Incarceration, Earnings, and Race

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Abstract

We study the implications of incarceration for the earnings and employment of different groups, characterized by their race, gender, and education. Our hidden Markov model distinguishes between first-time and repeat incarceration, along with other persistent and transitory nonemployment and earnings risks, and accounts for nonresponse bias. We estimate the model using the National Longitudinal Survey of Youth 1979 (NLSY79), one of the few panel datasets that includes incarcerated individuals. The consequences of incarceration are enormous: First-time incarceration reduces expected lifetime earnings by 39% (59%) and employment by 8 (13) years for black (white) men with a high school degree. Conversely, nonemployment and adverse earnings shocks increase expected years in jail. Among less-educated men, differences in incarceration and nonemployment can explain a significant portion of the black-white gap in lifetime earnings—44% of the gap for high school graduates and 52% of the gap for high school dropouts.

Keywords: earnings dynamics, incarceration, racial inequality

JEL Codes: C23, D31, J15

1 Introduction

Between 1980 and 2016, the incarceration rate in the United States rose from 0.22% to 0.67% (US Department of Justice, Bureau of Justice Statistics, 2018). The impact of this three-fold increase has fallen disproportionately on those who are male, black, or less educated: The imprisoned population is overwhelmingly (91-93%) male and less educated (Ewert and Wildhagen, 2011), and the imprisonment rate for black men (2.2%) is nearly six times that for white men (US Department of Justice, Bureau of Justice Statistics, 2019, Table 10).[1] Within certain groups, incarceration is now pervasive: Western and Pettit (2010, Table 1) find that among black high school dropouts born between 1975 and 1979, 68% had been incarcerated at least once.

Despite the prevalence and growth of incarceration in the United States, much remains unknown about the relationship between incarceration, employment, earnings, and demographics.[2] Our goals in this paper are to (1) quantify the dynamic relationship between incarceration, employment, and earnings and (2) measure the contribution of incarceration and other forms of nonemployment to the earnings gap between black and white men.[3] To this end, we estimate a statistical model of incarceration, employment, and earnings over the life cycle, using a flexible framework that controls semi-parametrically for race, education, and gender. Our hidden Markov model allows for transitory and persistent nonemployment spells, movements up and down the (positive) earnings distribution, and arbitrarily long-lasting effects of incarceration. Transition probabilities depend on age, gender, race, education, and previous incarceration. We estimate the model using the National Longitudinal Survey of Youth 1979 (NLSY79), one of the few panel datasets that reports incarceration. We explicitly account for missing data and allow for the possibility that its incidence is not random.

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[1]The majority of style guides currently recommend that neither "black" nor "white" be capitalized, so we follow this convention. The incarceration rate and the imprisonment rate are distinct measures, as only the former includes people held in local jails. While the measure we use in our analyses is incarceration, many national statistics are available only for the imprisoned.

[2]As Neal and Rick (2014) observe, there is a need for more research on the effects of incarceration on "the employment and earnings prospects of less-skilled men, and less-skilled black men in particular."

[3]Although we study both men and women, we focus on reporting results for men because they comprise the vast majority of the incarcerated. We report a few results and statistics for women in Section 5 and in the Appendix. Additional results are available upon request.

Our estimates show that the income losses associated with incarceration and long-term nonemployment are enormous. A typical 25-year-old black (white) male high school graduate entering jail for the first time will, relative to an otherwise identical man, suffer a lifetime income loss of $121,000 ($273,000) in 1982-1984 dollars, a 40% (54%) drop. For those without a high school degree, the losses amount to $103,000 and $170,000, respectively, resulting in 54% and 49% drops (respectively) for black and white men. The large lifetime effects are a consequence of essentially permanent reductions in flow earnings after an incarceration spell. The earnings losses from a transition to persistent nonemployment are also significant. For black male high school graduates, the loss ($113,000) is comparable to the loss from incarceration, while the loss for white men ($154,000) is somewhat smaller.

Although the *effects* of incarceration and nonemployment are profound for both black and white men, their *incidence* differs markedly. For high school graduates, our estimates indicate that while 24% of black men will eventually be incarcerated, only 3% of white men will.[4] Differences in nonemployment outside of incarceration are also quite large. Between ages 22 and 57, black men with a high school degree will on average experience 8.5 years of nonemployment, 4.5 years more than whites.

To summarize, the likelihood of nonemployment and incarceration is higher for black men than for their white counterparts, while the effects on earnings are typically larger for white men. What, then, is the net effect of these forces on the lifetime earnings gap between the two groups?[5] One way we answer this question is to eliminate incarceration and/or nonemployment and recalculate the gap. In the baseline, white male high school graduates earn 65% more than black male high school graduates over their lifetimes. Eliminating incarceration alone would reduce this to 59%, while eliminating nonemployment alone would reduce it to 44%. If both incarceration and nonemployment were eliminated, the lifetime earnings of white male high school graduates would exceed those of black males by 37%. Alternatively, a formal decomposition suggests that 46% of the lifetime earnings gap for high school graduates is attributable to nonemployment and/or incarceration. This fraction is higher (67%)

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[4]Because the NLSY79 cohort came of age before the height of the incarceration boom, their incarceration rates, while high, fall *below* those realized at the height of the boom.

[5]We again use numbers for male high school graduates, but again, similar patterns hold across all education levels.

for high school dropouts and lower (20%) for college graduates.

