Single Moms and Deadbeat Dads: The Role of Earnings, Marriage Market Conditions, and Preference Heterogeneity*

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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 decisions. We consider the extent to which low earnings, the availability and characteristics of potential spouses, and preference heterogeneity can explain the prevalence of non-marital childbearing and deadbeat fatherhood as well as racial differences in these outcomes. We estimate the model by indirect inference using data from the NLSY79. We simulate several counterfactual environments: eliminating the black-white earnings gap, equalizing black-white population supplies, equalizing black-white preferences, and perfect child support enforcement.

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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 the age of 30 were to single mothers.[1] As President Obama points out in the quote above, many of these families suffer from a lack of resources. In 2013, the poverty rate among households headed by a female with children was 39.6 percent.[2] This problem is due in part to the fact that single mothers tend to receive little financial support from the fathers of their children. Two questions naturally arise: (1) Why are so many women willing to have children outside of marriage when they receive little support from fathers? (2) Why do men father children outside of marriage and not provide support?

To shed light on these questions, we develop and estimate a dynamic equilibrium model of marriage, employment, fertility, and child support decisions. The model is motivated by several stylized facts documented in the literature (see for example Bartfeld and Meyer, 1994; Clarke et al., 1998; Mincy and Sorensen, 1998; Freeman and Waldfogel, 2001; Cancian and Meyer, 2004). First, single mothers, particularly those that do not receive support, tend to be less educated than other women.[3] Second, single motherhood and absent fatherhood are more common among blacks than whites. Third, the majority of absent fathers of either race do not pay support, and these deadbeat fathers tend to have lower education levels, employment rates, and earnings than other men. Table 1 presents statistics from the 1993 wave of the National Longitudinal Survey of Youth 1979 Cohort (NLSY79) that highlight these patterns. These facts suggest any model that aims to explain single motherhood and deadbeat fatherhood must account for heterogeneity in labor and marriage market conditions across racial and educational groups as well as any preference heterogeneity that may drive these decisions.

Our goal is to determine the extent to which low earnings, marriage market conditions, and preference heterogeneity can explain non-marital childbearing, deadbeat fatherhood, and racial differences in these outcomes. The model allows for racial differences in the availability and educational composition of potential spouses, differences in earnings across racial and educational groups, and preference heterogeneity with regards to marriage and fertility across races. The basic

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

[2] Source: 2013 Current Population Survey Annual Social and Economic Supplement.

[3] Throughout the paper, we define single mothers as mothers of children born outside of a cohabiting relationship as well as divorced mothers. Absent fathers refer to fathers of children born outside of a cohabiting relationship as well as divorced fathers, and a deadbeat father is an absent father that does not pay any child support.

intuition is the following: both men and women may prefer to have children within marriage, but if faced with a shortage of suitable (e.g. high-income) husbands, it may be optimal for women to have children with low-income men outside of marriage. In turn, if women are willing to have children outside of marriage, 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 support. These channels are especially salient for black individuals, as the ratio of men to women has been consistently lower for blacks than for whites, and racial wage gaps (both conditional and unconditional on education) have been extensively documented (see for example Neal and Johnson, 1996; Altonji and Blank, 1999; Black et al., 2006).

More specifically, in our dynamic discrete choice model, single men and women decide whether to work and single men additionally decide whether to provide child support for children from prior relationships. Individuals match in marriage markets segmented by age, region, and race, and the rate at which men and women meet is driven by the ratio of single men to single women (i.e. the sex ratio). The characteristics of singles, such as their education and whether they have children from past relationships, determine their desirability as spouses. The probability of meeting a partner with given educational attainment and with children from past relationships depends on the population distribution of these characteristics within each segmented marriage market. If matched, a couple makes the following decisions jointly: whether to marry, have a child, work, and provide support for the male's children from prior relationships. Both the number of single men relative to single women and the composition of singles evolve endogenously in the model.

We estimate the parameters of the model by 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, the supply of men and women in the marriage market, and preference heterogeneity account for non-marital childbearing, deadbeat fatherhood, and racial differences in these outcomes. In the first experiment, we eliminate the black-white gap in labor earnings that exists conditional on education. Closing the racial earnings gap explains a substantial portion of the differences in outcomes across races: black marriage rates rise by 31 percent, black non-marital childbearing rates fall by about 30 percent, black male employment increases to parity with white men, and conditional on being an absent father, black deadbeat fatherhood rates fall by 9 percent. 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, and we find differences in population supplies do not play a large role in explaining racial differences in behavior. In the third experiment, we assume blacks have the same preferences as whites for marriage and fertility. We find preference heterogeneity explains a large portion of racial differences in marriage and non-marital births, but not employment or deadbeat fatherhood (conditional on being an absent father).

In light of the proliferation of state-level policies that focus on increased child support enforcement, we analyze a counterfactual policy experiment in which there is perfect child support enforcement. Across both races, we find perfect enforcement leads to increases in marriage rates and substantial reductions in births outside of marriage. An advantage of the structural approach is we can examine how welfare changes as a result of this policy. The majority of women experience welfare gains especially black women and those with less education, and most men experience welfare losses. However, not all women gain. Perfect enforcement alters incentives to marry, resulting in changes in the availability and characteristics of potential partners over time. We find the women who are worse off are those who end up marrying less-educated men due to these marriage market changes. This finding highlights the importance of modeling the marriage market equilibrium.

Finally, we compare child poverty rates across the counterfactuals, and we find the elimination of the racial gap in earnings conditional on education leads to the largest reduction in 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. These results suggest policies directed toward boosting the employment and earnings of 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 (see for example Akerlof et al., 1996; Willis, 1999). Willis (1999) shows in populations where females are in excess supply and men have low absolute levels of income and low levels of income relative to women, men will tend to have children outside of marriage. This occurs because absent fatherhood may require a lower financial commitment than present fatherhood and higher-earning women can produce high-quality children without the support of fathers. Furthermore, if females are in excess supply, men know they can match with women frequently and avoid the commitment of marriage. We extend Willis (1999) by quantifying the effects of low earnings and the scarcity of spouses on patterns of employment, fertility, marriage, and deadbeat fatherhood.

We also contribute to the literature explaining racial differences in marriage behavior. Wood (1995) and Brien (1997) empirically test Wilson's (1987) hypothesis that a shortage of marriageable men is behind racial differences in marriage. 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 marriage decisions interact with labor and marriage market differences across races.

The paper is also related to work that estimates structural models of female labor supply and marriage decisions. van der Klaauw (1996) estimates a dynamic structural model of 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 women's school attendance, marriage, work, fertility, and welfare use, and use the estimated model to quantify the importance of labor market opportunities, marriage market opportunities, and preference heterogeneity in explaining minority-majority differences in outcomes. Tartari (2015) formulates and estimates a dynamic model of couples' behavior starting from marriage to examine how divorce affects the cognitive achievement of children. She endogenizes child support transfers in the event of divorce, and studies how better enforcement of child support affects children's cognitive achievement.[4]

The above-mentioned structural papers model behavior in a partial equilibrium setting, and except for Tartari (2015), they focus only on the behavior of women. We extend this literature by modeling decisions and solving the equilibrium problem in a two-sided marriage market. The equilibrium analysis is important for considering the implications of policies that change the relative value of marriage, fertility, employment, or child support provision. A policy change, such as stronger child support enforcement, that alters marriage rates, fertility, employment, or child support provision today has implications for the marriage market in future periods that individuals must consider when making current period decisions. Partial equilibrium models do not capture these feedback effects.

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 account for black-white differences in marriage and employment. We extend Seitz (2009) by augmenting the choice set to include fertility and child support decisions. Allowing for this richer choice set is more computationally demanding and important for a comprehensive analysis of the factors that drive single motherhood and deadbeat fatherhood and policies that affect these outcomes. Furthermore, we go beyond studying racial differences in marriage and employment and use our model to analyze racial differences in single motherhood, deadbeat fatherhood, family structure, and child poverty.

The rest of the paper proceeds as follows. Section 2 outlines the dynamic equilibrium model and Section 3 discusses identification of the structural parameters. Section 4 describes the NLSY79 data used for estimation. Sections 5 and 6 cover the estimation procedure and results, respectively. In Section 7 we simulate counterfactual experiments and examine child poverty rates, and in Section 8 we offer some final thoughts on child support policy, marriage, and childbearing.

2 Model

We present the dynamic discrete choice model and discuss identification first to make clear the key ideas and mechanisms. Section 4 describes in detail the features and limitations of the NLSY79 that influence some of our modeling choices.

We model the decisions of men and women from one narrow birth cohort starting from their exit from full-time school (as early as 1979) until 1993.[5] Modeling behavior from the completion

[4]Brown and Flinn (2011) formulate and estimate a continuous time model starting from the time of marriage in which the husband and wife engage in a simultaneous-move game to make decisions about fertility, child quality investments, and divorce. They use the model to analyze how divorce-related policies such as child support orders and child custody and placement regulations impact fertility, child investments, divorce, and family members' welfare.

[5]The terminal period is 1993 due to changes in the NLSY survey frequency which we discuss later.

of full-time school implies education is exogenous and not modeled as a choice.[6] A period, denoted by t, is a year in length, where $t = 1$ corresponds to 1979. Since we only follow a single cohort over time, time and age are used interchangeably throughout. Individuals are forward-looking and make choices that maximize their expected discounted lifetime utility.

