$$\begin{aligned} V_t^m(a_t, \Omega_t) &= \max_{j_t \in A^m} V_t^m(j_t, \Omega_t) \\ &+ \frac{1}{2}\Big[\tilde{V}_t^f(a_t, \Omega_t) - \max_{k_t \in A^f} V_t^f(k_t, \Omega_t) \\ &+ \tilde{V}_t^m(a_t, \Omega_t) - \max_{j_t \in A^m} V_t^m(j_t, \Omega_t)\Big] \end{aligned} \tag{19}$$

and likewise for a matched woman with choice set $A_t^{mf} = (r_t, b_t, l_t^m, l_t^f, d_t^m)$

$$\begin{aligned} V_t^f(a_t, \Omega_t) &= \max_{k_t \in A^f} V_t^f(k_t, \Omega_t) \\ &+ \frac{1}{2}\Big[\tilde{V}_t^f(a_t, \Omega_t) - \max_{k_t \in A^f} V_t^f(k_t, \Omega_t) \\ &+ \tilde{V}_t^m(a_t, \Omega_t) - \max_{j_t \in A^m} V_t^m(j_t, \Omega_t)\Big] \end{aligned} \tag{20}$$

where $\tilde{V}_t^m(a_t, \Omega_t)$ for a matched male is

$$\begin{aligned} \tilde{V}_t^m(a_t, \Omega_t) &= u^m(a_t, \Omega_t) \\ &+ \beta \mathbb{E}_\epsilon \Big[r_t \sum_{i=0}^{1} Pr(d_{t+1}^f = i | K_{t+1}^{pf}, N^f, e, t+1) \max_{a_{t+1} \in A^{mf}} V_{t+1}^m(a_{t+1}, \Omega_{t+1} | a_t \in A_t^{mf}) \\ &+ (1 - r_t) \Big[\gamma^m(S_{t+1}^e) \sum_{i=0}^{1} \sum_{N^f, K_{t+1}^{pf}} \Phi_e^m(N^f, K_{t+1}^{pf}, t+1) Pr(d_{t+1}^f = i | K_{t+1}^{pf}, N^f, e, t+1) \\ &\cdot \max_{a_{t+1} \in A^{mf}} V_{t+1}^m(a_{t+1}, \Omega_{t+1} | a_t \in A_t^{mf}) \\ &+ \Big(1 - \gamma^m(S_{t+1}^e)\Big) \max_{a_{t+1} \in A^m} V_{t+1}^m(a_{t+1}, \Omega_{t+1} | a_t \in A_t^{mf}) \Big] \Big] \end{aligned} \tag{21}$$

[41]For ease of presentation, we assume a common threat point (or outside option) for matched individuals, which is the optimal choice they would make if unmatched. This is the natural threat point for a newly matched individual. Model simulations where threat points differ for those newly matched and those who enter the period matched to their spouse from the prior period (and therefore dynamically changing threat points) reveal the same simulated choice distributions, suggesting this assumption does not substantially alter utility estimates.

and $\tilde{V}_t^f(a_t, \Omega_t)$ for a matched female is

$$\begin{aligned}
\tilde{V}_t^f(a_t, \Omega_t) &= u^f(a_t, \Omega_t) \\
&+ \beta \mathbb{E}_\epsilon \sum_{i=0}^{1} Pr(d_{t+1}^f = i | K_{t+1}^{pf}, N^f, e, t+1) \Big[r_t \max_{a_{t+1} \in A^{mf}} V_{t+1}^f(a_{t+1}, \Omega_{t+1} | a_t \in A_t^{mf}) \\
&+ (1 - r_t) \Big[\gamma^f(S_{t+1}^e) \sum_{N^m, K_{t+1}^{pm}} \Phi_e^f(N^m, K_{t+1}^{pm}, t+1) \max_{a_{t+1} \in A^{mf}} V_{t+1}^f(a_{t+1}, \Omega_{t+1} | a_t \in A_t^{mf}) \\
&+ \Big(1 - \gamma^f(S_{t+1}^e)\Big) \max_{a_{t+1} \in A^f} V_{t+1}^f(a_{t+1}, \Omega_{t+1} | a_t \in A_t^{mf}) \Big] \Big].
\end{aligned} \tag{22}$$

Note that the expected value functions for matched individuals depend on whether the individuals decide to marry or not in period t. If they decide to marry (or stay married), we assume they are matched to the same partner in period $t+1$. If a matched individual decides to be single (or get divorced), he or she (re)enters the marriage market in $t+1$, and faces a problem similar to that of an unmatched individual.

Decisions are modeled from 1979 ($t = 1$) until 1993 ($t = 15$).[42] The terminal value function serves to capture the future consequences of decisions made in 1993, and we assume it is a linear function of decisions made in 1993 and state variables entering 1994 ($t = 16$). The terminal value functions for men and women are given by

$$V_{16}^m(\Omega_{16} | a_{15}) = \delta_1 r_{15} I(M_{15} = 0) + \delta_2 r_{15} I(M_{15} \neq 0) + \delta_3 K_{16}^c + \delta_4 (1 - Bl^m) K_{16}^{pm} + \delta_5 Bl^m K_{16}^{pm} \tag{23}$$

$$V_{16}^f(\Omega_{16} | a_{15}) = \delta_1 r_{15} I(M_{15} = 0) + \delta_2 r_{15} I(M_{15} \neq 0) + \delta_3 K_{16}^c + \delta_6 (1 - Bl^f) K_{16}^{pf} + \delta_7 Bl^f K_{16}^{pf} \tag{24}$$

We follow Khwaja (2010) and define the terminal value function parsimoniously to avoid over-fitting the model. We include endogenous state variables such as the stock of children within the current marriage and the stock of past children entering 1994. We distinguish between new marriages and old marriages in 1993 to prevent a glut of marriages or divorces in the final decision period of the model. The parameters of the terminal value function are estimated along with the other structural

[42] Starting in 1994, the NLSY respondents were surveyed biennially which does not allow us to accurately measure marriage and cohabitation spells as well as fertility, employment, and child support decisions at an annual basis. Thus, we treat 1993 as the terminal period.

parameters.

3.8 Solution Method

The dynamic programming problem is solved by backward recursion given a set of model parameters and the terminal value function. In the last period, expected values of the optimal choice are calculated for each feasible state space $\Omega_{t=15}$ and each potential choice set via Monte Carlo simulation. For example, for a set of terminal period state variables $\Omega_{t=15}$, n draws of the preference shocks and income shocks are drawn and the maximum of the choice-specific value functions is calculated and recorded for each draw.[43] The average of the maximum value functions over the n draws is the expected maximum value of arriving at time $t = 15$ with that choice set available and state space $\Omega_{t=15}$. Moving back one period, that expected value is used to do the same calculation for period $t = 14$, and this procedure is repeated until the first period is reached. This process is described in greater detail in Keane and Wolpin (1994). The expected value functions are calculated at all feasible state space points for each period t; thus, no interpolation is used. When we solve the optimization problem, we must take into account every type of partner an individual could match with in the marriage market conditional on his or her current state space and last period's choices. To ease the computational burden, we put upper bounds on some state variables. Marriage duration takes on values from zero through 5 years, which implies that the utility from 6 or more years of marriage is the same as the utility from 5 years of marriage. We also only track up to 2 children within marriage and up to 2 children from past relationships.[44]

3.9 Equilibrium

The sex ratios evolve endogenously in the model since marriage decisions of individuals in period t determine the sex ratio and demographic composition of singles in $t+1$. Current period marriage decisions depend on future conditions in the marriage market; thus, individuals must determine the value of the sex ratio in the next period when making choices in the current period. From the

[43] 40 draws are used for the numerical integration.