In addition to our substantive findings, our paper introduces a rich yet relatively tractable framework for earnings processes. Our framework integrates nonemployment, incarceration and earnings, imposes few distributional assumptions, and builds on a well-established statistical literature. Whenever incarceration, or more generally any discrete outcome, is important to understanding earnings, our framework provides a flexible way to account for it.

1.1 Related literature

Our paper contributes to three bodies of work: the study of the impact of incarceration on employment and earnings, the study of the black-white earnings gap, and the study of earnings processes in general.

The data show unambiguously that "labor market prospects after prison are bleak" (Travis et al., 2014, page 233). In their review (and borrowing from Pager, 2008), Travis et al. (2014) discuss three potential explanations. The first is selection: Individuals with poor job market prospects are more likely to acquire a criminal record.[6] The second is transformation: Time spent in jail or prison changes individuals in ways undesirable to employers. The third is labeling: A history of imprisonment in and of itself makes an individual less desirable to employers. There are legal restrictions (and/or liability concerns) regarding what positions those with a criminal record can fill. Moreover, consistent with the first two mechanisms, a criminal record may signal undesirable traits.

The leading empirical issue in this literature is controlling for the first mechanism, non-random selection into incarceration. Travis et al. (2014) describe several methodological responses. Among studies using survey data, the leading strategy is to construct "control groups" of nonincarcerated individuals who otherwise resemble the incarcerated. This has many parallels with our approach, where we condition on an individual's incarceration and earnings history, as well as their education, gender, and race. These studies generally find that incarceration depresses subsequent labor market outcomes. Among studies using administrative data, a popular strategy is to

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[6]Throughout the document, we use "criminal record" to mean a record that includes time spent in jail or prison.

exploit exogenous variation in incarceration due to the random assignment of judges (Kling 2006, Loeffler 2013, Mueller-Smith 2015). As a whole, studies that use administrative data—with or without the judge instrument—provide mixed support for a causal interpretation.[7]

Like most models of earnings processes, our framework is statistical, and episodes of incarceration therein are not strictly exogenous. On the other hand, most individuals in our data go to jail or prison after we first observe them, allowing us to show that individuals with low earnings are more likely to transition into incarceration. Moreover, the NLSY79 cohort happened to live through a period where aggregate incarceration rates increased dramatically, implying that much of the variation in incarceration is exogenous to the individual.

Irrespective of whether incarceration is driven by worker characteristics or by chance, it is valuable to know how labor market outcomes change in its aftermath, and our framework allows us to do this. In particular, our framework allows us to track earnings and employment for decades, enabling us to study the long-run dynamics and cumulative effects of incarceration.

In addition to the purely empirical literature discussed by Travis et al. (2014), there are a number of structural studies that incorporate incarceration, including Lochner (2004), Fella and Gallipoli (2014), Fu and Wolpin (2018), and Guler and Michaud (2018). These generate earnings losses in various ways. For example, Guler and Michaud (2018) assume that incarceration leads to human capital depreciation and a higher proclivity for crime. Relative to these structural studies, our approach allows for a more flexible specification, with a rich set of age and demographic controls. Our results can also complement structural analyses by providing estimation targets like those used in Guler and Michaud (2018).

Our paper also contributes to the empirical literature on the black-white earnings gap. As Bayer and Charles (2018) document, this gap has proven remarkably persistent: As a proportion of the median earnings of white men, the median earnings of black men are no higher today than they were in 1950. They attribute much of the difference to a large and expanding gap in employment; the gap in median earn-

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[7]This may reflect limitations of administrative data; although accurate, most administrative sources have fewer variables, explanatory or outcome, than do surveys.

ings among male *workers* has in fact narrowed considerably.[8] As the growth of the employment gap has coincided with the surge in incarceration, it is natural to ask whether the two are related.

The third literature to which our paper contributes is the estimation and analysis of earnings processes. This literature is huge; an incomplete list of papers includes Abowd and Card (1989), Meghir and Pistaferri (2004), Bonhomme and Robin (2009), Guvenen (2009), Bonhomme and Robin (2010), Altonji et al. (2013), Hu et al. (2019), De Nardi et al. (2020) and Guvenen et al. (2020). Our paper adds to this literature in three ways. The first is that it explicitly accounts for incarceration. Earlier earnings process studies have not differentiated between incarceration and other forms of nonemployment. Because of data limitations—many data sets exclude the institutionalized—they might not have had the capacity to do so. Second, many earnings process studies have focused on the continuously employed. Our approach combines incarceration, nonemployment, and positive earnings in a unified framework. This allows us to account for the possibility that incarceration is likely to be preceded, as well as followed, by low earnings.[9]

We also make a methodological contribution to the literature. Like Arellano et al. (2017), we define transition probabilities in terms of quantiles, rather than levels, which allows for nonnormal shocks and variable persistence. We target a different set of quantiles, however, which allows us to utilize existing work on latent Markov Chains (e.g., Bartolucci et al. 2010, Bartolucci et al. 2012). One advantage of our framework is that it allows us to differentiate between short- and long-term spells of nonemployment. Hence, we can capture varying levels of labor market attachment. Our framework also lets us deal with missing data flexibly, allowing its incidence to be nonrandom and persistent over time.

The rest of the paper is organized as follows. In section 2, we introduce our statistical model, and in section 3, we describe the data. In section 4, we interpret our parameter estimates. In section 5, we discuss the model's implications for employment,

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[8]Bayer and Charles (2018) also emphasize the role of race-neutral increases in the returns to education, which have amplified the effects of education differences.