2.1 Contact Rates

As in Seitz (2009), 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, Census region, and time. All meetings occur within marriage markets segmented by race and region. Let e denote the race-region marriage markets, $e \in \{1, 2, ...E\}$.[7] 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. The gender in excess demand makes a contact with certainty. Specifically, 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 $\gamma^m(S_t^e) = \min(1, \frac{1}{S_t^e})$. The second part of the contact rate is denoted $\Phi_e^g(N^{g'}, K_t^{pg'}, t)$, which is the probability conditional on making a contact that the potential spouse of gender g' 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.[8] 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. Completed education is discretized into the following mutually exclusive categories: less than high school education, high school education (or GED), and college graduate.

2.2 Choice Set

If a contact is made, the matched man and woman jointly decide whether to marry, r_t, whether to have a birth, b_t, and whether they each 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 they decide to have a birth in period t, the child arrives in period $t+1$. If a male has a child from a past relationship such as a marriage that ended in divorce or a match where a child was born outside of marriage, he decides whether to provide financial support to the child, $(1 - d_t^m)$, where d_t^m is an indicator equal to one if the father does not provide any support (i.e. is a deadbeat dad). Agents that do not make a contact in the marriage market do not make marriage or birth decisions. The choice set for unmatched men, denoted A_t^m, contains four elements corresponding to each mutually exclusive combination of l_t^m and d_t^m. There are two elements in the choice set for

[6] We acknowledge that treating education as given is a limitation; however, allowing schooling to be a choice would lead to an unmanageable choice set and state space.

[7] We assume there is no regional mobility. Less than 3 percent of our estimation sample experiences a change in Census region between periods.

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

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 32 elements corresponding to combinations of the marriage choice, the birth choice, whether the male provides child support, and the employment decisions of both partners.[9] Each element of the choice set is denoted a_t.

2.3 Children

Individuals may have children from their current marriage, K_t^c, and from 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.[10] 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

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

If an individual divorces in period t, the children from that marriage become part of the stock of children from prior relationships upon entering period $t+1$. 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 $t+1$.

2.4 Preferences

We start by describing the utility functions of matched individuals. First, individuals have preferences over consumption, c_t^g. Following Tartari (2015) and Eckstein and Lifshitz (2015), we assume consumption is a public good within marriage but a private good when single. Thus, there are economies of scale within marriage due to joint consumption. Individuals also derive utility from the duration of their marriage, M_t, which accumulates according to:

$$M_{t+1} = \begin{cases} M_t + 1 & \text{if } \ r_t = 1 \\ 0 & \text{if } \ r_t = 0. \end{cases} \tag{3}$$

There is a utility cost to initiating a marriage which varies linearly with age as well as a utility cost from dissolving a marriage, which captures the legal, economic, and other non-pecuniary costs of divorce.[11] Individuals receive flow utility from children within their current marriage (if married),

[9] For tractability and to avoid an exceedingly large choice set, we treat cohabiting couples as married.

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

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

K^c_t. Matched individuals have preferences over the decision to have a birth within or outside marriage and these preferences vary with race. We also include a utility shifter that allows the utility from marriage to differ for blacks. Preferences over marriage and fertility vary by race because several studies have found that blacks enjoy lower utility from marriage than whites (Brien et al., 2006; Sheran, 2007; Seitz, 2009; Keane and Wolpin, 2010). We constrain the above-mentioned parameters to be the same for matched men and women because we cannot identify gender-specific parameters that are related to birth and marriage decisions. We discuss this issue in Section 3.

Further, individuals have preferences over leisure, l^g_t, which differ by gender and marital status. Individuals derive flow utility from their own children from past relationships, K^{pg}_t, and these preferences vary with the individual's gender and current marital status.[12] This utility flow is distinct from the utility an individual receives from children within their current marriage. The rationale is children can be thought of as a type of marital-specific capital that is worth more inside marriage than outside, and children from past relationships may be a source of conflict within one's current marriage (Becker et al., 1977; Waite and Lillard, 1991). Men have preferences for paying support to children from prior relationships and these preferences vary with his current marital status. The preferences over providing support capture the father's concern for the financial well-being of his children from prior relationships and that providing support could be a source of friction within a current marriage. Last, there are idiosyncratic shocks to the utility from marriage and birth, ε_{rt} and ε_{bt}, respectively, gender-specific shocks to the utility from leisure, ε^g_{lt}, and a shock to the male's utility from providing support, ε^m_{dt}. The shock to the utility from marriage can be thought of as a time-varying draw of marriage match quality. Once married, new draws may lead to divorce. We assume the ε's are serially independent and normally distributed with covariance matrix Σ to be estimated.

Preferences for matched men are described by

$$\begin{aligned} &u^m(r_t, b_t, l^m_t, d^m_t, K^{pm}_t, K^c_t, c^g_t, M_t) = \\ &\quad \ln(c^g_t) + (\alpha_1 + \alpha_2 t)1(M_t = 0)r_t + \alpha_3 1(M_t \neq 0)(1 - r_t) + \alpha_4 M_t r_t + \alpha_5 Bl^m r_t \\ &\quad + \alpha_6(1 - Bl^m)b_t(1 - r_t) + \alpha_7(1 - Bl^m)b_t r_t + \alpha_8 Bl^m b_t(1 - r_t) + \alpha_9 Bl^m b_t r_t + \alpha_{10} K^c_t r_t \\ &\quad + \alpha_{11} l^m_t(1 - r_t) + \alpha_{12} l^m_t r_t + \alpha_{13} K^{pm}_t r_t + \alpha_{14} d^m_t 1(K^{pm}_t > 0)(1 - r_t) + \alpha_{15} d^m_t 1(K^{pm}_t > 0)r_t \\ &\quad + \varepsilon^m_{lt} l^m_t + \varepsilon^m_{dt} d^m_t + \varepsilon_{bt} b_t + \varepsilon_{rt} r_t \end{aligned} \tag{4}$$

[12] 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.

and preferences for matched women are described by

$$
\begin{aligned}
&u^f(r_t, b_t, l_t^f, K_t^{pf}, K_t^c, c_t^g, M_t) = \\
&\quad \ln(c_t^g) + (\alpha_1 + \alpha_2 t)1(M_t = 0)r_t + \alpha_3 1(M_t \neq 0)(1 - r_t) + \alpha_4 M_t r_t + \alpha_5 Bl^f r_t \\
&\quad + \alpha_6(1 - Bl^f)b_t(1 - r_t) + \alpha_7(1 - Bl^f)b_t r_t + \alpha_8 Bl^f b_t(1 - r_t) + \alpha_9 Bl^f b_t r_t + \alpha_{10} K_t^c r_t \\
&\quad + \alpha_{16} l_t^f(1 - r_t) + \alpha_{17} l_t^f r_t + \alpha_{18} K_t^{pf} r_t + \varepsilon_{lt}^f l_t^f + \varepsilon_{bt} b_t + \varepsilon_{rt} r_t.
\end{aligned} \tag{5}
$$

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

$$
\begin{aligned}
&u^m(r_t, b_t, l_t^m, d_t^m, K_t^{pm}, K_t^c, c_t^g, M_t) = u^m(0, 0, l_t^m, d_t^m, K_t^{pm}, 0, c_t^g, 0) = \\
&\quad \ln c_t^m + \alpha_{11} l_t^m + \alpha_{14} d_t^m 1(K_t^{pm} > 0) + \varepsilon_{lt}^m l_t^m + \varepsilon_{dt}^m d_t^m.
\end{aligned} \tag{6}
$$

Preferences for unmatched women are described by

$$
\begin{aligned}
&u^f(r_t, b_t, l_t^f, K_t^{pf}, K_t^c, c_t^g, M_t) = u^f(0, 0, l_t^f, K_t^{pf}, 0, c_t^g, 0) = \\
&\quad \ln c_t^g + \alpha_{16} l_t^f + \varepsilon_{lt}^f l_t^f.
\end{aligned} \tag{7}
$$

2.5 Earnings and Non-Labor Income

Each period agents receive a job offer that is associated with an annual earnings amount. Annual earnings, w_t^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_{wt}^g, that are normally distributed and serially independent. Annual earnings offers are given by

$$
\ln w_t^g = \kappa_0^g + \kappa_N^g N^g + \kappa_{Bl}^g Bl^g + \kappa_{Reg}^g Reg^g + \kappa_t^g t + \kappa_{t^2}^g t^2 + \varepsilon_{wt}^g, \tag{8}
$$

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.

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 the individual's employment status as well as interactions between some state variables to capture welfare and unemployment benefit receipt patterns. Non-labor income for singles is described by

$$
\begin{aligned}
y_t^g &= \zeta_0^g + \zeta_N^g N^g + \zeta_{Bl}^g Bl^g + \zeta_{Reg}^g Reg^g + \zeta_t^g t + \zeta_{t^2}^g t^2 \\
&\quad + \zeta_p^g K_t^{pg} + \zeta_l^g(1 - l_t^g) + \zeta_{l,p}^g(1 - l_t^g)K_t^{pg} + \zeta_{Bl,p}^g K_t^{pg} Bl^g
\end{aligned} \tag{9}
$$

and non-labor income for married couples is

$$\begin{aligned} y_t^{mf} &= \zeta_0^{mf} + \zeta_{N^f}^{mf} N^f + \zeta_{N^m}^{mf} N^m + \zeta_{Bl}^{mf} Bl^m + \zeta_{Reg}^{mf} Reg^m + \zeta_t^{mf} t + \zeta_{t^2}^{mf} t^2 \\ &+ \zeta_{pf}^{mf} K_t^{pf} + \zeta_{pm}^{mf} K_t^{pm} + \zeta_c^{mf} K_t^c + \zeta_{l^f}^{mf}(1 - l_t^f) + \zeta_{l^m}^{mf}(1 - l_t^m) \end{aligned} \tag{10}$$

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 estimates imply negative non-labor income for an individual, we assign that individual zero non-labor income.