[44] Less than 7 percent of individuals in our sample have more than 2 children within marriage or more than 2 children from past relationships.

model outlined above the choice-specific value functions for agents choosing choice a_t in time t can be expressed as

$$\begin{aligned} &\mathbf{V}\left(a_t, \Omega_t, E\left[S^e_{t+1}, \Phi^g_e(N^{g'}, K^{pg'}_{t+1}, t+1)\right]\right) \\ &\quad = \mathbf{V}\left(a_t, \Omega_t, E\left[S^e_{t+1}, \Phi^g_e(N^{g'}, K^{pg'}_{t+1}, t+1) | \mathbf{V}(a_t, \Omega_t), S^e_t, \Phi^g_e(N^{g'}, K^{pg'}_t, t)\right]\right) \end{aligned} \tag{25}$$

where $\mathbf{V}(\cdot)$ collects the four different choice-specific value functions (corresponding to matched and unmatched, male and female agents). The expectation of future marriage market conditions (i.e. the sex ratio and the demographic composition of singles) is a function of current period choices through three endogenous channels and the exogenous flow of new singles entering into the marriage market. That is, the stocks of single men and women in the marriage market in $t+1$ are composed of four groups: (1) the number of single individuals in t who did not meet a match; (2) the number of single individuals who matched but decided to stay single; (3) the number of married individuals who divorce; and, (4) the number of individuals who (newly) enter the marriage market upon completing their schooling. The stock of married individuals in $t+1$ is the sum of: (1) the number of married individuals entering period t who stay married and (2) the number of single agents in t who formed a match and married. Equilibrium requires the decisions of all individuals in t generate values of the sex ratios and population stocks in $t+1$ that are consistent with the marriage decisions made by all men and women today. In other words, the sequence of choices (particularly marriage and birth choices) made by each individual must generate the distributions of singles and married couples and sex ratios that agents used to make those choices (i.e. we must solve a fixed point problem).

Conditional on a set of structural parameters and initial distributions for the singles and married couples, we solve the equilibrium problem as follows. First, a sequence of the utility shocks and shocks to the income processes are drawn for every person in our sample. Given this set of draws, each individual's dynamic programming problem is solved by backward recursion. This then allows us to simulate marriage, employment, fertility, and child support decisions for each individual. Second, given the sequence of simulated choices, we recompute the distributions of singles, married couples, and the sex ratio for every period and for each marriage market. Conditional on the updated distributions and sex ratios, we repeat the above two steps until the distributions converge.[45] More detail on solving the equilibrium problem can be found in Seitz (2009). We do not impose the equilibrium conditions in estimation because we assume individuals have perfect foresight about the evolution of the sex ratios and population composition which we discuss further in Section 5, but we do need to solve the equilibrium problem explicitly in order to perform counterfactual simulations.

3.10 Connecting the Model and the Stylized Facts

Before proceeding to the estimation of the model, we review how the model mechanisms link to the stylized facts outlined in the introduction. First, the rate at which men and women match in the marriage market is a function of the sex ratio. Preferences are modeled such that individuals may prefer children inside to outside marriage. However, since individuals are forward-looking, women may be willing to have children outside of marriage if future matches are unlikely. This tradeoff is especially salient for black women. In 1990, the ratio of single black men to single black women was 0.74, while the ratio of single white men to single white women was 1.2. Further, the type of match an individual meets is a function of the population distribution of characteristics such as education and children from prior relationships. In addition, labor earnings, non-labor income, and child support transfers depend on characteristics like race, education, and region, and income in turn impacts the desirability of marriage, fertility, and the extent to which fathers provide support for children. Thus, women in marriage markets with a large proportion of men with lower education (or low income more generally) are unlikely to meet men who are willing to tradeoff own consumption for marriage and present fatherhood. As a result, in such markets, having a birth outside of marriage may be optimal for some women, and these low-income men may have little incentive to provide child support. Again, this issue is particularly important for black women since they face marriage markets with a large proportion of less educated men.

[45]We do not model or include permanent unobserved heterogeneity because it makes solving the equilibrium problem even more difficult. The equilibrium solution would then also require solving a fixed point problem over the distribution of unobserved types, adding to the already large computational burden.

4 Identification

As is standard in dynamic discrete choice models, variation in choices across individuals and across time identifies many of the parameters, particularly those of the utility function. Exclusion restrictions, functional form and distributional assumptions, and normalizations made throughout the model also aid in identification. In what follows, we provide heuristic arguments for identification of some parameters where identification is more complex.

The marriage initiation utility cost parameters, α_1 and α_2, are identified off transitions from being single to being married at different ages conditional on the sex ratio in that period (since as we discuss below, the equilibrium conditions are not imposed in estimation, and sex ratios are treated as exogenous by agents). The functional form assumption that initiation costs vary linearly with age also assists in identification. The marriage separation cost, α_3, is identified off transitions from being married to being single (regardless of marriage duration). The utility from marital specific capital, α_4, is identified off the decision to stay married or not over different marriage durations. Again, functional form is important as we assume utility is linear in marital specific capital. Last, the (dis)utility from marriage for blacks, α_5, is identified off any remaining systematic level differences in marriage decisions for blacks relative to whites that remain conditional on identifying α_1 through α_4.

There are some utility parameters which are constrained to be the same for men and women such as the parameters related to marriage discussed above, the utility from the birth decision, and the utility from children within the current marriage. Since we only observe marriage and birth decisions when individuals are matched, it is not possible for us to separately identify these parameters by gender.[46] However, we do observe work decisions when individuals are unmatched and single which allows us to identify the utility from leisure separately by gender and marital status. In addition, we can identify utility from one's own children from past relationships when married separately by gender off differential transitions in marital status for men and women with past children.

[46] See Arcidiacono et al. (2013) for a discussion and application of identifying gender differences in preferences from only observed matches.

Identification of the parameters of the labor earnings equations and the child support payment equation for men can be viewed as a sample selection problem since we only observe realized labor earnings and child support paid by men. The solution to the dynamic programming problem generates the sample selection rules, and the parameters are identified off covariation in realized labor earnings and state variables in the earnings offer equations as well as covariation in actual child support paid by men and the state variables in the support equation. In addition, selection into work and providing child support are driven in part by non-labor income and variables that appear in the non-labor income equations that do not appear in the earnings and support equations. Selection into work and providing child support are also driven by underlying family size, the distribution of children within the current marriage and children from past relationships, and spousal characteristics (which affect spousal earnings and spousal work decisions).[47]

5 Estimation

As discussed in Section 2, data on child support paid by men is unavailable from 1979 to 1980 and from 1988 to 1992. If we were to estimate the model using simulated maximum likelihood, calculating the choice probabilities in estimation would require integrating over missing information on deadbeat dad status and transfer amounts, adding a large computational burden, or not using those observations. To avoid this additional burden (and potential loss of observations), we estimate our model using efficient method of moments, a type of indirect inference (see Gourieroux et al., 1993; Gallant and Tauchen, 1996). The basic idea is to fit simulated data obtained from the structural model to an auxiliary statistical model. This auxiliary statistical model should be easily estimated and must provide a complete enough statistical description of the data to be able to identify the structural parameters. Following van der Klaauw and Wolpin (2008), Tartari (2014), and Skira (2014) the auxiliary model we use includes a combination of approximate decision rules that link outcomes of the model to elements of the state space as well as structural relationships such as the earnings and child support equations.

[47]The number of children is a commonly used exclusion restriction (or instrument) that is assumed to affect labor supply but not earnings (see for example Mroz, 1987; Mulligan and Rubinstein, 2008). See Huber and Mellace (2013) for a summary of several papers which employ this identification strategy.

Specifically, using the actual NLSY data, y_A, we estimate a set of M_A auxiliary statistical relationships with parameters θ_A. By construction, at the maximum likelihood estimates, $\widehat{\theta}_A$, the scores of the likelihood function, L_j for $j = 1, \dots, M_A$, are zero. That is, $\frac{\partial L_j}{\partial \theta_{A,j}} = 0$ where $\theta_{A,j}$ is the vector of model j's parameters. Denoting θ_B the parameters of the structural model, the idea behind EMM is to choose parameters that generate simulated data, $y_B(\theta_B)$, that make the score functions as close to zero as possible. The EMM estimator of the vector of structural parameters is obtained by minimizing the weighted squared deviations of the score functions evaluated at the simulated data, and is given by

$$\widehat{\theta}_B = \underset{\theta_B}{\operatorname{argmin}} \frac{\partial L}{\partial \theta_A} \left(y_B(\theta_B); \widehat{\theta}_A \right) \Lambda \frac{\partial L}{\partial \theta'_A} \left(y_B(\theta_B); \widehat{\theta}_A \right), \tag{26}$$

where Λ is a weighting matrix and $\frac{\partial L}{\partial \theta_A} \left(y_B(\theta_B); \widehat{\theta}_A \right)$ is a vector collecting the scores of the likelihood functions across auxiliary models. The weighting matrix used in estimation is the identity matrix.[48]

The equilibrium conditions are not imposed during estimation because of the large computational costs imposed by doing so. The distributions of single and married individuals used in the dynamic programming problem (i.e. used to compute the value functions) are the empirical distributions from the reweighted NLSY data. This simplification implies that agents have perfect foresight about the evolution of the sex ratios and population composition over time and the sex ratios are treated as exogenous by individuals in estimation. This assumption ignores the fact that the structural parameters that determine the evolution of the sex ratios also determine the choices made in the model. The drawback of this assumption is efficiency loss since we are not imposing all the restrictions of the model in estimation. However, this assumption should not result in biased estimates if the marriage market is sufficiently large so that the marriage choice of any one individual has a negligible effect on the sex ratio itself (Seitz, 2009). When policy experiments are conducted with the model, the equilibrium conditions are imposed.