[9]In estimating the earnings process for their structural model, Caucutt et al. (2018) assume that ex-convicts transition into either unemployment or the lowest possible positive earnings quintile. On the other hand, they assume that the probability that an individual becomes incarcerated in the future depends only on whether the individual is incarcerated at present.

incarceration, and earnings over the life-cycle and calculate the changes in lifetime earnings and employment that follow an episode of incarceration. In section 6, we assess the contributions of incarceration and other forms of nonemployment to the racial gap in lifetime earnings. We conclude in section 7.

2   Statistical Model and Methodology

Our model of earnings contains two variables: an unobserved latent state that follows a Markov chain; and a discrete-valued observed outcome, the distribution of which depends only on the current latent state. This is a variant of the ubiquitous state-space framework, arguably most akin to Hamilton's (1989) regime-switching model.[10]

2.1   Latent States and Observed Outcomes

Let $\ell_{n,t} \in \mathbb{L} = \{L_0, L_1, ..., L_{I-1}\}$ denote individual n's underlying, latent labor market state at date t, and let $m_{n,t} \in \mathbb{M} = \{M_0, M_1, ..., M_{J-1}\}$ denote the earnings outcome observed by the researcher. The set of latent states, $\mathbb{L}$, consists of incarceration, long-term nonemployment, and Q^* earnings *potential* bins.[11] This set of latent outcomes is then interacted with a $\{0, 1\}$ criminal record flag, so that $\mathbb{L}$ contains $I = 2(Q^* + 2)$ elements. The set of observed outcomes, $\mathbb{M}$, consists of incarceration, current nonemployment, Q positive earnings bins, and not interviewed/missing. The nonmissing outcomes are also interacted with the criminal record flag, so that $\mathbb{M}$ contains $J = 2(Q + 2) + 1$ elements.

We discretize the distributions of both earnings potential and observed earnings (when positive). This both simplifies the estimation process and produces estimates that port directly into dynamic structural models. As we show below, we can increase the number of earnings bins without increasing the number of model parameters. It also bears noting that the bins represent quantile *rank* (conditional on race, gender, education, and age), rather than level, groupings. As the extensive literature on copulas (see, e.g., Trivedi and Zimmer 2007) has shown, working in quantile space

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[10]See also Farmer (2020). Bartolucci et al. (2010) provide an introduction.

[11]An individual's earnings potential is his or her unobserved earnings capacity.

is an effective way to model non-normal shocks and variable persistence.[12] Let p_q, where $q = 0, 1, ..., Q$, denote the probability cutoffs for the earnings bins; in a modest abuse of notation we will also use q to index the bin given by the interval (p_{q-1}, p_q), $q = 1, 2, ..., Q$. We partition earnings into deciles, so that $p_q \in \{0.0, 0.1, ..., 0.9, 1\}$, and there are $Q = 10$ bins. We assume further that the bins for latent earnings potential are the same as those for observed earnings, so that $Q^* = Q$; this is straightforward if tedious to relax. We estimate the deciles for observed earnings, semi-parametrically, in a separate procedure.

Our model is based on two key assumptions. The first is that $\ell_{n,t}$ is conditionally Markov, with the $I \times I$ transition matrix, $\mathbf{A}_x$:

$$\mathbf{A}_{j,k \,|\, x} = \Pr(\ell_{n,t+1} = L_k \,|\, \ell_{n,t} = L_j, \, x_{n,t}) = \Pr(\ell_{n,t+1} = L_k \,|\, \mathcal{F}_t), \qquad (1)$$

where: $x_{n,t}$ is a vector of exogenous variables; $\mathcal{F}_t$ denotes the time-t information set; and $\mathbf{A}_{j,k \,|\, x}$ denotes row j and column k of $\mathbf{A}_x$. In our case, $x_{n,t}$ contains an individual's age (which enters parametrically) and their race, gender, and education level (which enter semi-parametrically, as there are separate sets of parameters for each group).[13] The second assumption is that the distribution of the observed outcome $m_{n,t}$ depends on only the contemporaneous realization of $\ell_{n,t}$. We place the probabilities that map $\ell_{n,t}$ to $m_{n,t}$ in the $I \times J$ matrix $\mathbf{B}_z$:

$$\mathbf{B}_{j,k \,|\, z} = \Pr(m_{n,t} = M_k \,|\, \ell_{n,t} = L_j, \, z_{n,t}) = \Pr(m_{n,t} = M_k \,|\, \mathcal{F}_{t-1}, \ell_{n,t}). \qquad (2)$$

The vector $z_{n,t}$ is the concatenation of $x_{n,t}$ and an indicator of whether the individual was interviewed in period $t-1$, which captures the persistence of nonresponse. The final element of our model is the $1 \times I$ row vector μ_1, which gives the unconditional distribution of the initial latent state $\ell_{n,1}$ conditional on $x_{n,1}$.

For the remainder of the section, we will drop the individual index n and suppress the probabilities' dependence on x and z.

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[12]Arellano et al. (2017) also rely heavily on quantiles, for similar reasons. As we discuss in Appendix A, however, the structure of their approach is very different from ours.