2.6 Child Support Payment and Receipt

Below we describe how child support payment and receipt are modeled and briefly highlight the data limitations that motivate our assumptions. In Section 4.3, we discuss the child support data in detail. We assume fathers have the choice to financially support children from past relationships, K_t^{pm}.[13] Women can receive support, $(1 - d_t^f)$, for children from past relationships, K_t^{pf}, where d_t^f is an indicator equal to one if the woman does not receive any child support. Women treat the probability of child support receipt as given. We estimate this probability outside the structural model and let it depend on the female's stock of prior children, education, race, region, and age.[14]

Annual child support transfers are denoted τ_t^g. Child support received by women, τ_t^f, is modeled separately from support paid by men, τ_t^m. Estimating one unified child support process requires observing all of an individual's former matches' state variables, which we do not have in our data. It is also possible the number of past relationships that produced children differs across a particular mother-father pair. Hence, the total amount of child support paid by that father may not equal the total amount of support received by that mother. By modeling separate transfer processes, we allow for such differences.[15] Thus, support received by a woman is a function of her state variables and support paid by a man is a function of his state variables. To capture the fact that child support award amounts vary across regions and 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, $\varepsilon_{\tau t}^g$, to capture unobservable factors which affect

[13] 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.

[14] Estimates of this probability can be found in Table 8.

[15] 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.

award amounts such as variation in judicial discretion and variation in guidelines across states.[16] The amount of child support received by women is given by

$$\ln \tau_t^f = \eta_0^f + \eta_N^f N^f + \eta_{Bl}^f Bl^f + \eta_{Reg}^f Reg^f + \eta_t^f t + \eta_{t^2}^f t^2 + \eta_p^f K_t^{pf} + \varepsilon_{\tau t}^f. \tag{11}$$

Equation 11 is estimated outside the model since women's receipt of support is treated as given. The amount of child support paid by men is estimated within the structural model and given by

$$\ln \tau_t^m = \eta_0^m + \eta_N^m N^m + \eta_{Bl}^m Bl^m + \eta_{Reg}^m Reg^m + \eta_t^m t + \eta_{t^2}^m t^2 + \eta_p^m K_t^{pm} + \varepsilon_{\tau t}^m. \tag{12}$$

If a male decides to pay support ($d_t^m = 0$), he pays τ_t^m above. If he is a deadbeat father ($d_t^m = 1$), he pays nothing. We focus on the extensive margin of child support provision and not the intensive margin (i.e. whether he pays some fraction of a pre-specified amount) because in the data we do not observe the amount of child support the father is legally obliged to pay. We only observe the amount paid and do not know how that compares to the court-ordered award amount.

2.7 Household Budget Constraints and Consumption

As in Tartari (2015) and Eckstein and Lifshitz (2015), we assume married couples pool their resources, consumption is a public good within marriage, and a given fraction of household income is devoted to resident children. We denote ψ the fraction of household income that is allocated to children and let this fraction depend on the number of children in the household, keeping in mind that we assume children born outside of marriage and children from dissolved marriages reside with their mother. We use the same values of ψ as Eckstein and Lifshitz (2015) which are based on OECD equivalent scales.[17] Thus, a married individual's consumption is given by[18]

$$c_t^g = \left(1 - \psi(K_t^c + K_t^f)\right)\left(w_t^m(1 - l_t^m) + w_t^f(1 - l_t^f) + y_t^{mf} + \tau_t^f(1 - d_t^f) - \tau_t^m(1 - d_t^m)\right). \tag{13}$$

[16] 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 for deviating from the guidelines was issued (Lerman and Sorensen, 2003).

[17] $\psi = 0.2$ for one-child households; $\psi = 0.32$ for two-child households; $\psi = 0.41$ for three-child households; and, $\psi = 0.48$ for households with more than three children.

[18] 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.

Consumption is private when individuals are single. A single woman's consumption is given by

$$c_t^f = \Big(1 - \psi(K_t^c + K_t^f)\Big)\Big(w_t^f(1 - l_t^f) + y_t^f + \tau_t^f(1 - d_t^f)\Big) \tag{14}$$

and a single man's consumption is given by

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

2.8 Value Functions

In every period, agents maximize the expected present discounted value of lifetime utility. The maximized value is given by $V_t^g(\Omega_t)$, where Ω_t denotes the vector of state variables

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

and $\epsilon_{\mathbf{t}}$ contains the full set of preference, earnings, and child support shocks.[19] By including e and t, the state space vector conditions in the current sex ratio and demographic composition of singles in an individual's marriage market as well as one's race and Census region.

The value function, $V_t^g(\Omega_t)$, 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 $V_t^f(a_t, \Omega_t)$. We start by considering the choice-specific value functions for unmatched men and women and then proceed to matched men and women.

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

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

where β is the discount factor and the expectation is taken with respect to the future stochastic components of utility and income processes.[20] 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, $\gamma^m(S_{t+1}^e)$, and the probability that woman has a certain level of education and children from prior relationships is given by $\Phi_e^m(N^f, K_{t+1}^{pf}, t+1)$. Further, the value of marriage depends in part on whether she receives support for those children,

[19] If an individual is unmatched, several of these state variables are zero or irrelevant to the individual's decisions.
[20] We set the discount factor equal to 0.96.

$Pr(d^f_{t+1} = 0|K^{pf}_{t+1}, N^f, e, t+1)$. 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 differs 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

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

Unmatched women take into account that if they have children from prior relationships, there is a probability 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.[21] Joint surplus is defined as the additional expected present discounted lifetime utility the matched man and woman enjoy from a particular choice relative to what they would enjoy as single agents. Thus, for those who are newly matched, the threat point is the expected lifetime utility they would receive from the optimal choice they would make if unmatched. For those who enter the period matched to their spouse from the prior period, the threat point is the expected lifetime utility they would receive as divorced agents that do not have a birth. The choice-specific value function for a matched man with choice set $A^{mf}_t = (r_t, b_t, l^m_t, l^f_t, d^m_t)$ is

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

[21]For recent examples of empirical analyses of household decision-making that assume symmetric Nash bargaining, see Gemici (2011) and Bronson and Mazzocco (2013).

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

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

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

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

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

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

The expected value functions for matched individuals depend on whether they decide to marry or not in period t. If they decide to marry (or stay married), 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 ($t = 15$). 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

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

$$V_{16}^{f}(\Omega_{16}|a_{15}) = \delta_1 r_{15} I(M_{15}=0) + \delta_2 r_{15} I(M_{15}\neq 0) + \delta_3 K_{16}^{c} + \delta_5 K_{16}^{pf}. \tag{24}$$

We follow Khwaja (2010) and define the terminal value function parsimoniously to avoid overfitting 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 and old marriages in 1993 to prevent a glut of marriages or divorces in the final period of the model. The parameters of the terminal value function are estimated along with the other structural parameters.

2.9 Solution Method

The dynamic programming problem is solved by backward recursion given a set of model parameters and the terminal value function. We calculate the expected value functions using Monte Carlo integration as described in detail in Keane and Wolpin (1994).[22] 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. 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 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.[23]

2.10 Equilibrium

The sex ratios evolve endogenously in the model since marriage decisions in period t determine the sex ratio and demographic composition of singles in $t+1$. Current period marriage decisions depend on future marriage market conditions; thus, individuals must determine next period's sex ratio when making current period choices. From the model outlined above, the choice-specific value functions for agents choosing choice a_t in time t can be expressed as

$$\begin{aligned} &\mathbf{V}\left(a_t, \Omega_t, E\left[S_{t+1}^{e}, \Phi_e^{g}(N^{g'}, K_{t+1}^{pg'}, t+1)\right]\right) \\ &\quad = \mathbf{V}\left(a_t, \Omega_t, E\left[S_{t+1}^{e}, \Phi_e^{g}(N^{g'}, K_{t+1}^{pg'}, t+1)|\mathbf{V}(a_t,\Omega_t), S_t^{e}, \Phi_e^{g}(N^{g'}, K_t^{pg'}, t)\right]\right) \end{aligned} \tag{25}$$

[22] 40 draws are used for the numerical integration.

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

where $\mathbf{V}(\cdot)$ collects the four different choice-specific value functions (corresponding to matched and unmatched, male and female agents). Future marriage market conditions (i.e. the sex ratio and the demographic composition of singles) depend on current period choices through three endogenous channels and the exogenous flow of individuals entering into the marriage market. That is, the stocks of single men and women in the marriage market at the start of $t+1$ 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 in t who matched but decided to stay single; (3) the number of married individuals who divorced in t; 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 they made in t. 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. Thus, each period we must solve a fixed point problem for each marriage market.