[48]The optimal weighting matrix (a block diagonal matrix where each of the diagonal matrices is the inverse of the Hessian of the auxiliary model evaluated at the actual data) is not used in this case since Keane and Smith Jr. (2003) note that estimates of the optimal weighting matrix in applications of indirect inference often do not perform well in finite samples. The parameter estimates remain consistent, though there is a loss of asymptotic efficiency.

5.1 Auxiliary Statistical Models

One set of auxiliary models consists of parametric approximations of the decision rules generated from the solution of the optimization problem. The decision rules are such that the optimal choice made in a period is a function of the state space in that period. We follow van der Klaauw and Wolpin (2008), Tartari (2014), and Skira (2014) and specify these decision rules as parametric functions of subgroups of state space elements to keep the approximations parsimonious. A second set of auxiliary models includes quasi-structural relationships related to the earnings and transfer equations. To aid in the identification of the terminal value function parameters, we include a set of auxiliary models related to decisions made in 1993. The auxiliary models imply 515 score functions which are used to identify 59 structural parameters.[49]

In particular our auxiliary models include:

1. Logits of the work decision, separately by gender, on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, and whether married or not last period.

2. Logits of the marriage decision, separately by gender, on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, marital specific capital, and the sex ratio.

3. Logits of the birth decision, separately by gender, on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, and whether married or not last period.

4. Logits of the deadbeat fatherhood decision for men who have children from past relationships on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, and whether married or not last period.[50]

[49]Estimates of the auxiliary parameters are not reported but are available upon request.

[50]For the years when information on child support paid by men is unavailable, we simply do not estimate the deadbeat fatherhood logit (or multinomial logit) in those years, but we still use the male observations in those years for estimation of the other auxiliary models.

5. Logits of transitions from single to married, separately by gender, on combinations of education, race, region, and time.

6. Logits of transitions from married to single, separately by gender, on combinations of education, race, region, time, and marital specific capital.

7. Separate logits of the marriage decision and birth decision, separately by gender, and a logit of the deadbeat decision (for men only) in 1993 on education, region, race, number of children from past relationships, the interaction between race and the number of children from past relationships, number of children within marriage, and whether married or not last period. The deadbeat logit is estimated conditional on having children from past relationships.

8. Multinomial logits of the combined work and marriage decisions, separately by gender, on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, whether married or not last period, and the sex ratio.

9. Multinomial logits of the combined birth and marriage decisions, separately by gender, on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, whether married or not last period, and the sex ratio.

10. Multinomial logits of the combined marriage and deadbeat fatherhood decisions for men who have children from past relationships on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, and whether married or not last period.

11. Multinomial logits of the combined deadbeat fatherhood and work decisions for men who have children from past relationships on combinations of education, race, region, time, time squared, number of children from past relationships, number of children within marriage, and whether married or not last period.

12. Multinomial logits of the combined birth and marriage decisions in 1993, separately by gender, on education, region, race, number of children from past relationships, the interaction between race and the number of children from past relationships, number of children within marriage, and whether married or not last period.

13. Regressions of accepted log earnings, estimated separately by gender, on education, race, region, time, and time squared.

14. Regressions of logged child support paid by fathers, on education, race, region, time, time squared, and the number of children from past relationships.

5.2 Simulating Data for Estimation

We perform path simulations as follows. At a given set of structural parameters, having solved the optimization problem conditional on those parameters, we simulate one-step-ahead decisions. That is, given the state variables of an individual in a given period, we simulate his or her decisions by drawing a vector of the shocks and choosing the alternative with the highest value function. For agents who were not married in the prior period, we simulate whether he or she makes a contact in the marriage market in the current period and if so, the characteristics of that partner. For agents who were married in the prior period, we use the spousal information provided in the NLSY to construct the partner's characteristics. The score functions from the auxiliary models are evaluated using the simulated decisions and the objective function is calculated.[51] We iterate on the parameters using the Nelder-Mead simplex method until the objective function is minimized.

6 Results

6.1 Parameter Estimates

Tables 5 and 6 show the structural parameter estimates. Parameters estimated outside the model can be found in Tables 7 to 10. There is a large utility cost of initiating a marriage that

[51] For the purpose of calculating the score function, we perform 30 simulations for each sample observation and average that observation's score functions over the simulations.

increases with age. Keane and Wolpin (2010) also find large fixed utility costs of getting married. Similar to Sheran (2007), there is a large utility cost of dissolving a marriage, which captures the legal, economic, and other non-pecuniary costs of divorce.[52] Surprisingly, utility from marriage is decreasing in marriage duration. Sheran (2007) also finds negative duration dependence in the preference for marriage; however, she also allows utility from marriage to vary with age, and finds utility from marriage is increasing in age. Consistent with Sheran (2007), Seitz (2009), and Keane and Wolpin (2010), we find blacks derive less utility from marriage than whites. Both married men and women enjoy less utility from leisure than single individuals. Children from an individual's current marriage increase the utility gains from marriage. Children from a male's past relationships decrease utility gains from marriage while children from a female's past relationships increase the utility gains from marriage but to a lesser extent than children from the current relationship. This may reflect the idea that children from a relationship other than the current marriage may be a source of conflict within marriage (Sheran, 2007). Single men derive disutility from not providing child support to past children while married men derive very small positive utility from not providing support. This difference could reflect child support provision being a source of conflict within a current marriage. The estimates of the log labor earnings equations and child support paid by men equation are reasonable and as expected. We find a 49 percent earnings gap between black and white men, and a 4.5 percent earnings gap between black and white women. It is important to keep in mind that the earnings gap we estimate reflects differences in both hourly wages and annual hours worked across races.[53]

6.2 Model Fit

To examine the within-sample fit of the model, the parameter estimates are used to create a simulated sample consisting of 10 replicas of each sample individual's initial state variables. As mentioned above, the equilibrium conditions were not imposed in estimation. Thus, the model simulations used for model fit analysis do not impose the equilibrium conditions either. Table

[52]Since we treat cohabiting couples as married, this parameter combines cohabitation exit costs and divorce costs.

[53]To ensure the racial earnings gap we estimated is not an artifact of the NLSY, we estimated reduced-form earnings equations using CPS data and found quantitatively similar racial earnings gaps for the age cohort we study over the sample time frame.

11 reports the actual and simulated proportions of various choices and outcomes for men and women. Overall, the model fits the data reasonably well, especially regarding work, deadbeat fatherhood, and birth decisions. The model slightly overpredicts marriage for men and women, and underpredicts births outside of marriage for women while overpredicting them for men.

Table 12 shows choice proportions by race. The model predictions fit the data closely for white individuals, and fit most aspects of the data for blacks. The model overpredicts births outside of marriage for black men, and slightly underpredicts marriage for black men and women. Figure 2 shows time profiles of simulated and actual marriage rates by race. The model underpredicts marriage in the early periods for whites, but generally fits the data closely for white marriage time profiles. For blacks, the model has a slight tendency to underpredict marriage rates for most of the sample period.

Finally, while we do not impose the equilibrium conditions in estimation or the simulations used for model fit, we check to see whether the sex ratios endogenously generated by the model simulations match the aggregate sex ratios observed in the data. Figure 3 shows a comparison of the implied simulated sex ratios and the empirical sex ratios over time separately by race. For whites, the model tends to overestimate the sex ratios which is likely due to the model underpredicting white marriage rates at the beginning of the sample period. For blacks, the simulated and actual sex ratios are quite close.

6.3 External Validation

In the mid-1980's the Wisconsin Department of Health and Social Services launched a pilot program in 20 Wisconsin counties (ten pilot, ten control) to evaluate the effectiveness of percentage-of-income standards and routine (immediate) income withholding on child support payments. Percentage-of-income standards specify the proportion of income a non-custodial parent must pay in child support by law. Immediate income withholding means the child support payment is withheld from the non-custodial parent's wages, in a manner similar to income and payroll taxes. Evidence from the Wisconsin experiment suggests that wage withholding policies are effective tools for increasing the frequency and level of child support payments. Despite some problems with the execution of the experimental design, Garfinkel (1986) shows that non-resident parents in pilot counties were substantially more likely to make support payments. Even after controlling for the assignability and presence of fathers' income at the time of the award (the major endogeneity issue related to whether a support case was subject to wage withholding), Garfinkel (1986)'s results imply that an increase in the utilization of income withholding from zero to 70 percent increases the frequency of payments by 18 percent and increases payment amounts by 13 percent.