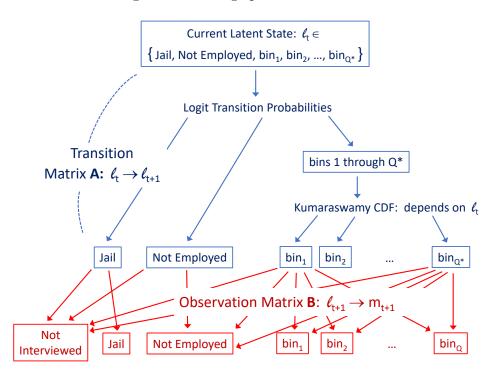[13]Recall that $\ell_{n,t}$ includes whether the individual has been previously incarcerated.

Figure 1: Earnings process transitions

2.2 Latent State Transitions

As the top half of Figure 1 shows, we populate the transition matrix **A** in two steps. First, we use a multinomial logit regression to determine the one-period-ahead probabilities of incarceration, long-term nonemployment, or employment (bins 1 to Q^*). We assume that an incarceration record is backward-looking and permanent, so that once a person is incarcerated, he will have an incarceration record in all *subsequent* periods.

The variables in this regression include the current state, age, and interactions. Appendix A presents our exact specification. An important simplification is that we characterize the earnings potential bins by their midpoint rank, $\tilde{p}_q := [p_q + p_{q-1}]/2$. By way of example, when earnings are partitioned into deciles, $\tilde{p}_q \in \{0.05, 0.15, ..., 0.95\}$. Because we treat $\tilde{p}_q$ as continuous rather than categorical, the number of variables in the logistic regression is invariant to the number of bins.

Second, we estimate the distribution of next period's earnings potential, conditional on being employed, across the bins. To do this, we assume that the conditional distribution of ranks follows the Kumaraswamy (1980) distribution. Like the Beta

distribution, the Kumaraswamy distribution is a flexible function defined over the $[0, 1]$ interval; however, its CDF is much simpler:

$$K(p;\, \alpha, \beta) = \Pr(y \leq p;\, \alpha, \beta) = 1 - (1 - p^\alpha)^\beta.$$

The parameters α and β are both strictly positive. It follows that if earnings bin q covers quantiles p_{q-1} to p_q,

$$\Pr(\text{bin } q) = K(p_q;\, \alpha, \beta) - K(p_{q-1};\, \alpha, \beta). \tag{3}$$

We allow α and β to depend on the current state ℓ_t and the explanatory vector x_t, so that $\alpha = \alpha(\ell_t, x_t)$ and $\beta = \beta(\ell_t, x_t)$. When the current state is the earnings bin q_t, we characterize it by its midpoint value, $\tilde{p}_{q_t}$. Appendix A presents the full specification.

Our functional forms place relatively few restrictions on the earnings transitions. As Jones (2009) argues, the Kumaraswamy distribution appears well-suited for "quantile-based" statistical modeling, permitting a wide variety of shapes. Moreover, given enough terms, $\alpha(\cdot)$ and $\beta(\cdot)$ can vary in arbitrarily complicated ways, allowing the conditional CDF $K\big(p;\, \alpha(\ell_t, x_t), \beta(\ell_t, x_t)\big)$ to vary in arbitrarily complicated ways. Strictly speaking, our approach is valid only when the true conditional distribution of earnings potential is smooth. This is a standard assumption, however, and we have separate nonemployment and incarceration states that absorb the mass of zero-earnings outcomes. In Appendix B, we assess the ability of the Kumaraswamy distribution to approximate a standard Gaussian AR(1) process and show that the approximation works well.

Because we use the midpoint value $\tilde{p}_{q_t}$ to characterize the current earnings bin, the number of parameters in $\alpha(\cdot)$ and $\beta(\cdot)$ need not increase with the number of bins (see Appendix A). Even if we treat $\alpha(\cdot)$ and $\beta(\cdot)$ as sieve estimators, the number of parameters will grow more slowly than the sample size. As the number of bins grows large, we get the conditional CDF $K\big(p_{t+1};\, \alpha(p_t, x_t), \beta(p_t, x_t)\big)$, where p_t and p_{t+1} are both quantile ranks; at this point, $K(\cdot)$ is a copula. The probability difference in equation (3), appropriately deflated, likewise converges to the density of the underlying Kumaraswamy distribution.

2.3 Observation Dynamics

The bottom half of Figure 1 shows how we populate the observation matrix **B**. The first step of the process is determining the probability that an individual is interviewed by the NLSY at time t.[14] We use a logistic specification. The explanatory variables include the current latent state, age, and an indicator of whether the individual was interviewed in the previous wave. Including these variables helps us control for non-random attrition.

Conditional on being observed, we impose the following mapping from latent states to measured outcomes. We assume that the NLSY79 measures incarceration accurately, so that the latent incarceration state maps directly into the incarceration outcome. Because our latent nonemployment state is meant to capture long-term disengagement from the labor force, we assume the persistent nonemployment state maps directly into nonemployment (again, conditional on being observed). Finally, each earnings potential bin can map into nonemployment and any of the observed earnings bins. The probability of nonemployment is logistic. Conditional on being employed, the distribution of earnings across bins follows a formula akin to equation (3), the main difference being that the Kumaraswamy distribution is replaced by a truncated univariate logistic distribution. Because multiple combinations of **A** and **B** can produce similar patterns of observed outcomes, we seek a specification where the distribution of observed earnings shifts rightward in earnings potential. Using the symmetric logistic distribution, which we further center around the earnings potential rank $\tilde{p}_q$, ensures that the mapping from the latent states to the observed outcomes has this property.