Conditional on a set of structural parameters and initial distributions for the singles and married couples, we solve the equilibrium problem as follows. First, the utility shocks and shocks to the income processes are drawn for every person for each period in our sample. Given these draws, each individual's dynamic programming problem is solved by backward recursion. We then 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.[24] 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. However, when we perform the counterfactual simulations, we solve the equilibrium problem explicitly.

2.11 Connecting the Model and the Stylized Facts

Before proceeding, we review how the model mechanisms are linked to non-marital childbearing, deadbeat fatherhood, and racial differences in outcomes. 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.

[24]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.

This tradeoff is especially salient for black women. In our estimation sample in 1990, the ratio of single black men to single black women was 0.7, while the ratio of single white men to single white women was 1.1. Further, the characteristics of a match, such as their education and whether they have children from prior relationships, are a function of the population distribution of those characteristics in an individual's marriage market. 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 willing to tradeoff own consumption for 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. To the extent preferences over marriage and the decision to have a birth vary by race, these mechanisms may be amplified or dampened.

3 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 marriage duration, α_4, is identified off the decision to stay married or not over different durations. Again, functional form is important as we assume utility is linear in marital duration. 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 conditional on identifying α_1 through α_4.

Some utility parameters 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.[25] 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 identify utility from one's own children from past relationships when married separately by gender off differential marriage transitions for men and women with past children.

Identification of the parameters of the labor earnings offer 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 child support paid and the state variables in those equations. 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).[26]

4 Data

Data is collected from the NLSY79 for calendar years 1979 to 1993. The NLSY79 is useful for our purposes for several reasons. In addition to standard demographic information, it contains detailed relationship and fertility information 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 provide financial support to children. In addition, it contains information on an individual's employment, earnings, and non-labor income across time. We treat 1993 as the terminal decision period in the model because starting in 1994, the NLSY respondents were surveyed biennially which does not allow us to accurately measure marriage spells, fertility, employment, and child support decisions at an annual basis.

4.1 Marriage Variables

We use annual information on marital status and cohabitation to create an indicator for whether an individual is married for each year in the data. An individual is defined as married if they are currently married or list an opposite sex adult as a partner on the household roster. Consecutive periods of cohabitation or marriage are treated as a single marriage spell as are transitions from

[25] See Arcidiacono et al. (2013) for a discussion and application of identifying gender differences in preferences from only observed matches, which requires a non-cooperative model.

[26] The number of children is a commonly used exclusion restriction (or instrument) 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.

cohabitation to marriage.[27] We make these assumptions to maintain consistency in our definition of marital status and our measurement of marriage spells across years.[28]

4.2 Children Variables

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. 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. All remaining children, including children from dissolved relationships, are included in the stock of children from past relationships.[29] It is possible that multiple past relationships produced children. We cannot accurately identify such cases in the data if the parents never cohabit; thus, the stock of children from prior relationships includes all children even if they have different fathers or mothers. In the model, this means all children from past relationships are treated the same. From a computational standpoint, the state space becomes exceedingly large if agents treat children from each possible past relationship differently.

4.3 Child Support Payment and Receipt Variables

We create an indicator for being a deadbeat father, equal to one if a male has children from past relationships and did not pay at least one dollar of child support in that calendar year. If the individual is female, we generate an indicator equal to one if she has children from a past relationship but did not receive any support in that calendar year. During our sample period, we do not observe whether a male respondent is under an explicit court order to pay child support (and only observe whether a female respondent's prior partner is under a court order in calendar years 1992 and 1993). Thus, a deadbeat father is an absent father who does not provide any financial support, regardless of whether a formal support award has been established.[30] The lack of

[27]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 146 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.

[28]We do not use the start and end dates of marriage to determine marital status 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.

[29]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 above and to not overstate deadbeat fatherhood.

[30]A potential concern is never-married men are less likely to pay because they are less likely to have court-ordered child support payments (since paternity is less likely to be established). Descriptive statistics from the sample period show that women who were ever married to (or cohabited with) the father were only 4 percentage points more likely to

information regarding court-ordered awards also motivates our decision to focus on child support provision on the extensive margin. In the data, we cannot determine whether a man pays or a woman receives the full amount of support owed, only that some amount was paid or received. Thus, the child support transfers we estimate may reflect an intensive margin choice to provide a proportion of a court-mandated award.

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.[31] 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.[32] Our non-likelihood-based estimation strategy allows us to still use male observations in years which data on child support provision is unavailable.

In the model, we assume a woman's probability of support receipt is taken as given and depends on her state variables and the amount of support paid by men and received by women are separate functions that depend on their own state variables. There are several reasons for these modeling choices. First, relaxing these assumptions requires including the characteristics of all of an individual's past matches in the state space. However, in our data (or any dataset to our knowledge), we do not observe the state variables of an individual's previous partners, only those of partners they are currently married to or cohabiting with. Even if we did, keeping track of those state variables would be computationally demanding. Second, it is possible multiple prior relationships produced children; thus, the number of children from past relationships may differ between a mother and father. The data, however, does not include disaggregated information on the recipients of payments made by men or the sources of child support received by women. Thus, the transfers observed in the data and specified in Section 2.6 reflect aggregate payments made by men to possibly multiple women and aggregate support received by women from possibly multiple fathers.

4.4 Earnings, Employment, and Non-Labor Income Variables

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 in the calender year for which hours are recorded. Non-labor income is composed of unemployment insurance, welfare, food stamps, income from a farm or business, workman's compensation, disability, and veteran's

receive support than never-married women. Similarly, men who were ever married to (or cohabited with) the mother were only 8 percentage points more likely to provide support than men who were never married to the mother.

[31] 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 alimony. In 1981, conditional on receiving alimony or child support, on average alimony makes up 1.6 percent of combined alimony and support receipt (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.

[32] 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.

compensation.[33] 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.

4.5 Demographics

We create indicators for whether an individual's highest level of education is high school or college. The indicator for high school education is equal to one if the individual completed 12 years of school or obtained a GED. The indicator for college graduate is equal to one if the individual obtained a Bachelor's degree or higher.

As described in the model, 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. 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: about 97 percent of whites and 93 percent of blacks have same-race spouses.[34] Our decision to segment the marriage market by race is motivated by these low rates of interracial marriage and the fact that data on the race of the spouse is not available in the NLSY79.[35,36] 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.[37]

4.6 Sample Selection and Descriptive Statistics

The original NLSY sample in 1979 consists of 6,403 males and 6,283 females. We remove individuals serving in the military as well as individuals once they miss an interview. We also remove those with missing or inconsistent information that does not allow us to accurately measure their marital status transitions. As mentioned above, we restrict the sample to women ages 15 to 19 years and men ages 17 to 21 years in 1979. The final sample consists of 3,019 women and 2,489 men, with a total of 59,699 person-year observations.

[33] Earnings, non-labor income, and child support transfers are converted to real terms with 2000 as the base year.

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

[35] Wong (2003) finds that interracial marriage rates are generally unresponsive to improvements in black male human capital endowments as well as increases in the rate at which black males meet white females. Thus, even if we could allow for interracial marriage, it seems unlikely to substantively alter the qualitative implications of our model.

[36] 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.

[37] 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.

Table 2 contains sample statistics by race and gender for all person-years in our sample. Marriage rates are higher for white men and women than for blacks. Women of both races and men of both races have similar fertility rates, but conditional on having a birth, black men and women are much more likely to have a birth outside of marriage. As a result, black individuals are more likely to have children from prior relationships. Conditional on having children from prior relationships, the majority of men across both races are deadbeat fathers, with black men about 6 percentage points less likely to pay support. Employment rates are higher for whites than blacks. There is a labor earnings gap between blacks and whites, with the male black-white earnings gap being larger than the female black-white gap both in absolute and relative terms. Regarding education, the largest differences exist between black and white men, with white men being 2.3 times more likely to have completed college.

4.7 Sex Ratio and Population Stock Construction

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 for estimation, we follow Seitz (2009) and reweight the NLSY using the Current Population Survey (CPS). As described above, we define the marriage market by age, region, and race. We then create sampling weights such that the number of single and married men and women in each marriage market in each year in our NLSY sample match the corresponding numbers in the CPS. The stocks of single men and women in each marriage market as well as the sex ratios are then created using the reweighted NLSY data.[38] We cannot use the CPS to directly calculate the stocks because individual-level transitions in and out of marriage must be used to measure sex ratio changes over time to be consistent with the model. In the model, marriage market equilibrium requires that marriage transitions (the flows) be completely consistent with the sex ratio (the stocks). The panel nature of the NLSY allows us to observe individual-level marriage transitions, but we do not observe such transitions in the CPS. Thus, the stocks must be calculated directly from the reweighted NLSY79.[39] Importantly, this reweighting strategy allows us to capture differences in population supplies across groups that arise from differences in mortality and incarceration rates.

Figure 1 shows the sex ratio time profiles 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

[38]To maintain consistency between the CPS data and our NLSY data, we exclude individuals in the CPS who serve in the military and who are Hispanic when constructing the weights. 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 7.4 percent of our NLSY sample.

[39]The fact that individual-level marriage transitions in the NLSY79 are used to construct sex ratios over time also motivates our decision not to segment the marriage market at a finer geographic level, such as the state level. The sample size of the panel limits the extent to which we can geographically segment the marriage market.

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.