As an external validation test we simulate the Wisconsin experiment and compare our results to the prior experimental and policy evaluation estimates in the literature. We implement the experiment as a surprise in 1985 and it is effective only for new child support cases (to be consistent with the actual experiment). Child support payments are specified according to the Wisconsin program—17 percent of the father's labor income if he has one child and 25 percent of his income if he has two children. Wage withholding is implemented as follows. If the father works, he must provide child support and cannot be a deadbeat. If he relies on non-labor (or spousal) income, he is not subject to withholding.

We compare deadbeat fatherhood frequencies and child support payments in 1985 in the baseline simulation (used for within-sample model fit) and the simulation with the experiment imposed. The experiment simulation shows that 66 percent of non-custodial fathers with new child support cases worked in 1985, which means their support payments were immediately withheld. We find a 17 percent increase in the frequency of child support payments by men in 1985 relative to the baseline, which is quite close to the result in Garfinkel (1986), especially since we find a utilization rate of immediate income withholding that is close to 70 percent. We find child support payment amounts increased by 37 percent in the experiment relative to the baseline, which is larger than the increase found in Garfinkel (1986). However, this discrepancy is likely due to the fact that percentage-of-income standards were not always imposed in the Wisconsin pilot counties, but are strictly imposed in our simulation.[54]

A related literature uses cross-state variation in policy changes to evaluate the impact of child

[54] Garfinkel (1986) cites a survey of Wisconsin judges in pilot counties, finding only 38 percent regularly used the percentage-of-income standards after the policy change. Subsequent legislation made the formula presumptive, requiring judges construct a written explanation for deviations.

support legislation on payment frequency and levels. Sorensen and Hill (2004) use CPS data from 1977 through 2001 and find that wage withholding increases the probability of child support receipt among ever-married female welfare recipients by 4.2 percentage points. A comparable estimate comes from Beller and Graham (1991) who study the effect of child support laws and policies in 1978 on child support payments in 1981. They find wage withholding laws increased the probability of child support receipt by 6 percentage points among ever-married women. Our Wisconsin experiment simulations show a 6.7 percentage point increase in the frequency of child support paid by men who were ever married to the mother (without conditioning on welfare receipt of the mother).[55] Finally, Case et al. (2003) use PSID data over the period 1968 to 1997, and estimate the effect of various policies on child support payments. Their regression estimates imply wage withholding and numerical guidelines combined would increase payments by roughly $240 per case in 1982 dollars, and our experiment simulation produces a $216 increase when converted to 1982 dollars. Overall, comparing moments predicted by our model with the Wisconsin experiment imposed with the estimates from the reduced-form literature on wage withholding and numerical guideline policies shows our model generates policy effects which are reasonably close to those of prior studies.

7 Counterfactual Experiments

7.1 Eliminating the Racial Gap in Earnings

We present the results of several counterfactual simulations to further explore the implications of the model.[56] In the first counterfactual simulation, we eliminate the racial gap in labor earnings. We do so by setting the black indicators in the labor earnings equations to zero for men and women. The relatively low labor market return for black males may deter marriage and employment, as black men have less incentive to work and may be less attractive in the marriage market (Seitz,

[55] In the experiment simulation, we measure support payment through the male side, and cannot condition on female characteristics since we do not keep track of former match's state variables.

[56] In the analysis of the counterfactuals, the baseline results are those generated from the model with the equilibrium conditions imposed. For the baseline and counterfactual simulations we create simulated samples consisting of 50 replicas of each sample individual's initial state variables. The same draws of idiosyncratic shocks are used across the simulations.

2009). Further, this low labor market return may affect the ability to pay child support. This counterfactual allows us to examine what would happen if blacks with the same observed characteristics as whites received the same earnings.

Results of this simulation are found in Table 13. We find marriage rates for black men increase by 30 percent relative to the baseline and black women's marriage rates increase by 27 percent. The increases in marriage rates can be different for men and women because of remarriage and the differential supply of men and women. We also find a large increase in employment for black men. Further, births outside of marriage among blacks decline by about 12 percentage points relative to the baseline (which amounts to a 23 and 24 percent decline for men and women, respectively), and deadbeat fatherhood (conditional on having past children) falls by 5.5 percentage points (which amounts to an 8 percent decline).[57] These results are qualitatively similar to those of Keane and Wolpin (2010) who simulate the impact of eliminating the black-white gap in labor earnings for women in a partial equilibrium context.

Table 14 shows how family structure changes among blacks in the counterfactuals relative to the baseline simulation. With the elimination of the racial gap in labor earnings, there is a decrease in single parenthood among black men and women. More generally, this counterfactual increases the prevalence of intact families. Since black males now enjoy a larger labor market return, marriage becomes a more attractive alternative for both black men and women. In particular, there is an increase in the percentage of individuals who are married and have children from past relationships relative to the baseline. Previously, women who were matched with a male with past children faced a potential loss of household consumption if that male provides child support, which decreases the value of marrying that male. The higher labor market return for black males in the counterfactual dampens this effect and makes marrying a male with past children more attractive relative to the baseline.

[57]We recognize that a woman's probability of receiving child support (which we treat as given) would likely increase in this counterfactual relative to the baseline. Given that we find the prevalence of deadbeat fatherhood falls by 5.5 percentage points, we re-perform the counterfactual with various increases in the probability a black woman receives child support, ranging from 5 to 10 percentage points. The results are nearly identical to those presented.

7.2 Equalizing Population Supplies

As mentioned in the introduction, a hypothesis raised by Wilson (1987) is that marriage rates are lower among blacks because black women face a shortage of marriageable men. In particular, many black men have characteristics, such as lower levels of education, that limit their desirability as spouses. Combined with the higher mortality and incarceration rates for black males than white males, marriageable black men are in excess demand (Seitz, 2009). This counterfactual allows us to examine what would happen to marriage, employment, fertility, and support decisions if the stocks of black men and women were the same as those of whites. The following experiment is performed. The black population is given the same stocks of men and women, by age and education, as in the white population. Although the characteristics of blacks change in the experiment, the parameters in the utility function as well as the income and transfer equations remain as in the baseline.

The results of this simulation are presented in Tables 13 and 14. There is a 1.1 percentage point increase in marriage rates for black women and a 5 percentage point decrease in marriage rates for black men. This result can be explained in part by the fact that the higher sex ratio for blacks means black women now face less search friction in the marriage market, and can meet matches more easily (i.e. with a larger probability) than in the baseline. As a result, black women can delay marriage to wait for a better match in the future. Further, it is still the case in this simulation that black males face a substantial earnings gap relative to white males, which makes it difficult for a black male to make marriage an attractive alternative for a black woman. We also find employment for black women increases which is due to the larger number of college-educated women in the black population relative to the baseline. We find a slight decrease in births among black men, but very little change in the proportion of births that occur outside of marriage.

Thus, it appears the racial earnings gap can explain a substantial portion of the difference in employment, marriage, non-marital childbearing, and deadbeat fatherhood rates across blacks and whites. The marriage gap between black and white men and women falls by 43 and 29 percent, respectively, and black male employment rates resemble those of white males when the black-white earnings gap is eliminated. Differences in marriage market conditions, however, are not able to explain much of the racial differences in behavior.

7.3 Perfect Child Support Enforcement

In order to understand how the option of not providing child support over the lifecycle affects marriage, fertility, and work decisions, we simulate a counterfactual policy experiment in which there is perfect enforcement of child support provision. This means all women with children from prior relationships receive child support, and there is no deadbeat choice for men (i.e. they must provide child support).[58] A priori, it is not clear how perfect enforcement of child support would affect non-marital childbearing. Perfect enforcement increases the costs of non-marital births for men since they have a mandatory financial obligation to the child, which would make non-marital childbearing less attractive. However, perfect enforcement may lower the costs of children for single women and could make them more willing to have children outside of marriage (Aizer and McLanahan, 2006).

Results from this experiment are shown separately by race in Tables 13 to 16. We find perfect enforcement leads to declines in marriage rates for men and women, particularly for blacks. The decrease in marriage rates for blacks is driven by multiple factors. First, the fact that blacks derive less utility from marriage relative to whites combined with perfect enforcement makes being single without children a more preferable alternative than being married (with or without children) or having children outside of marriage. Table 14 shows there are substantial increases in the percentage of black individuals who are single without children relative to the baseline. In addition, women can now be choosier and more hesitant about marrying a male with past children since she knows part of her household consumption will go towards child support for his past children, which can be seen in the large drop in the prevalence of black individuals with children from a past relationship who are married (see Table 14).