In the standard earnings model, transitory shocks capture both short-term earnings shocks and measurement error. A similar sort of ambiguity applies here. We believe that transitions from latent earnings to nonemployment reflect short-term spells of nonemployment. Transitions between latent and observed employment bins may reflect measurement error as well.

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[14]Individuals who die are dropped from the likelihood function at their date of death, rather than treated as missing. We view attrition via death as qualitatively distinct from nonresponse. For similar reasons, we also remove individuals when they are dropped from the NLSY79's Supplemental Sample in 1991.

2.4 Initial Probabilities

We construct the initial distribution of latent states, $\mu_1(\ell_1|\tilde{x}_1)$, in much the same way we found their transition probabilities. (Here, $\tilde{x}_1$ consists of race, gender, and education.) First, we find the probability that the individual is incarcerated, nonemployed (long-term), or in one of the earnings potential bins. Conditional on having positive earnings, we find the distribution across initial earnings potential bins using the Kumaraswamy distribution; the calculations parallel those in equation (3). The final step is to estimate the probability that the individual has a criminal record, conditional on the other latent states, using a logistic regression. The product of these two probabilities gives us our initial distribution.

2.5 Likelihood

We estimate our model using maximum likelihood, utilizing the forward recursion described in, e.g., Bartolucci et al. (2010) and Scott (2002). This is quite similar to the methodology for the regime-switching model presented in Hamilton (1994, chapter 22). Appendix A provides a more detailed description. We estimate separate sets of transition and observation probabilities for each race-gender-education combination. We weight each individual's log-likelihood using the NLSY79 sampling weights for 1979.[15]

For some groups—white men with a college degree, white women with at least a high school diploma, and black women with either a high school or a college degree—the incidence of incarceration is so low that their incarceration-related parameters cannot be estimated with any precision. In these cases, we drop individuals with a criminal record and estimate a simplified model of employment and earnings. To this set of parameters, we add incarceration-related parameters estimated for other, similar groups, namely white men with some college education, white women without a high school diploma, or black women with some college experience. In making these imputations, we adjust the constant terms for the incarceration probabilities to match the ever-incarcerated rate observed for that group in the NLSY79;[16] with a

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[15]Within each race-gender-education group, the weights are scaled to have an average value of 1.

[16]For white men and black women with college degrees, and white women with a high school degree, the fraction of individuals with a criminal record is implausibly low, 0.03% or less. In these

logistic formulation, this is simple to do. Appendix F describes the adjustments. These imputations are somewhat *ad hoc*, but the groups to which they are applied have very low rates of incarceration, implying that any imputation error will be relatively unimportant in the aggregate.

2.6   Quantiles and Conditional Means

To complete our model, we need to delineate the earnings bins and assign a level of earnings to each bin. We estimate bin cutoffs by age, for each race-gender-education group, using quantile regression. Using these cutoffs, we then assign individuals to bins and take averages by age. While the estimation procedure works with any set of cutoffs, to reduce sampling error we estimate the cutoffs and within-bin conditional means from the Current Population Survey (CPS), which contains far more observations than the NLSY79.

3   Data

We now describe how we use our two data sources, the NLSY79 and the CPS.

3.1   The NLSY79

Our primary source of data is the 1979 cohort of the National Longitudinal Survey of Youth (NLSY79), a nationally representative panel survey of young men and women born between 1957 and 1964. From 1979-1994, respondents were interviewed every year; since 1994, interviews occur every other year. The NLSY collects information about education, employment, family, and finances. It is also one of the few nationally representative surveys that enables us to observe an individual's incarceration status. Specifically, the variable that reports a person's residence status and location allows "jail/prison" as a response.[17] Coupled with the available earnings and employment data, this information makes the NLSY79 well-suited for our study and enables us to carry out our analysis largely using this single dataset.

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cases we impute the rates using data from other race and education groups.

[17]We use "jail" henceforth to refer to either jail or prison.

The NLSY79 has three subsamples: the (core) cross-sectional sample, a supplemental sample of minority and/or disadvantaged individuals, and a military sample. We exclude the military sample, as earnings for this group are hard to interpret, and we drop Hispanic respondents. This leaves us with roughly 9,600 individuals, of which 4,747 are male. We include both workers and the self-employed; Appendix C describes our employment and earnings measures in some detail.

We have four education categories: less than a high school diploma, high school diploma, some college, and bachelor's degree or higher. Exploiting the panel design of the NLSY79, we classify individuals on the basis of their highest observed attainment, treating education as a permanent characteristic. We categorize individuals by years of schooling, except for GED recipients, whom we classify as high school dropouts. As Heckman et al. (2011) and others have noted, GED recipients on average have worse labor market outcomes than those receiving high school diplomas. It is also the case that many recipients earn their GEDs while incarcerated.

Table 1 shows summary statistics for men, the main focus of our analysis.[18] Our data cover the years 1980-2014. The first panel illustrates the education gradient in earnings and shows that at every education level, black men earn significantly less than their white counterparts. By way of example, median earnings for a black high school dropout are 41% (4.93/12.00) those of his white counterpart. The second panel shows incarceration rates. For most groups, incarceration rates are highest for men in their 30s. This may reflect to some extent a conflation of time and age effects: The national transition toward mass incarceration in the 1980s and 1990s occurred at the same time the NLSY79 cohort aged out of their 20s and into their 30s. Another notable feature is that men with some college experience are more likely to be incarcerated than high school graduates; recall that we classify GED recipients as high school dropouts. As expected, incarceration rates differ markedly by race. The largest absolute differences are among high school dropouts: The difference across all ages is over 6 percentage points (pp). The largest proportional differences, however, are among those with at least a high school degree.