5 Estimation

As discussed in Section 4, 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 outcomes obtained from the structural model to an auxiliary statistical model. The auxiliary statistical model should be easily estimated and must capture enough of the statistical correlations in the data to identify the structural parameters. Following van der Klaauw and Wolpin (2008), Tartari (2015), and Skira (2015), the auxiliary model we use includes 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.

Using the actual NLSY data, denoted y_A, we estimate a set of M_A auxiliary statistical relationships. By construction, at the maximum likelihood estimates of these auxiliary models, $\widehat{\theta}_A$, the scores of the likelihood function, $\frac{\partial L_j}{\partial \theta_{A,j}}$, are zero for $j = 1, \ldots, M_A$, where $\theta_{A,j}$ is the vector of model j's parameters. The idea behind EMM is to obtain structural model parameters, θ_B, 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 $\frac{\partial L}{\partial \theta_A}(\cdot)$ is a vector containing the scores of the likelihood functions across auxiliary models. The weighting matrix used in estimation is the identity matrix.[40]

The equilibrium conditions are not imposed in estimation because of the large computational costs of doing so. The distributions of single and married individuals used in the dynamic programming problem are the empirical distributions from the reweighted NLSY data. This implies that

[40] We do not use 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) because 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.

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 do not impose 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 choices of any one individual have a negligible effect on the sex ratio itself (Seitz, 2009). When counterfactual experiments are conducted with the model, the equilibrium conditions are imposed.

5.1 Auxiliary Statistical Models

One group of auxiliary models includes approximations of the decision rules generated from 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) and Tartari (2015) and specify these decision rules as parametric functions of subsets of state space elements to keep the approximations parsimonious. A second group includes 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. For the years when information on child support paid by men is unavailable, we simply do not estimate the auxiliary models related to deadbeat fatherhood in those years, but we still use the male observations in those years for estimation of the other auxiliary models. Appendix A contains a list of the auxiliary models used in estimation. The auxiliary models imply 515 score functions which are used to identify 57 structural parameters.[41]

5.2 Simulating Data for Estimation

We solve the optimization problem conditional on a given set of structural parameters and then simulate one-step-ahead decisions. 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 (his or her education and number of children from prior relationships). The score functions from the auxiliary models are evaluated using the simulated decisions and the objective function is calculated.[42] We iterate on the parameters using the Nelder-Mead simplex method.

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

[42]We perform 30 simulations for each sample observation and average that observation's score functions over the simulations.

6 Results

6.1 Parameter Estimates

Tables 3 and 4 show the structural parameter estimates. Parameters estimated outside the model can be found in Tables 5 to 8. There is a large utility cost of initiating marriage that 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. 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 Brien et al. (2006), Sheran (2007), Seitz (2009), and Keane and Wolpin (2010), we find blacks derive less utility from marriage than whites. We also find whites derive more disutility from the decision to have a child outside of marriage than blacks. The estimated preference heterogeneity in marriage and fertility may reflect differences across races in the characteristics of available spouses other than education and children from past relationships and suggests factors in addition to the ones we consider contribute to racial differences in marriage and fertility.

We find 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. The finding that children from prior relationships decrease men's utility when married may reflect that children from a relationship other than the current marriage are a source of potential friction within marriage. Single men derive disutility from not providing child support to past children while married men derive very small positive utility from not providing support. Similar to the finding above, this result suggests the provision of financial support to prior children may be a source of conflict within a current marriage. The estimates of the log labor earnings offer equations and child support paid by men equation are reasonable and as expected. We find a 53.5 percent earnings offer gap between black and white men and a 7.6 percent earnings offer gap between black and white women conditional on education. 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.[43]

6.2 Model Fit

To examine the within-sample fit, 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 simulations used for model

[43] 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.

fit analysis do not impose the equilibrium conditions. Table 9 reports the actual and simulated proportions of various choices and outcomes for men and women. Overall, the model fits the data reasonably well except it overpredicts non-marital births among men by about 6 percentage points.

Table 10 shows choice proportions by race. The model predictions fit most aspects of the data for both races. The model overpredicts births outside of marriage for both black and white men, and it underpredicts marriage for black women by about 5 percentage points. Figure 2 shows time profiles of simulated and actual marriage rates by race. The model fits the data closely for black and white male marriage profiles. For females, the model has a slight tendency to underpredict marriage rates for most of the sample period.

While we do not impose the equilibrium conditions in estimation or the simulations used for model fit, we check 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 by race. For whites, the model tends to slightly underestimate the sex ratios. For blacks, the simulated and actual sex ratios are quite close.

6.3 External Validation

In the mid-1980s 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. After controlling for the assignability and presence of fathers' income at the time of the award, 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. 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 70.5 percent of non-custodial fathers with new child support cases worked in 1985, which means their support payments were immediately withheld. We find a 15 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 70 percent utilization rate of immediate withholding. Child support payment amounts increase by 33 percent in the experiment relative to the baseline, which is larger than the increase found in Garfinkel (1986). 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.[44]

A related literature uses cross-state variation in policy changes to evaluate the impact of child 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 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 an 8.3 percentage point increase in the frequency of support paid by men who were ever married to the mother (without conditioning on her welfare receipt).[45] 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 \$214 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.

[44] 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.

[45] 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.

7 Counterfactual Experiments

7.1 Eliminating the Racial Gap in Earnings

We present the results of several counterfactuals.[46] In the first counterfactual simulation, we eliminate the racial gap in labor earnings that exists conditional on education.[47] We do so by setting the coefficients on being black in the male and female labor earnings equations, κ_{Bl}^{m} and κ_{Bl}^{f}, to zero. The low labor market return for black males may discourage marriage and employment, as they have less incentive to work and may be less attractive in the marriage market (Seitz, 2009). Further, this low labor market return may affect the ability to pay child support. This counterfactual allows us to examine what happens if blacks with the same observed characteristics as whites receive the same earnings.

Results of this simulation are found in Table 11. Marriage rates for black men and women increase by 10 and 9 percentage points, respectively, relative to the baseline (a 31 percent increase). Employment among black men increases to parity with white men. Births outside of marriage among blacks decline by 14 percentage points relative to the baseline (a 28 and 30 percent decline for men and women, respectively), and deadbeat fatherhood (conditional on having past children) falls by about 6 percentage points (a 9 percent decline).[48]

Table 12 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 an increase in the prevalence of intact families. Since black males enjoy a larger labor market return, marriage becomes a more attractive alternative relative to the baseline. We also find an increase in the percentage of individuals who are married and have children from past relationships. Previously, women who were matched with a male with past children faced a potential loss of 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.

[46] 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 40 replicas of each sample individual's initial state variables. When we calculate the sex ratios and population stocks to solve the equilibrium problem in these simulations, we weight individuals' marriage decisions by the sampling weights created using the CPS. The same draws of idiosyncratic shocks are used across the counterfactuals.

[47] We acknowledge the racial earnings gap reflects labor market discrimination, pre-market factors, and skill endowments. As in Seitz (2009) and Keane and Wolpin (2010), our goal is to understand the extent to which low labor market earnings for blacks impact behavior, not to disentangle the source of the earnings gap.

[48] 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 deadbeat fatherhood falls by 5.9 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, Wilson (1987) hypothesizes 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). In this counterfactual, we examine what happens to marriage, employment, fertility, and support decisions when 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 structural parameters remain as in the baseline.

The results of this simulation are presented in Tables 11 and 12. There is a 2.6 percentage point increase in marriage rates for black women and a 2.7 percentage point decrease in marriage rates for black men (amounting to a 9 percent increase for women and an 8 percent decrease for men). The intuition is as follows. The higher sex ratio for blacks means black women face less search friction in the marriage market and meet matches with a larger probability than in the baseline. As a result, black women can delay marriage to wait for a better match. Further, it is still the case in this simulation that black males face a low labor market return, making it difficult for a black male to make marriage an attractive alternative for a black woman. We also find employment for black women increases due to the larger number of college-educated women in the black population relative to the baseline. We find a slight increase in births among black women but a decrease among black men, and small increases in non-marital births.

7.3 Equalizing Preferences

In the next experiment, we give black individuals the same preferences as whites over marriage and fertility. Specifically, we set the utility from marriage shifter for blacks (α_5) to zero and give blacks the same utility from non-marital and marital births as whites (we set α_8 and α_9 equal to the estimated values of α_6 and α_7, respectively). Equalizing preferences has a large impact on marriage and non-marital births among blacks, increasing marriage rates by about 20 percentage points for men and women (a 65 percent increase) and decreasing non-marital births by about 37 percentage points (a 77 percent decrease). Employment increases by less than 5 percentage points among black men and women, and conditional on being an absent father, deadbeat fatherhood increases slightly. Our findings regarding preference heterogeneity are similar to those in Keane and Wolpin (2010). They analyze a counterfactual experiment in a partial equilibrium setting in which black women's preference for marriage is the same as white women's and their potential husbands' income distribution is equalized to that of white men. They find black female marriage rates increase to almost parity with whites and female non-marital births decrease substantially.

Thus, preference heterogeneity over marriage and fertility is important for explaining racial differences in those particular outcomes but not other outcomes such as employment or child support provision. On the other hand, closing the racial earnings gap significantly impacts all the outcomes we consider (not just employment), but does not account for as much of the racial gap in marriage and non-marital births as preference heterogeneity. These results highlight the complexity of understanding racial differences in behavior. Some factors, such as preference heterogeneity, play a sizable role in explaining just a few outcomes, while other factors, such as low earnings, impact all the outcomes we study to some extent.