Across races, there is a decrease in births overall, and striking decreases in non-marital births. Thus, it appears the disincentive for men to have a child outside of marriage outweighs the incentive for women to have a child outside of marriage. Perfect child support enforcement can be thought of as a tax on non-marital childbearing for men. Willis (1999) attributes high levels of non-marital

[58]In the event providing child support would require the male to borrow (i.e. his household consumption would be negative), we instead make him provide a child support payment that is equivalent to half of his household income. Our results are robust to requiring the male to provide more or less than half of his household income.

childbearing to the free-riding behavior of men. Empirically, we find this "tax" has a dramatic effect on births outside of marriage. This result is consistent with several reduced-form studies which analyze the relationship between strictness of child support enforcement and non-marital childbearing such as Huang (2002), Aizer and McLanahan (2006), and Plotnick et al. (2007), as well as the theoretical prediction in Willis (1999) that strictly enforced collection of child support reduces the attractiveness of non-marital fatherhood and decreases the equilibrium fraction of children born outside of marriage. The decrease in births overall and non-marital births more specifically is especially pronounced among the black population. There is a 31 and 32 percentage point decrease in non-marital births for black men and women, respectively, compared to the baseline. Huang (2002) and Plotnick et al. (2007) also find the impact of stronger enforcement on non-marital childbearing is especially large for blacks. Perfect enforcement leads to a small increase in female employment, which we find is concentrated among women who are married to men with children from past relationships. Since these men must provide child support for those children, these women now have an incentive to work to compensate for the decrease in household consumption.

We also analyze how perfect enforcement affects marital dissolution. A priori, the effect is not clear. Perfect enforcement increases the ability of mothers to raise children outside of a dissolved marriage, but increases the cost of divorce to fathers since they must pay support. We find perfect enforcement decreases marriage dissolution (not shown in tables). By the final period in the baseline simulation, 39 percent of individuals who were ever married have been divorced at some point in the sample period, compared to 34 percent in the perfect enforcement simulation. Our result is consistent with Nixon (1997) which finds stronger child support enforcement reduces marital breakup as well as Walker and Zhu (2006) which finds an increase in child support liabilities in the United Kingdom significantly reduced marriage dissolution risk.[59]

An advantage of our structural approach is that we can examine the welfare implications of the perfect enforcement experiment. We follow Haan and Prowse (2010) and interpret individual-specific value functions as the measure of an individual's well-being. We compare an individual's

[59]We note that Heim (2003) finds minimal effects of stronger child support enforcement on divorce.

realized value function in the baseline simulation to their realized value function in the perfect enforcement simulation for each period in the model. We then calculate the proportion of individual-years made better or worse off by perfect enforcement. Table 17 shows the proportion of men and women in different race and education groups that experienced welfare gains. Not surprisingly, most women gain from perfect enforcement, but black females and females with higher education benefit most. Surprisingly, we also find that many men benefit from the perfect enforcement policy, with the majority of black men being better off. On average, college-educated and white men lose; relative to higher-educated men, male high school drop-outs fare better.

The welfare gains and losses arise from both support transfers and endogenous changes in employment and family structure across time. To shed light on the patterns of welfare gains and losses, we compare marriage and fertility outcomes in the baseline and perfect enforcement simulations for those who gain and lose. In our discussion, we focus on men since the vast majority of women gain from perfect enforcement. Table 18 shows that men who experience welfare gains tended to have more children from previous relationships in the baseline compared to men who are worse off. Perfect enforcement increases the cost of having children outside of marriage or from a dissolved marriage, which leads these men to have fewer children from prior relationships. As a result, these men face less potential loss of own consumption over the lifecycle due to child support provision relative to their baseline behavior, generating welfare gains. Men who are worse off have much higher marriage rates and consequently more children within marriage than men who gain. While marriage and within-marriage births are still optimal for these men (i.e. their behavior changes little in response to perfect enforcement), they face more risk in the event of divorce since they will have a mandatory financial obligation to their children.

It is important to note that our analysis does not consider the administrative costs associated with increased child support enforcement. Further, Freeman and Waldfogel (2001) suggest that the comprehensiveness of child support legislation, rather than a particular law or policy, matters for child support effectiveness. Thus, perfect (or increased) enforcement may require the strengthening (or establishment) of several policies such as paternity establishment, tax intercept programs, and wage withholding, among others. Last, while several European countries have deadbeat fatherhood rates similar to or greater than those of the United States, (near) perfect enforcement is already a reality in some OECD countries. For example, according to OECD Family database reports, the percentage of single parents receiving child support in Denmark and Sweden was over 98 percent in 2004.[60]

7.4 Child Poverty

Next, we compare the time profiles of child poverty rates across the counterfactuals. A child is considered to be in a poor household if the household's income is below the poverty threshold set by the US Census Bureau in that year. To determine family size (which affects the poverty threshold), we maintain our assumption that children of divorced couples and children born outside of marriage reside with their mother. The child poverty rate is calculated as the number of children who reside in a household with income below the poverty threshold divided by the total number of children.[61] Figure 4 shows the time profiles of child poverty rates across the simulations, separately by race. The elimination of the racial gap in labor earnings is most effective at decreasing the black child poverty rate. In the final period of the no racial gap in earnings experiment, the black child poverty rate is 38 percent smaller than in the final period of the baseline simulation.[62] The population supplies and perfect enforcement experiments decrease child poverty but to a lesser extent. In the final period of the population supplies and perfect enforcement experiments, the black child poverty rate is 12 and 9 percent smaller, respectively, than in the equivalent period in the baseline. It is important to note that the perfect enforcement policy experiment also results in a substantial decline in births and children overall, and thus fewer children who are at risk of residing in a poor household.

[60]Source: http://www.oecd.org/els/family/41920285.pdf.

[61]Our calculations of the child poverty rate are likely understated since we cap the number of children within current marriage at 2 and the number of children from past relationships at 2.

[62]This experiment understates the gains for children, who not only see large gains in material inputs but also experience increases in the probability of residing in an intact family, which Tartari (2014) shows significantly improves cognitive achievement. The improvement comes through decreased parental conflict and increased parental time.

8 Conclusion

In this paper we formulate and estimate a dynamic equilibrium model of marriage, employment, fertility, and child support to account for the prevalence of non-marital childbearing and deadbeat fatherhood in the United States, as well as racial differences in outcomes. We build upon prior structural partial equilibrium models of marriage, employment, and fertility in several ways. First, we endogenize child support decisions across time. Second, in the counterfactual simulations we allow sex ratios and population stocks to evolve endogenously and solve the resulting equilibrium problem. Third, we analyze the role that black-white differences in earnings and population supplies play in generating observed differences in outcomes across races.

We find convincing evidence that the earnings gap observed across races plays an important role in generating large racial gaps in marriage rates, non-marital childbearing, and the fraction of children growing up in poverty. At the same time we find that child support enforcement, or the lack thereof, plays a critical role in the overall levels of non-marital childbearing. Removing the option to not provide financial support from men not only directly increases resources available to mothers, but also changes the circumstances into which many children are born. This is because enforcing child support results in large decreases in non-marital childbearing, particularly among blacks, which contributes to moderate decreases in child poverty rates. Consistent with other recent research this is an important avenue through which policy could dramatically impact child poverty and the inequality of both time and resources available to children.

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Tables and Figures

Table 1: Descriptive Statistics, Men Aged 31-35 in 1993 Cross-Section of NLSY79

			Absent Fathers	
	Non-Fathers	Present Fathers	Paying	Non-Paying
% High school drop-outs	17.6	15.2	28.5	40.9
% With high school diploma	58.3	62.3	68.7	56.1
% With college degree	24.2	22.5	2.8	3.0
% Ever married/cohabiting	57.5	100.0	89.3	83.5
% Currently married/cohabiting	39.8	97.1	42.5	52.0
% Have been divorced[a]	26.2	12.0	77.6	58.1
Annual non-labor income	1,547	1,780	761	1,415
% Employed	79.4	90.8	89.7	66.5
Years of work experience	10.0	11.6	11.5	9.6
If employed				
Annual hours worked	2,288	2,445	2,249	2,148
Annual earnings	35,027	47,229	29,381	28,087
Observations	621	693	214	394

NOTES: All dollar amounts are in constant 2000 dollars.