The third panel of Table 1 shows our measure of a "criminal record," namely a personal history of at least one *previous* incarceration spell.[19] The fourth panel shows

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[18]Appendix D shows the summary statistics for women. Statistics calculated using 1979 weights.

[19]Because our measure of a criminal record is backward-looking, our estimation sample starts in

Table 1: Summary Statistics by Race and Education for Men, NLSY79

	Black Men				White Men			
	LTHS	HS	SC	CG	LTHS	HS	SC	CG
Earnings (in $1,000s)								
Mean	7.73	11.90	14.35	24.00	13.45	19.65	22.53	32.44
10th percentile	0	0	0	0.93	0	4.29	2.91	3.01
25th percentile	0	2.74	4.99	10.11	4.40	11.01	10.90	12.32
50th percentile	4.93	10.50	13.20	19.21	12.00	17.57	18.69	24.11
75th percentile	12.32	17.06	20.48	30.60	18.55	25.08	28.07	38.42
90th percentile	19.35	24.90	28.80	45.93	26.57	34.21	40.38	65.22
Currently Incarcerated (%)								
All ages	9.61	2.54	3.40	0.41	3.30	0.26	0.53	0.01
22-29	10.87	2.10	3.13	0.69	3.60	0.25	0.59	0
30-39	12.39	4.03	4.59	0.24	3.23	0.41	0.58	0
40-49	5.93	1.84	2.74	0	3.26	0.09	0.55	0
50 and older	3.02	0.67	1.69	0.66	1.98	0.07	0	0.11
Previously Incarcerated (%)								
All ages	27.52	9.75	9.21	2.80	13.18	0.95	2.44	0.02
22-29	18.72	4.40	5.89	1.99	9.23	0.45	1.38	0
30-39	31.11	10.95	10.13	3.01	13.29	0.99	2.82	0
40-49	34.55	14.65	13.17	3.85	19.11	1.50	3.32	0
50 and older	35.87	16.94	11.36	3.14	19.74	1.87	3.89	0.21
Fraction Employed (%)								
All	55.00	69.90	71.21	78.51	68.56	78.25	77.48	81.44
Previously incarcerated	32.17	41.60	33.62	47.89	46.09	43.66	53.31	50.00
Not previously incarcerated	63.55	72.98	75.03	79.45	71.91	78.56	78.04	81.43
Mean Values								
Year of birth	1960.4	1960.4	1960.4	1960.3	1960.5	1960.2	1960.1	1960.3
Age	29.76	30.05	28.80	29.77	27.62	27.86	28.09	28.99
Fraction of male population (%)	4.67	4.76	3.01	2.12	15.61	28.12	17.37	24.34
Observations	8,475	9,071	5,829	3,935	10,035	16,081	9,755	14,315
Individuals	479	499	322	209	781	1,016	603	838

Note: [LTHS,HS,SC,CG] denote less than high school/high school/some college/college graduate.

employment. The first row of this panel, which shows aggregate results, reveal that the earnings gaps found in the first panel are to some extent employment gaps. This is consistent with the findings of Bayer and Charles (2018) described earlier: The earnings gaps among the fully-employed, although still significant, are smaller. The second and third rows of this panel show that the employment rates for men with a criminal record are 25-40pp lower than those of men without. There may also be incarceration-related differences in the earnings of those who work.

The final panel shows the distribution of respondents by race and education. The first line shows proportions calculated using the NLSY79 sample weights, while the last two lines show unweighted counts. Including the supplemental sample provides us with a large number of black respondents.

3.2   The Current Population Survey (CPS)

Although the NLSY79 is our principal data source, to calculate the cutoffs that delineate the earnings quantiles, we make use of the larger sample available in the CPS (downloaded from IPUMS; Ruggles et al. 2020). CPS data are available from 1962 to 2019; however, we limit our sample to 1976 onward because data on hours worked, which we need for our measure of employment, are not available prior to that year. Since the CPS is not a panel, we employ a synthetic cohort approach. Ideally, we would limit the sample to those born in the same years as our NLSY79 cohort (1957 to 1964) but, to have a sufficient number of observations, we include individuals born between 1941 and 1980 (i.e., the NLSY79 +/- two cohorts) and use cohort dummies to account for any cohort effects within this group. This consists of around 4.2 million observations. We restrict the sample to white and black individuals, who together make up about 94% of the sample. We also exclude those for whom educational attainment is not reported. We limit observations to those aged between 22 and 66. Starting the sample at age 22 helps ensure that those who chose to attend college have entered the workforce. We choose 66 as the upper limit since that is the normal Social Security retirement age for the NLSY79 cohort. After applying these age restrictions, around 3 million individuals remain in the sample.

The CPS elicits income information for the year prior to the survey year. Our

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1980, allowing us to use the 1979 incarceration measure.

focus is on earnings, which we define broadly to include not just wage and salary income, but also the labor portions of farm and business income. Since we have separate categories for the nonemployed and incarcerated, we limit ourselves to those who were employed in the previous year. Those who remain (about 2.4 million) form our sample of employed individuals. Appendix C describes our employment and earnings measures in more detail. We weight the data to ensure that the sample is representative of the population.