7.4 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 men who are absent fathers must provide child support.[49] A priori, it is not clear how perfect enforcement 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 11 to 14. Across races, we find increases in marriage rates for men and women, with a larger increase for whites because blacks derive less utility from marriage. Fertility rates are generally similar to those in the baseline, but there are substantial decreases in non-marital births for all groups, with blacks experiencing a 16 percentage point decline (about a 33 percent decrease). Thus, the disincentive for men to have a child outside of marriage outweighs the incentive for women to have a child 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.

Tables 12 and 14 show there are decreases in the percentage of individuals who are single with children relative to the baseline. In addition, marriage rates among black women with children from prior relationships increase. Relative to the baseline, when enforcement is perfect, women with children from past relationships become more attractive in the marriage market because they receive support with certainty, increasing household income. On the other hand, men with children from past relationships become less attractive as they must provide child support, decreasing household

[49] 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.

income available for consumption. Indeed, marriage rates among these males decrease with perfect enforcement. Thus, perfect enforcement creates an additional disincentive to have children outside of marriage, as such children decrease the attractiveness of men in the marriage market. By modeling the marriage market in an equilibrium setting, we capture this effect.

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, 34.3 percent of individuals who were ever married divorced at some point in the sample period, compared to 32.5 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.[50]

An advantage of our structural approach is that we can examine the welfare implications of perfect enforcement. 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 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 15 shows the proportion of men and women in different racial and educational groups that experienced welfare gains. Most women gain from perfect enforcement, with black females and females with less education benefiting most. Not surprisingly, the majority of men are worse off, especially black men.

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 Table 16. Given that perfect enforcement guarantees women child support in the event of divorce or a non-marital birth, it may seem surprising that some women experience welfare losses. There are several characteristics of this group worth noting. Compared to women who gain, they have lower baseline marriage rates and fewer children in the baseline both from a current marriage and past relationships. Thus, child support enforcement affects them less. Changes in the marriage market also play a role. Marriage rates increase among all females, but among those who gain, there is an increase in marriage to more highly-educated men, and among those who lose, there is an increase in marriage to less-educated men and a decrease in marriage to college-educated men. The intuition is that perfect enforcement changes the incentives to marry, which results in changes in the availability and characteristics of potential spouses over time. Women who lose are those who end up marrying less-educated men. This result underscores the importance of modeling the marriage market equilibrium.

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

It is not surprising that most men lose from perfect enforcement. Men who lose are those who have higher baseline marriage rates and more children both from a current marriage and past relationships relative to those who gain. While it is straightforward to see why men with children from past relationships tend to have welfare losses, it is perhaps less obvious why married men with children from that marriage are worse off. While marriage and within-marriage births are still optimal for these men, 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 or how to achieve stronger enforcement. Freeman and Waldfogel (2001) suggest the comprehensiveness of child support legislation, rather than a particular law or policy, matters for child support effectiveness. Thus, increased enforcement may require the strengthening of several policies such as paternity establishment, tax intercept programs, and wage withholding. 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.[51]

7.5 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 residing in a household with income below the poverty threshold divided by the total number of children.[52] Figure 4 shows the time profiles of child poverty rates across the simulations by race. Closing the racial earnings gap is most effective at decreasing the black child poverty rate followed by equalizing preferences. In the final period of the racial earnings gap and preference heterogeneity experiments, the black child poverty rate is 39 and 28 percent smaller, respectively, than in the final period of the baseline simulation.[53] Perfect enforcement decreases child poverty but to a lesser extent and particularly in the earlier periods of the model.

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

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

[53] These experiments likely understate the gains for children, who not only see gains in material inputs but also experience increases in the probability of residing in an intact family, which Tartari (2015) 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 decisions 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 the availability and characteristics of potential spouses to evolve endogenously and solve the resulting equilibrium problem. Third, we analyze the roles that black-white differences in earnings, population supplies, and preferences play in generating observed differences in outcomes across races.

We conclude that single motherhood, deadbeat fatherhood, and racial differences in behavior are generated from a combination of factors. The earnings gap observed across races (conditional on education) plays an important role in generating racial gaps in many outcomes including marriage rates, non-marital childbearing, male employment, child support provision, and the fraction of children growing up in poverty. Racial preference heterogeneity has a large impact on marriage and non-marital childbearing, but not employment or child support provision. Surprisingly, population supplies do not account for much of the behavior or racial differences we study. In terms of policy, 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 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.

Appendix

A Auxiliary Models

The following list consists of auxiliary models used in estimation:

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, marriage duration, 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.

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 marriage duration.

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.

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Tables and Figures

Table 1: Characteristics of Men Aged 31-35 and Women Aged 29-33 in 1993 Wave of NLSY79

			Single Mothers:	
	Non-Mothers	Married Mothers	Paid Support	Not Paid Support
% White	69.71	73.01	36.20	22.14
% Black	30.29	26.99	63.80	77.86
% Less than high school	5.02	10.04	17.18	21.77
% High school education	54.12	70.27	71.17	75.65
% College education	40.86	19.70	11.66	2.58
% Not working	12.72	35.04	39.88	45.76
% Working	87.28	64.96	60.12	54.24
Mean annual earnings	$32,100	$22,476	$20,973	$20,145
N	558	1,056	163	271
			Absent Fathers:	
	Non-Fathers	Present Fathers	Paying Support	Not Paying Support
% White	70.88	84.62	45.71	25.93
% Black	29.12	15.38	54.29	74.07
% Less than high school	9.64	9.19	15.43	27.57
% High school education	55.62	61.35	80.00	67.08
% College education	34.74	29.46	4.57	5.35
% Not working	17.27	6.19	14.86	33.33
% Working	82.73	93.81	85.14	66.67
Mean annual earnings	$36,980	$48,205	$30,357	$27,883
N	498	533	175	243

NOTES: Men and women are divided into the mutually exclusive groups above based on their marriage, fertility, and child support payment or receipt status. Married mothers and present fathers include those who are currently cohabiting. The married mothers group includes women who are currently married but have children from prior relationships. Working is defined as working at least 775 hours in the calendar year. Mean annual earnings are calculated for those who work at least that amount. All dollar amounts are in constant 2000 dollars. Percentages refer to column percentages.

Table 2: Sample Statistics by Race and Gender

	Women		Men	
	White	Black	White	Black
% Single	38.52	65.32	48.02	67.03
% Married	61.48	34.68	51.98	32.97
% Decide no birth	88.54	88.38	90.52	90.10
% Decide birth	11.46	11.62	9.48	9.90
% Births outside marriage	7.54	48.30	3.63	40.97
% Births within marriage	92.46	51.70	96.37	59.03
% Not working	33.24	43.27	13.79	26.74
% Working	66.76	56.73	86.21	73.26
% Not a deadbeat[a]			39.70	33.27
% Deadbeat[a]			60.30	66.73
Mean annual earnings	$20,721	$18,105	$32,106	$22,953
% No children from prior relationships	83.28	46.96	91.61	60.63
% Have children from prior relationships	16.72	53.04	8.39	39.37
% Less than high school	17.47	19.87	16.88	29.56
% High school education	66.61	71.75	63.09	61.81
% College education	15.92	8.38	20.03	8.64
Person-year observations	22,023	10,826	18,503	8,347

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

Earnings are calculated for the sample that works.

Table 3: Utility Parameter Estimates

Description	Parameter	Estimate	S.E.
Utility Parameters-Same for Men and Women			
Marriage initiation intercept	α_1	-0.600	0.017
Marriage initiation age trend	α_2	-0.106	0.002
Marriage separation cost	α_3	-3.177	0.018
Marriage duration	α_4	-0.207	0.001
Marriage for blacks	α_5	-0.224	0.008
Birth when single for whites	α_6	-2.971	0.023
Birth when married for whites	α_7	-2.219	0.018
Birth when single for blacks	α_8	-2.330	0.021
Birth when married for blacks	α_9	-2.186	0.025
Children from current marriage	α_{10}	0.356	0.002
Utility Parameters-Men			
Leisure when single	α_{11}	1.695	0.038
Leisure when married	α_{12}	0.143	0.033
Past children when married	α_{13}	-0.257	0.028
Not providing support when single	α_{14}	-0.194	0.016
Not providing support when married	α_{15}	0.003	0.030
Utility Parameters-Women			
Leisure when single	α_{16}	0.955	0.012
Leisure when married	α_{17}	0.572	0.019
Past children when married	α_{18}	0.354	0.027
Preference Shock Variances			
Marriage decision	σ_r^2	2.742	0.050
Birth decision	σ_b^2	3.193	0.028
Men's leisure[a]	σ_{lm}^2	1.000	
Women's leisure[a]	σ_{lf}^2	1.000	
Men deadbeat	σ_d^2	0.167	0.008
Terminal Value Function Parameters-Same for Men and Women			
New marriage in 1993	δ_1	-0.592	0.095
Old marriage in 1993	δ_2	-0.283	0.066
Children from current marriage	δ_3	0.035	0.012
Terminal Value Function Parameters-Men			
Past children	δ_4	-0.772	0.051
Terminal Value Function Parameters-Women			
Past children	δ_5	-0.340	0.428

NOTES: [a]Normalized.