[a]Includes individuals who ever ended a cohabitation spell.

Table 2: Descriptive Statistics, Women Aged 29-33 in 1993 Cross-Section of NLSY79

		Married or	Single Mothers	
	Non-Mothers	Cohabiting Mothers	Paid	Not Paid
% High school drop-outs	8.9	20.5	29.8	40.9
% With high school diploma	61.4	65.5	68.0	56.8
% With college degree	29.6	14.0	2.2	2.3
% Ever married/cohabiting	66.0	100.0	67.4	61.4
% Currently married/cohabiting	47.5	100.0	0.0	0.0
% Have been divorced[a]	32.9	25.6	67.4	61.4
% on welfare	4.2	12.8	45.9	53.6
Annual non-labor income	1,600	2,050	3,562	4,385
% Employed	84.8	63.2	62.4	52.2
Years of work experience	9.4	8.0	7.3	5.7
If employed				
Annual hours worked	2,139	1,875	1,998	1,957
Annual earnings	31,197	22,096	20,154	17,421
Observations	638	1,207	181	347

NOTES: All dollar amounts are in constant 2000 dollars.

[a]Includes individuals who ever ended a cohabitation spell.

Table 3: Prevalence of Single Motherhood and Deadbeat Dads by Race, 1993 Cross-Section of the NLSY79

	White	Black
Women		
% Non-mothers	29.7	21.0
% Married/cohabiting mothers	58.3	35.8
% Single mothers	12.0	43.2
% Receiving support|Single mother	43.6	30.0
Men		
% Non-fathers	35.2	27.1
% Present fathers	46.6	17.1
% Absent fathers	18.2	55.8
% Deadbeat dads|Absent father	53.8	71.3

Table 4: Prevalence of Deadbeat Dads by Marital Status of Mothers, 1993 Cross-Section of the NLSY79

	Have Ever Married or Cohabited	Never Married or Cohabited
% Receive support	36.4	30.6
% Do not receive support	63.6	69.4

Table 5: Utility Parameter Estimates

Description	Parameter	Estimate	S.E.
Utility Parameters-Same for Men and Women			
Marriage initiation intercept	α_1	-0.490	0.020
Marriage initiation age trend	α_2	-0.086	0.002
Marriage separation cost	α_3	-3.075	0.019
Marital specific capital	α_4	-0.147	0.001
Marriage for blacks	α_5	-0.192	0.017
Birth when single for whites	α_6	-2.836	0.054
Birth when married for whites	α_7	-2.173	0.012
Birth when single for blacks	α_8	-2.327	0.038
Birth when married for blacks	α_9	-2.304	0.041
Children from current marriage	α_{10}	0.351	0.004
Utility Parameters-Men			
Leisure when single	α_{11}	2.288	0.029
Leisure when married	α_{12}	0.543	0.030
Past children when married	α_{13}	-0.099	0.023
Not providing support when single	α_{14}	-0.169	0.018
Not providing support when married	α_{15}	0.029	0.019
Utility Parameters-Women			
Leisure when single	α_{16}	1.026	0.019
Leisure when married	α_{17}	0.748	0.022
Past children when married	α_{18}	0.338	0.023
Preference Shock Variances			
Marriage decision	σ_r^2	2.849	0.029
Birth decision	σ_b^2	3.010	0.032
Men's leisure[a]	σ_{lm}^2	1.000	
Women's leisure[a]	σ_{lf}^2	1.000	
Men deadbeat	σ_d^2	0.146	0.006
Terminal Value Function Parameters-Same for Men and Women			
New marriage in 1993	δ_1	-0.933	0.128
Old marriage in 1993	δ_2	-0.539	0.085
Children from current marriage	δ_3	0.013	0.028
Terminal Value Function Parameters-Men			
White and past children	δ_4	-0.409	0.107
Black and past children	δ_5	0.224	0.181
Terminal Value Function Parameters-Women			
White and past children	δ_6	-0.722	0.212
Black and past children	δ_7	-1.131	0.368

NOTES: [a]Normalized.

Table 6: Labor Earnings and Child Support (Paid by Men) Parameters

Description	Parameter	Estimate	S.E.
Log Labor Earnings-Men			
Intercept	κ_0^m	9.365	0.016
High school education	$\kappa_{N,HS}^m$	0.408	0.026
College education	$\kappa_{N,Col}^m$	0.667	0.045
Black	κ_{Bl}^m	-0.486	0.027
North Central	κ_{NC}^m	-0.066	0.023
South	κ_{South}^m	-0.108	0.031
West	κ_{West}^m	-0.121	0.028
Time	κ_t^m	0.063	0.001
Time squared	$\kappa_{t^2}^m$	-0.001	0.0002
Variance to shock	$\sigma_{w^m}^2$	0.546	0.015
Log Labor Earnings-Women			
Intercept	κ_0^f	8.896	0.012
High school education	$\kappa_{N,HS}^f$	0.522	0.018
College education	$\kappa_{N,Col}^f$	1.106	0.024
Black	κ_{Bl}^f	-0.045	0.020
North Central	κ_{NC}^f	-0.367	0.021
South	κ_{South}^f	-0.271	0.020
West	κ_{West}^f	-0.155	0.050
Time	κ_t^f	0.045	0.001
Time squared	$\kappa_{t^2}^f$	-0.001	0.0002
Variance to shock	$\sigma_{w^f}^2$	0.551	0.015
Log Child Support Paid by Men			
Intercept	τ_0^m	6.972	0.049
High school education	$\tau_{N,HS}^m$	0.451	0.044
College education	$\tau_{N,Col}^m$	0.961	0.029
Black	τ_{Bl}^m	-0.149	0.038
North Central	τ_{NC}^m	0.119	0.035
South	τ_{South}^m	-0.259	0.035
West	τ_{West}^m	-0.095	0.049
Time	τ_t^m	0.073	0.003
Time squared	$\tau_{t^2}^m$	-0.002	0.0006
Past children	τ_p^m	0.191	0.020
Variance to shock	$\sigma_{\tau^m}^2$	1.397	0.091

Table 7: Non-Labor Income Estimates

Description	Parameter	Estimate	S.E.
Non-labor Income-Single Men			
Intercept	ζ_0^m	790.08	61.79
High school education	$\zeta_{N,HS}^m$	98.02	31.96
College education	$\zeta_{N,Col}^m$	313.76	51.99
Black	ζ_{Bl}^m	-156.78	34.16
North Central	ζ_{NC}^m	203.46	40.53
South	ζ_{South}^m	-238.94	37.70
West	ζ_{West}^m	30.56	46.21
Time	ζ_t^m	7.92	13.96
Time squared	$\zeta_{t^2}^m$	1.37	0.87
Past children	ζ_p^m	89.22	53.71
Working	ζ_l^m	-360.20	34.91
Working and past children	$\zeta_{l,p}^m$	-11.23	48.23
Black and past children	$\zeta_{Bl,p}^m$	-11.52	49.66
Non-labor Income-Single Women			
Intercept	ζ_0^f	1404.06	105.34
High school education	$\zeta_{N,HS}^f$	-562.03	53.71
College education	$\zeta_{N,Col}^f$	-301.96	87.77
Black	ζ_{Bl}^f	126.36	58.00
North Central	ζ_{NC}^f	477.15	63.29
South	ζ_{South}^f	-589.32	58.94
West	ζ_{West}^f	462.97	73.49
Time	ζ_t^f	107.24	23.20
Time squared	$\zeta_{t^2}^f$	-4.47	1.38
Past children	ζ_p^f	2826.02	58.77
Working	ζ_l^f	-969.88	60.88
Working and past children	$\zeta_{l,p}^f$	-2324.36	57.31
Black and past children	$\zeta_{Bl,p}^f$	215.88	59.06

Table 8: Non-Labor Income Estimates Continued

Description	Parameter	Estimate	S.E.
Non-labor Income-Married Couples			
Intercept	ζ_0^{mf}	3216.99	100.07
Wife high school education	$\zeta_{N^f,HS}^{mf}$	-262.27	38.58
Wife college education	$\zeta_{N^f,Col}^{mf}$	74.10	65.49
Husband high school education	$\zeta_{N^m,HS}^{mf}$	-351.87	38.06
Husband college education	$\zeta_{N^m,Col}^{mf}$	-159.59	60.86
Black	ζ_{Bl}^{mf}	-118.40	40.27
North Central	ζ_{NC}^{mf}	60.34	49.75
South	ζ_{South}^{mf}	-630.32	47.30
West	ζ_{West}^{mf}	-164.97	56.21
Time	ζ_t^{mf}	-49.54	20.15
Time squared	$\zeta_{t^2}^{mf}$	2.95	1.11
Wife's past children	ζ_{pf}^{mf}	422.46	28.26
Husband's past children	ζ_{pm}^{mf}	1.71	30.40
Children from current marriage	ζ_c^{mf}	133.10	20.69
Wife working	$\zeta_{l^f}^{mf}$	-461.15	33.54
Husband working	$\zeta_{l^m}^{mf}$	-1223.60	40.32