Within this sample, we estimate earnings bin cutoffs (deciles) separately for each race-gender-education group. In particular, in each group, for each quantile q, we run the following quantile regression:

$$y_t = \beta_{q,0} + \beta_{q,1}a_t + \beta_{q,2}a_t^2 + \beta_{q,3}a_t^3 + \sum_{m=2}^{5} \gamma_{q,m}cohort_m + \epsilon_{q,t}. \qquad (4)$$

Here y_t denotes earnings, a_t is age, and $cohort_m$ is a dummy variable for one of the five 8-year cohorts contained in our CPS sample.

With the results of Equation (4) in hand, we use post-estimation procedures to obtain the decile cutpoints for each race-gender-education-cohort group at each age. These are shown in Figures E.1 and E.2 for women and men, respectively, in Appendix E.

Applying the cutpoints to the CPS data, we calculate within-decile mean earnings at each age for each group. We then fit a cubic polynomial in age with cohort dummies through these age-specific means. Applying post-estimation procedures to the results of this regression yields life-cycle profiles of within-decile mean earnings for our cohort of interest. Figures E.3–E.4 show mean earnings and the fitted life-cycle profiles for women and men from the 1957-64 birth cohort.

4 Estimation Results

Given the nonlinear nature of the underlying model, the parameter estimates and standard errors, displayed in Tables F.1 and F.2 of Appendix F, are hard to interpret. Consequently, we instead highlight a few of the implied transition matrices (**A**) and observation matrices (**B**).

4.1 Latent Transition Matrices

We focus our discussion of the transition matrices on men without a high school degree, where the dynamics of incarceration are easiest to see, but all education groups display similar patterns. Tables 2 and 3 present the latent state transition probabilities for a 25-year-old black man and white man, respectively, without a high school degree. Rows index the current state ℓ_t, while columns index the future state ℓ_{t+1}.[20]

Table 2: Latent transition probabilities, 25-year-old black men without a high school diploma

Current State ↓		N	Jail Flag = 0 Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail	N	Jail Flag = 1 Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail
JF = 0	N	0.73	0.17	0.03	0.02	0.01	0.01	0.02							
JF = 0	Q1	0.14	0.52	0.18	0.06	0.01	0.00	0.08							
JF = 0	Q3	0.05	0.27	0.53	0.11	0.00	0.00	0.04							
JF = 0	Q5	0.02	0.01	0.23	0.63	0.09	0.00	0.02							
JF = 0	Q6	0.01	0.00	0.07	0.53	0.37	0.00	0.01							
JF = 0	Q8	0.01	0.00	0.01	0.12	0.55	0.31	0.01							
JF = 0	Q10	0.00	0.00	0.00	0.02	0.08	0.89	0.00							
JF = 0	Jail								0.16	0.31	0.10	0.06	0.03	0.01	0.34
JF = 1	N								0.56	0.18	0.03	0.02	0.01	0.01	0.18
JF = 1	Q1								0.07	0.35	0.13	0.05	0.01	0.00	0.39
JF = 1	Q3								0.03	0.20	0.44	0.10	0.00	0.00	0.23
JF = 1	Q5								0.01	0.01	0.19	0.58	0.09	0.00	0.12
JF = 1	Q6								0.01	0.00	0.06	0.48	0.37	0.00	0.09
JF = 1	Q8								0.00	0.00	0.01	0.11	0.52	0.31	0.05
JF = 1	Q10								0.00	0.00	0.00	0.02	0.08	0.87	0.03
JF = 1	Jail								0.04	0.10	0.04	0.02	0.01	0.00	0.79

Note: Rows are indexed by the latent state at age 25, columns by the latent state at age 26. JF or Jail Flag indicates a history of incarceration. "Jail" denotes currently incarcerated. N indicates not employed but not currently incarcerated. Qi denotes earnings potential decile i. Some transitions omitted.

The first of these general patterns is that men who are nonemployed or have low earnings potential are much more likely to transit to jail. A 25-year-old black man

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[20]To avoid presenting 24^2 numbers, we condense the matrix **A** in two ways: We present transition probabilities for only a subset of the current states, reducing the number of rows; and we combine future states by summing probabilities, reducing the number of columns.

with no criminal history (JF = 0) in the bottom decile of the earnings potential distribution (Q1) has a roughly 8% chance of becoming incarcerated at age 26. The incarceration probability for an otherwise identical man in the 8th earnings potential decile (Q8) is 1%. White men follow the same pattern, though their corresponding chances of being incarcerated are lower than for black men.