Table 4: Labor Earnings and Child Support (Paid by Men) Parameters

Description	Parameter	Estimate	S.E.
Log Labor Earnings-Men			
Intercept	κ_0^m	9.319	0.012
High school education	$\kappa_{N,HS}^m$	0.300	0.013
College education	$\kappa_{N,Col}^m$	0.685	0.048
Black	κ_{Bl}^m	-0.535	0.026
North Central	κ_{NC}^m	-0.106	0.018
South	κ_{South}^m	-0.031	0.011
West	κ_{West}^m	-0.080	0.010
Time	κ_t^m	0.061	0.001
Time squared	$\kappa_{t^2}^m$	0.00007	0.00009
Variance to shock	$\sigma_{w^m}^2$	0.520	0.015
Log Labor Earnings-Women			
Intercept	κ_0^f	8.927	0.012
High school education	$\kappa_{N,HS}^f$	0.579	0.015
College education	$\kappa_{N,Col}^f$	1.306	0.015
Black	κ_{Bl}^f	-0.076	0.020
North Central	κ_{NC}^f	-0.351	0.019
South	κ_{South}^f	-0.258	0.017
West	κ_{West}^f	-0.204	0.024
Time	κ_t^f	0.045	0.001
Time squared	$\kappa_{t^2}^f$	-0.003	0.0001
Variance to shock	$\sigma_{w^f}^2$	0.518	0.010
Log Child Support Paid by Men			
Intercept	η_0^m	7.068	0.009
High school education	$\eta_{N,HS}^m$	0.164	0.012
College education	$\eta_{N,Col}^m$	1.032	0.010
Black	η_{Bl}^m	-0.012	0.010
North Central	η_{NC}^m	0.116	0.010
South	η_{South}^m	-0.254	0.013
West	η_{West}^m	0.031	0.014
Time	η_t^m	0.103	0.003
Time squared	$\eta_{t^2}^m$	-0.003	0.0003
Past children	η_p^m	-0.055	0.011
Variance to shock	$\sigma_{\tau^m}^2$	0.923	0.026

Table 5: Non-Labor Income Estimates

Description	Parameter	Estimate	S.E.
Non-labor Income-Single Men			
Intercept	ζ_0^m	1347.300	130.339
High school education	$\zeta_{N,HS}^m$	310.311	71.395
College education	$\zeta_{N,Col}^m$	695.766	105.889
Black	ζ_{Bl}^m	-439.438	70.233
North Central	ζ_{NC}^m	245.983	82.648
South	ζ_{South}^m	-376.995	78.616
West	ζ_{West}^m	6.794	98.850
Time	ζ_t^m	-0.627	29.020
Time squared	$\zeta_{t^2}^m$	2.342	1.837
Past children	ζ_p^m	165.835	124.550
Working	ζ_l^m	-437.113	76.175
Working and past children	$\zeta_{l,p}^m$	13.948	106.338
Black and past children	$\zeta_{Bl,p}^m$	12.706	111.220
Non-labor Income-Single Women			
Intercept	ζ_0^f	1542.371	123.285
High school education	$\zeta_{N,HS}^f$	-454.163	68.671
College education	$\zeta_{N,Col}^f$	-384.143	101.972
Black	ζ_{Bl}^f	10.031	66.213
North Central	ζ_{NC}^f	465.237	72.613
South	ζ_{South}^f	-610.749	68.230
West	ζ_{West}^f	708.074	86.613
Time	ζ_t^f	114.433	26.843
Time squared	$\zeta_{t^2}^f$	-4.480	1.592
Past children	ζ_p^f	2966.814	71.588
Working	ζ_l^f	-1058.223	72.707
Working and past children	$\zeta_{l,p}^f$	-2419.972	66.729
Black and past children	$\zeta_{Bl,p}^f$	210.492	69.764

Table 6: Non-Labor Income Estimates Continued

Description	Parameter	Estimate	S.E.
Non-labor Income-Married Couples			
Intercept	ζ_0^{mf}	3529.367	227.858
Wife high school education	$\zeta_{N^f,HS}^{mf}$	-286.913	107.754
Wife college education	$\zeta_{N^f,Col}^{mf}$	809.779	159.554
Husband high school education	$\zeta_{N^m,HS}^{mf}$	-157.212	99.999
Husband college education	$\zeta_{N^m,Col}^{mf}$	-351.144	145.024
Black	ζ_{Bl}^{mf}	-637.770	95.753
North Central	ζ_{NC}^{mf}	48.480	114.585
South	ζ_{South}^{mf}	-803.582	110.415
West	ζ_{West}^{mf}	-111.481	134.029
Time	ζ_t^{mf}	16.022	46.472
Time squared	$\zeta_{t^2}^{mf}$	0.368	2.576
Wife's past children	ζ_{pf}^{mf}	796.816	75.408
Husband's past children	ζ_{pm}^{mf}	217.024	96.358
Children from current marriage	ζ_c^{mf}	452.749	49.768
Wife working	ζ_{lf}^{mf}	-165.074	80.304
Husband working	ζ_{lm}^{mf}	-1174.398	101.562

Table 7: Log Child Support Received by Women Estimates

Description	Parameter	Estimate	S.E.
Intercept	η_0^f	7.158	0.181
High school education	$\eta_{N,HS}^f$	0.281	0.059
College education	$\eta_{N,Col}^f$	0.859	0.128
Black	η_{Bl}^f	-0.353	0.052
North Central	η_{NC}^f	-0.066	0.085
South	η_{South}^f	0.029	0.077
West	η_{West}^f	-0.139	0.098
Time	η_t^f	0.018	0.034
Time squared	$\eta_{t^2}^f$	0.0002	0.002
Past children	η_p^f	-0.038	0.051
Variance to shock	$\sigma_{\tau^f}^2$	1.159	0.017

Table 8: Logit Estimates of Woman's Probability of Not Receiving Support

Description	Parameter	Estimate	S.E.
Intercept	μ_0	2.550	0.182
High school education	$\mu_{N,HS}$	-0.484	0.062
College education	$\mu_{N,Col}$	-1.201	0.152
Black	μ_{Bl}	0.508	0.055
North Central	μ_{NC}	0.124	0.089
South	μ_{South}	-0.203	0.080
West	μ_{West}	0.139	0.104
Time	μ_t	-0.072	0.035
Time squared	μ_{t^2}	0.0001	0.002
# Past children	μ_p	-0.368	0.054

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

Table 9: Model Fit

	Women		Men	
	Actual	Simulated	Actual	Simulated
% Single	47.36	49.80	53.93	52.12
% Married	52.64	50.20	46.07	47.88
% Decide no birth	88.49	89.03	90.39	89.19
% Decide birth	11.51	10.97	9.61	10.81
% Births outside marriage	21.27	20.05	15.71	21.91
% Births within marriage	78.73	79.95	84.29	78.09
% Not working	36.56	38.16	17.82	18.74
% Working	63.44	61.84	82.18	81.26
% Not a deadbeat[a]			35.20	35.03
% Deadbeat[a]			64.80	64.97
% $K_t^{pg} = 0$	71.31	69.56	81.98	77.54
% $K_t^{pg} = 1$	16.12	21.15	11.57	16.49
% $K_t^{pg} = 2+$	12.57	9.29	6.45	5.98
% $K_t^{c} = 0$	37.55	38.23	36.45	38.95
% $K_t^{c} = 1$	33.95	35.07	33.79	34.96
% $K_t^{c} = 2+$	28.50	26.70	29.76	26.09

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 10: Model Fit: Racial Differences in Outcomes

	Women				Men			
	White		Black		White		Black	
	Actual	Sim	Actual	Sim	Actual	Sim	Actual	Sim
% Single	38.52	39.53	65.32	70.68	48.02	45.88	67.03	65.92
% Married	61.48	60.47	34.68	29.32	51.98	54.12	32.97	34.08
% Decide no birth	88.54	88.48	88.38	90.15	90.52	89.52	90.10	88.48
% Decide birth	11.46	11.52	11.62	9.85	9.48	10.48	9.90	11.52
% Births outside marriage	7.54	8.34	48.30	47.86	3.63	8.95	40.97	48.01
% Births within marriage	92.46	91.66	51.70	52.14	96.37	91.05	59.03	51.99
% Not working	33.24	36.46	43.27	41.61	13.79	16.52	26.74	23.66
% Working	66.76	63.54	56.73	58.39	86.21	83.48	73.26	76.34
% Not a deadbeat[a]					39.70	36.30	33.27	34.18
% Deadbeat[a]					60.30	63.70	66.73	65.82

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

Table 11: Counterfactual Simulation Results for Black Men and Women

	Black Women					Black Men				
	Base-line	Earnings Gap	Pop. Supplies	Pref. Het.	Enforce-ment	Base-line	Earnings Gap	Pop. Supplies	Pref. Het.	Enforce-ment
% Single	70.49	61.35	67.84	51.29	62.29	66.31	55.95	69.04	44.67	56.75
% Married	29.51	38.65	32.16	48.71	37.71	33.69	44.05	30.96	55.33	43.25
% Decide no birth	90.22	89.82	88.89	90.24	90.31	88.29	87.88	89.08	88.56	88.45
% Decide birth	9.78	10.18	11.11	9.76	9.69	11.71	12.12	10.92	11.44	11.55
% Births outside marriage	47.15	33.08	49.59	10.24	31.56	49.32	35.26	50.61	11.27	33.54
% Births within marriage	52.85	66.92	50.41	89.76	68.44	50.68	64.74	49.39	88.73	66.46
% Not working	41.73	41.63	36.74	36.98	41.39	23.70	13.06	25.40	21.37	21.68
% Working	58.27	58.37	63.26	63.02	58.61	76.30	86.94	74.60	78.63	78.32
% Not a deadbeat[a]						33.79	39.68	32.34	31.40	100.0
% Deadbeat[a]						66.21	60.32	67.66	68.60	0.0