Table 9: Log Child Support Received by Women Estimates

Description	Parameter	Estimate	S.E.
Intercept	τ_0^f	6.965	0.183
High school education	$\tau_{N,HS}^f$	0.299	0.051
College education	$\tau_{N,Col}^f$	0.903	0.190
Black	τ_{Bl}^m	-0.344	0.050
North Central	τ_{NC}^f	-0.086	0.082
South	τ_{South}^f	-0.010	0.075
West	τ_{West}^f	-0.123	0.094
Time	τ_t^f	0.048	0.035
Time squared	$\tau_{t^2}^f$	-0.001	0.002
Past children	τ_p^f	0.037	0.050
Variance to shock	$\sigma_{\tau^f}^2$	1.088	0.016

Table 10: Logit Estimates of Woman's Probability of Not Receiving Support

Description	Parameter	Estimate	S.E.
Intercept	μ_0	2.870	0.185
High school education	$\mu_{N,HS}$	-0.449	0.053
College education	$\mu_{N,Col}$	-0.913	0.211
Black	μ_{Bl}	0.436	0.053
North Central	μ_{NC}	0.016	0.085
South	μ_{South}	-0.320	0.077
West	μ_{West}	0.064	0.098
Time	μ_t	-0.080	0.036
Time squared	μ_{t^2}	0.0004	0.002
Past children	μ_p	-0.422	0.052

NOTES: Estimates are conditional on the woman having children from a past relationship.

Table 11: Model Fit

	Women		Men	
	Actual	Simulated	Actual	Simulated
% Single	47.2	45.1	53.1	52.0
% Married	52.8	54.9	46.9	48.0
% Decide no birth	88.7	88.9	90.3	90.1
% Decide birth	11.3	11.1	9.7	9.9
% Births outside marriage	21.5	18.4	16.2	20.3
% Births within marriage	78.5	81.6	83.8	79.7
% Not working	38.3	38.7	22.4	22.9
% Working	61.7	61.3	77.6	77.1
% Not a deadbeat[a]			29.6	29.9
% Deadbeat[a]			70.4	70.1
% $K_t^{pg} = 0$	71.1	71.1	80.1	77.4
% $K_t^{pg} = 1$	16.3	20.0	13.1	17.3
% $K_t^{pg} = 2+$	12.6	8.9	6.7	5.3
% $K_t^c = 0$	36.8	35.8	35.4	36.9
% $K_t^c = 1$	33.7	33.7	34.2	33.6
% $K_t^c = 2+$	29.4	30.5	30.4	29.5

NOTES: [a]Conditional on having children from a past relationship.

Number of current children within marriage calculated conditional on being married the prior period.

Table 12: Model Fit: Racial Differences in Outcomes

	Women				Men			
	White		Black		White		Black	
	Actual	Sim	Actual	Sim	Actual	Sim	Actual	Sim
% Single	39.0	35.6	65.2	67.4	47.7	45.8	65.1	66.6
% Married	61.0	64.4	34.8	32.6	52.3	54.2	34.9	33.4
% Decide no birth	88.8	88.2	88.4	90.6	90.5	90.1	89.9	90.1
% Decide birth	11.2	11.8	11.6	9.4	9.5	9.9	10.1	9.9
% Births outside marriage	8.9	8.3	48.1	48.4	5.7	8.0	38.2	49.6
% Births within marriage	91.1	91.7	51.8	51.6	94.3	92.0	61.8	50.4
% Not working	35.8	38.5	43.8	39.2	18.0	19.9	32.1	29.9
% Working	64.2	61.5	56.2	60.8	82.0	80.1	67.9	70.1
% Not a deadbeat[a]					29.1	30.3	29.9	29.5
% Deadbeat[a]					70.9	69.7	70.1	70.5

NOTES: [a]Conditional on having children from a past relationship.

Table 13: Counterfactual Simulation Results for Black Men and Women

	Black Women				Black Men			
	Baseline	No Earnings Gap	Population Supplies	Perfect Enforcement	Baseline	No Earnings Gap	Population Supplies	Perfect Enforcement
% Single	65.7	56.4	64.5	71.6	66.6	56.5	71.6	72.7
% Married	34.3	43.6	35.4	28.4	33.4	43.5	28.4	27.2
% Decide no birth	90.0	89.5	90.1	95.6	89.9	89.2	91.9	95.6
% Decide birth	9.9	10.5	9.9	4.4	10.1	10.8	8.1	4.4
% Births outside marriage	48.6	37.0	48.6	16.9	50.7	38.9	49.6	19.4
% Births within marriage	51.4	63.0	51.4	83.1	49.2	61.1	50.4	80.6
% Not working	39.2	41.3	36.0	35.1	30.1	18.4	31.0	29.3
% Working	60.8	58.7	64.0	64.9	69.9	81.6	69.0	70.7
% Not a deadbeat[a]					29.4	34.9	29.0	100.0
% Deadbeat[a]					70.6	65.1	70.9	0.0

NOTES: [a]Conditional on having children from a past relationship.

Table 14: Family Structure Across Simulations for Black Men and Women

	Black Women				Black Men			
	Baseline	No Earnings Gap	Population Supplies	Perfect Enforcement	Baseline	No Earnings Gap	Population Supplies	Perfect Enforcement
% Single with no children	28.1	25.6	37.8	43.4	36.9	32.8	47.7	56.4
% Single with children	37.6	30.8	26.8	28.2	29.6	23.7	23.9	16.3
% Married with no children	9.9	11.9	13.3	10.4	8.7	11.1	9.7	12.1
% Married with children only from current marriage	8.3	11.8	10.4	9.6	7.2	11.2	8.0	10.1
% Married with children from past relationships[a]	16.1	19.9	11.7	8.4	17.6	21.2	10.7	5.1

NOTES: [a]These individuals may also have children from their current marriage.

Table 15: Counterfactual Simulation Results for White Men and Women

	White Women		White Men	
	Baseline	Perfect Enforcement	Baseline	Perfect Enforcement
% Single	33.6	35.6	43.2	44.7
% Married	66.4	64.4	56.8	55.3
% Decide no birth	87.8	89.4	89.5	90.9
% Decide birth	12.2	10.6	10.5	9.1
% Births outside marriage	7.5	1.1	7.9	1.2
% Births within marriage	92.5	98.9	92.1	98.8
% Not working	38.5	36.9	19.5	19.3
% Working	61.5	63.1	80.5	80.7
% Not a deadbeat[a]			31.0	100.0
% Deadbeat[a]			69.0	0.0

NOTES: [a]Conditional on having children from a past relationship.

Table 16: Family Structure Across Simulations for White Men and Women

	White Women		White Men	
	Baseline	Perfect Enforcement	Baseline	Perfect Enforcement
% Single with no children	25.8	31.9	35.9	41.8
% Single with children	7.8	3.67	7.2	2.9
% Married with no children	21.6	22.9	18.2	20.0
% Married with children only from current marriage	33.2	37.0	29.7	33.0
% Married with children from past relationships[a]	11.7	4.5	9.0	2.3

NOTES: [a]These individuals may also have children from their current marriage.

Table 17: Individuals with Welfare Gains from Perfect Enforcement by Race and Education

	Women	Men
% White	85.3	37.2
% Black	92.8	56.4
% High school drop-out	84.2	48.0
% High school completion	88.9	42.4
% College degree	88.0	34.4
% Total	87.5	42.9

NOTES: Each cell represents the percentage of men (or women) in that particular demographic group that experienced welfare gains from perfect enforcement.

Table 18: Comparison of Outcomes for those Who Gain and Lose from Perfect Enforcement

	Women				Men			
	Winners		Losers		Winners		Losers	
	Baseline	PE	Baseline	PE	Baseline	PE	Baseline	PE
% Single	44.8	49.8	35.5	21.7	74.4	80.9	30.6	30.8
% Married	55.2	50.2	64.5	78.3	25.6	19.1	69.3	69.2
% $K_t^{pg} = 0$	71.0	81.9	61.3	95.1	60.1	85.6	85.9	93.3
% $K_t^{pg} = 1$	19.7	15.2	28.3	3.9	32.2	12.8	9.0	5.7
% $K_t^{pg} = 2+$	9.3	2.8	10.4	1.0	7.7	1.6	5.1	1.0
% $K_t^{c} = 0$	69.8	71.2	45.0	46.5	87.9	88.5	57.5	59.5
% $K_t^{c} = 1$	15.7	13.3	33.3	34.3	7.8	4.4	21.3	20.5
% $K_t^{c} = 2+$	14.5	15.5	21.7	19.2	4.2	7.0	21.2	20.0

Figure 1: Sex Ratios by Race and Region

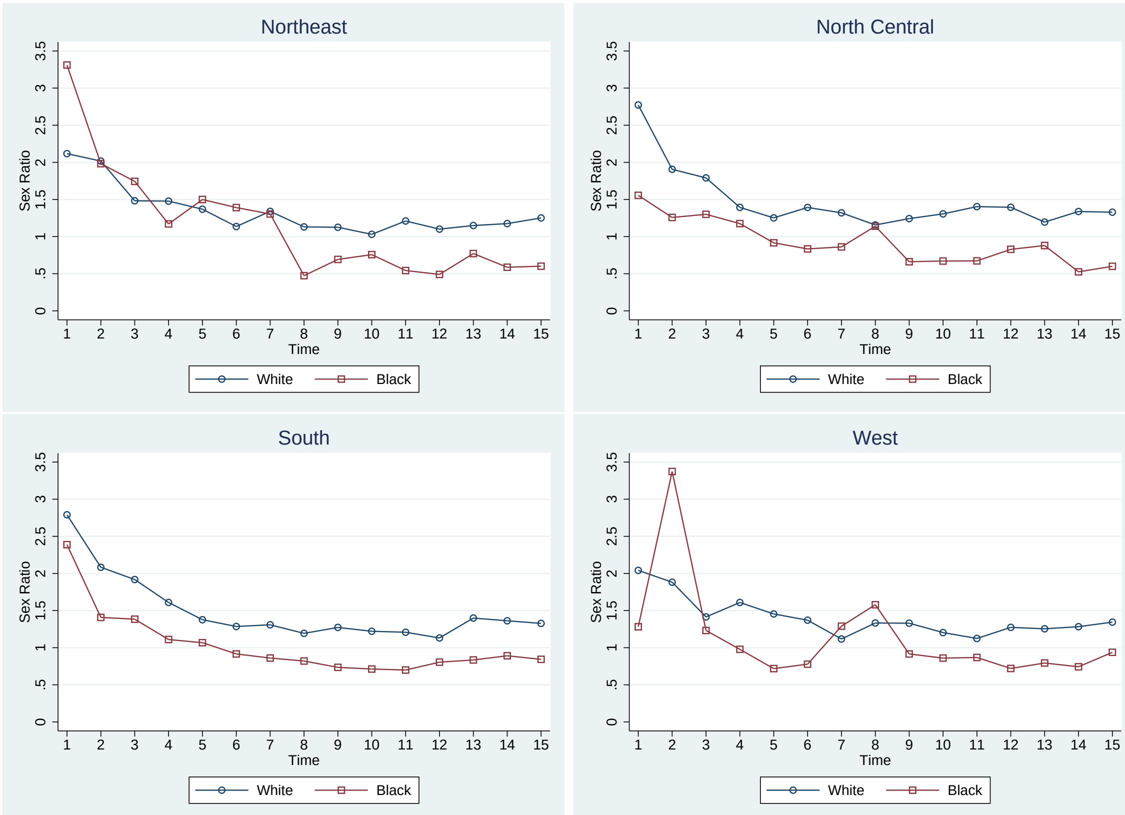

Figure 2: Comparison of Actual and Simulated Time Profiles of Marriage Rates by Race

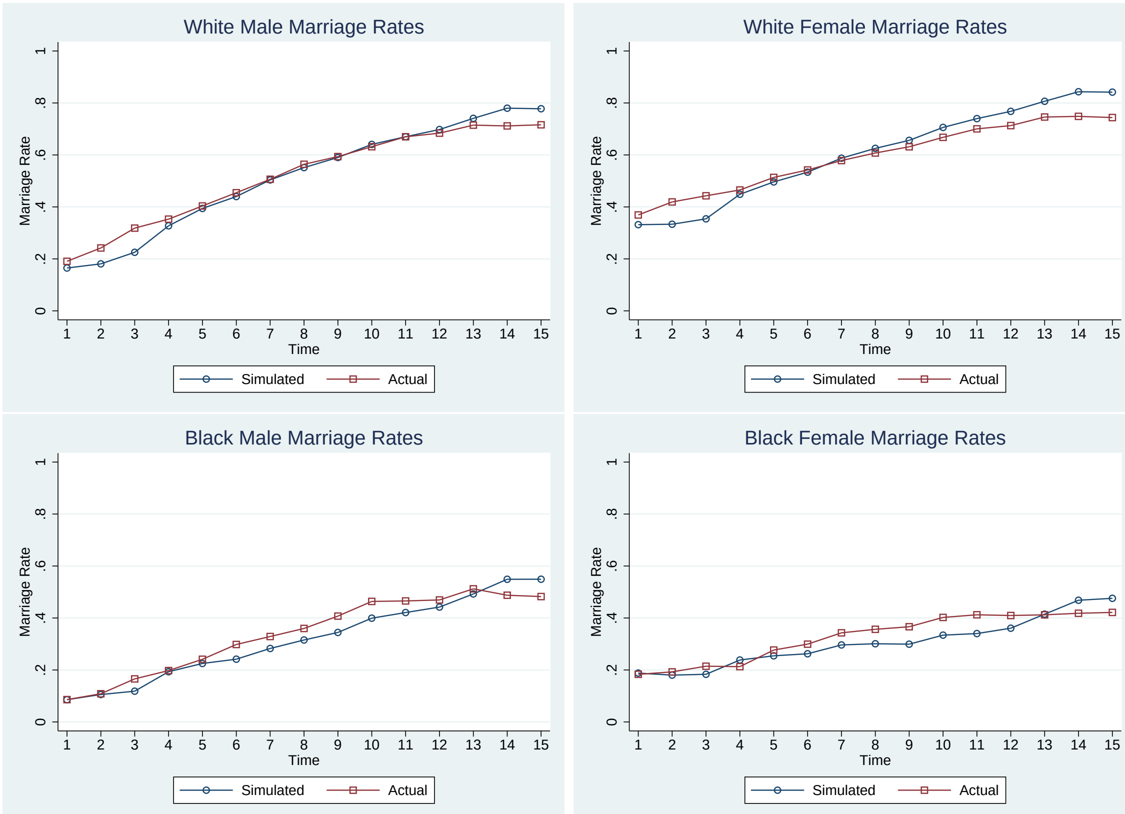

Figure 3: Comparison of Actual and Simulated Sex Ratios by Race

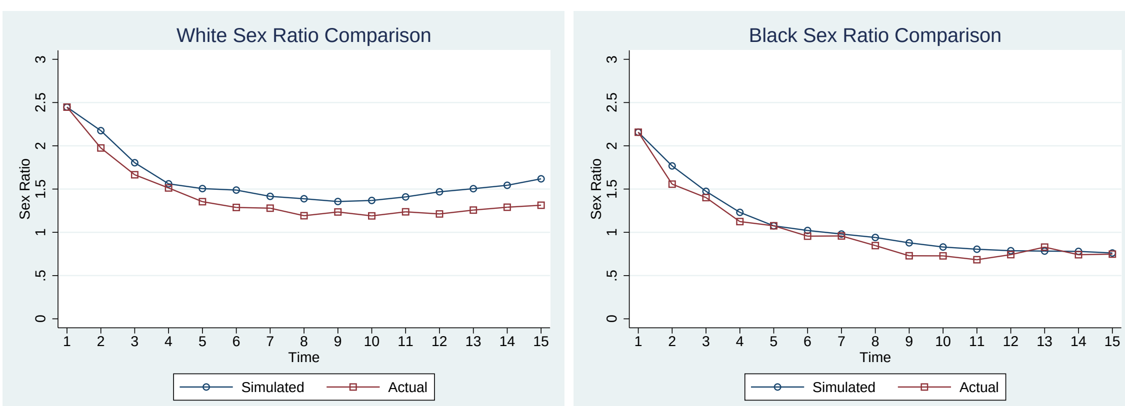

Figure 4: Comparison of Child Poverty Rates Across Simulations