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

Table 12: Family Structure Across Simulations for Black Men and Women

	Black Women					Black Men				
	Base-line	Earnings Gap	Pop. Supplies	Pref. Het.	Enforce-ment	Base-line	Earnings Gap	Pop. Supplies	Pref. Het.	Enforce-ment
% Single with no children	27.41	26.34	36.59	26.00	24.49	37.36	34.20	45.25	33.01	35.07
% Single with children	43.08	35.01	31.25	25.29	37.80	28.95	21.75	23.80	11.66	21.68
% Married with no children	8.34	10.42	11.97	13.31	10.12	9.02	11.68	10.55	16.45	16.40
% Married with children only from current marriage	8.27	12.25	10.31	19.39	11.77	8.46	13.16	9.11	22.45	18.56
% Married with children from past relationships[a]	12.91	15.99	9.87	16.00	15.83	16.21	19.21	11.30	16.43	8.29

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

Table 13: Counterfactual Simulation Results for White Men and Women

	White Women		White Men	
	Baseline	Enforcement	Baseline	Enforcement
% Single	40.95	27.57	42.56	29.90
% Married	59.05	72.43	57.44	70.10
% Decide no birth	88.65	86.80	88.90	87.22
% Decide birth	11.35	13.20	11.10	12.78
% Births outside marriage	8.00	3.01	8.22	3.05
% Births within marriage	92.00	96.99	91.78	96.95
% Not working	36.07	37.51	15.96	14.35
% Working	63.93	62.49	84.04	85.65
% Not a deadbeat[a]			35.68	100.0
% Deadbeat[a]			64.32	0.0

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

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

	White Women		White Men	
	Baseline	Enforcement	Baseline	Enforcement
% Single with no children	31.11	21.00	36.87	25.89
% Single with children	9.84	6.57	5.70	4.01
% Married with no children	21.77	25.69	21.61	27.04
% Married with children only from current marriage	28.42	38.10	27.69	38.97
% Married with children from past relationships[a]	8.86	8.64	8.13	4.09

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

Table 15: Individuals with Welfare Gains from Perfect Enforcement by Race and Education

	Women	Men
% White	57.55	48.97
% Black	66.01	22.13
% Less than high school	68.96	37.04
% High school completion	59.18	41.76
% College education	47.67	42.21
% Total	60.34	40.62

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

Table 16: Comparison of Outcomes for those Who Gain and Lose from Perfect Enforcement (PE)

	Women				Men			
	Winners		Losers		Winners		Losers	
	Baseline	PE	Baseline	PE	Baseline	PE	Baseline	PE
% Single	39.48	28.42	69.18	56.15	54.57	44.15	46.93	34.01
% Married	60.52	71.58	30.82	43.85	45.43	55.85	53.07	65.99
% Decide no birth	87.29	85.34	92.03	91.96	90.03	87.95	87.67	87.21
% Decide birth	12.71	14.66	7.97	8.04	9.97	12.05	12.33	12.79
% $K_t^{pg} = 0$	59.46	61.03	85.89	91.56	83.62	98.10	72.25	76.95
% $K_t^{pg} = 1$	27.99	30.98	10.12	6.26	13.17	0.97	19.45	13.79
% $K_t^{pg} = 2+$	12.55	8.00	3.98	2.18	3.21	0.92	8.29	9.26
% $K_t^{c} = 0$	61.27	51.35	90.27	83.75	89.14	85.49	61.67	49.82
% $K_t^{c} = 1$	21.91	25.86	5.42	8.63	7.17	5.59	21.47	28.84
% $K_t^{c} = 2+$	16.82	22.80	4.32	7.62	3.69	8.92	16.87	21.34
Spousal education:								
% No spouse	39.48	28.42	69.18	56.15	54.57	44.15	46.93	34.01
% Less than high school	15.50	16.03	5.45	11.99	10.70	12.03	12.69	16.04
% High school completion	37.39	43.09	16.84	26.34	28.71	36.56	34.84	42.97
% College education	7.62	12.46	8.53	5.52	6.03	7.26	5.54	6.98

Figure 1: Sex Ratios by Race and Region

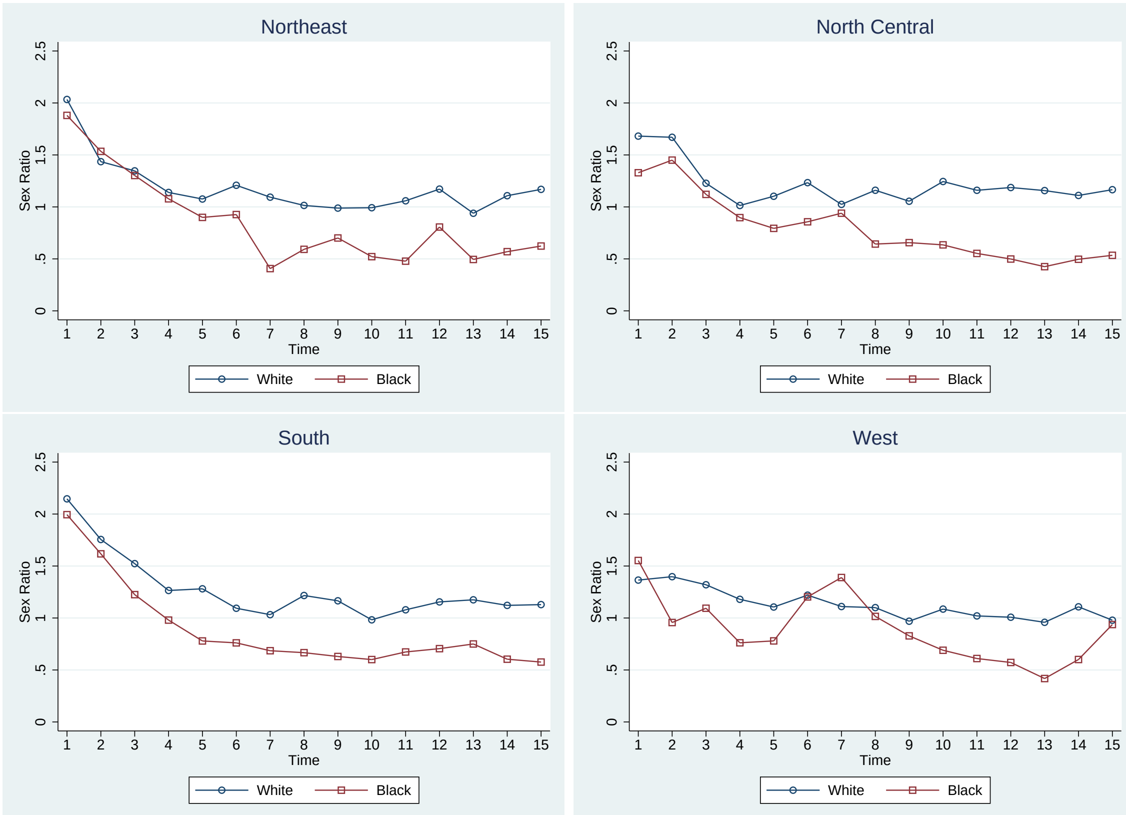

Figure 2: Comparison of Actual and Simulated Time Profiles of Marriage Rates by Race

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

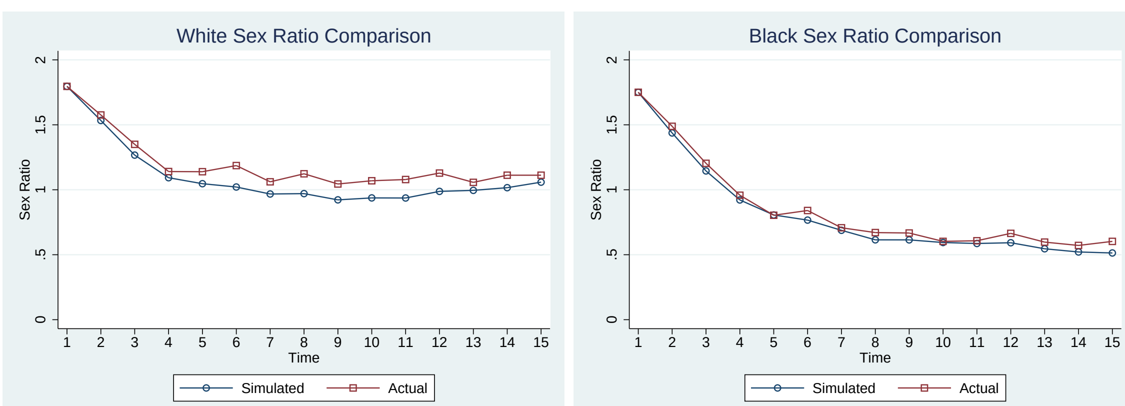

Figure 4: Comparison of Child Poverty Rates Across Simulations