Table 3: Latent transition probabilities, 25-year-old white men without a high school diploma

Current State ↓		N	Jail Flag = 0						N	Jail Flag = 1					
			Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail		Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail
JF = 0	N	0.69	0.17	0.06	0.04	0.02	0.01	0.01							
JF = 0	Q1	0.05	0.71	0.18	0.02	0.00	0.00	0.04							
JF = 0	Q3	0.03	0.28	0.63	0.04	0.00	0.00	0.02							
JF = 0	Q5	0.02	0.00	0.17	0.76	0.05	0.00	0.01							
JF = 0	Q6	0.01	0.00	0.02	0.52	0.44	0.00	0.00							
JF = 0	Q8	0.01	0.00	0.00	0.03	0.64	0.31	0.00							
JF = 0	Q10	0.00	0.00	0.00	0.00	0.06	0.93	0.00							
JF = 0	Jail								0.04	0.45	0.12	0.04	0.01	0.00	0.34
JF = 1	N								0.71	0.11	0.05	0.03	0.03	0.03	0.05
JF = 1	Q1								0.05	0.52	0.18	0.05	0.01	0.00	0.18
JF = 1	Q3								0.03	0.25	0.56	0.07	0.00	0.00	0.08
JF = 1	Q5								0.02	0.00	0.17	0.70	0.07	0.00	0.04
JF = 1	Q6								0.01	0.00	0.03	0.48	0.46	0.00	0.02
JF = 1	Q8								0.01	0.00	0.00	0.04	0.56	0.38	0.01
JF = 1	Q10								0.00	0.00	0.00	0.00	0.05	0.94	0.00
JF = 1	Jail								0.02	0.14	0.05	0.03	0.01	0.00	0.75

Note: Rows are indexed by the latent state at age 25, columns by the latent state at age 26. JF or Jail Flag indicates previous incarceration. N indicates not employed but not currently incarcerated. Qi denotes earnings potential decile i. Some transitions omitted.

The second is that recidivism is prevalent. A 25-year-old black (white) man currently in the bottom decile of earnings potential with a criminal record has a 39% (18%) chance of being in jail the following year, an increase of 31pp (14pp) over that for a man with no record. Moreover, men who are currently jailed, should they exit, are most likely to exit to nonemployment or to the bottom decile of earnings potential, where the odds of reincarceration are the highest. A man who is currently incarcerated and in possession of a criminal record will remain incarcerated nearly 80% of the time.

A third feature is that men with low earnings potential are more likely to transit to nonemployment than those with high earnings potential. On the other hand, men who stay employed are most likely to remain in their current earnings potential bin, as the large numbers on the diagonals indicate. For example, a 25-year-old man with no criminal record in the top earnings potential decile has around a 90% chance of being in the top two deciles in the following year. It also bears noting that the transition probabilities are not symmetric. It is much more common for a man in the bottom decile of earnings potential to transit to higher deciles than it is for a man at the top decile to transition down.

The patterns described above largely hold for both black and white men. In addition, the newly incarcerated in both groups face identical chances (34%) of remaining incarcerated the following year. There are, however, differences between the two groups, most notably that white men are much less likely to become incarcerated than their black counterparts. White men are also less likely to transition to nonemployment.[21]

4.2   Measurement Matrices

We turn next to the probabilities mapping from the latent states to observed outcomes, embodied in the matrix **B**. Table 4 presents the observation probabilities for a 25-year-old black man without a high school degree. Rows index the latent state ℓ_t, while columns index the observed outcome m_t. We condense the results in much the same way that we condensed those for the transition matrix **A**.

Perhaps the most notable feature of Table 4 is the high likelihood that a worker with low earnings potential will be nonemployed. For example, a man in the bottom earnings potential decile will be nonemployed 40% of the time if he has no criminal record and 60% of the time if he has one. Recall that this nonemployment spell is completely transitory. Conditional on latent earnings potential, realizing such a spell has no effect whatsoever on the probability of future nonemployment or, for that matter, any future outcome. Nonetheless, in every period, black men with low earnings potential face a significant risk of nonemployment. In addition to nonemployment, for

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[21]The one seeming exception involves nonemployed men with a criminal record, where the increased risk of nonemployment facing white men (71% vs. 56%) is almost completely offset by a decreased risk of incarceration (5% vs. 18%).

Table 4: Observation probabilities, 25-year-old black men without a high school diploma

Latent State ↓			Observed Outcome											
			Jail Flag = 0						Jail Flag = 1					
		N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail	N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail
JF = 0	N	1.00													
JF = 0	Q1	0.40	0.60	0.00	0.00	0.00	0.00								
JF = 0	Q3	0.17	0.22	0.57	0.04	0.00	0.00								
JF = 0	Q5	0.07	0.13	0.25	0.29	0.19	0.08								
JF = 0	Q6	0.04	0.11	0.20	0.27	0.24	0.15								
JF = 0	Q8	0.02	0.00	0.00	0.09	0.59	0.30								
JF = 0	Q10	0.01	0.00	0.00	0.00	0.00	0.99								
JF = 0	Jail							1.00							
JF = 1	N								1.00						
JF = 1	Q1								0.61	0.39	0.00	0.00	0.00	0.00	
JF = 1	Q3								0.31	0.22	0.33	0.11	0.02	0.00	
JF = 1	Q5								0.14	0.15	0.20	0.21	0.18	0.12	
JF = 1	Q6								0.09	0.10	0.19	0.25	0.22	0.14	
JF = 1	Q8								0.05	0.03	0.09	0.22	0.33	0.28	
JF = 1	Q10								0.03	0.00	0.00	0.00	0.01	0.96	
JF = 1	Jail														1.00

Note: Rows are indexed by the latent state at age 25, columns by the observed state at the same age. JF or Jail Flag indicates previous incarceration. "Jail" denotes currently incarcerated. N indicates not employed but not currently incarcerated. For rows, Qi denotes earnings potential decile i. For columns, Qj denotes observed earnings decile j. Some transitions omitted.

most earnings potential deciles, the distribution of observed outcomes spans a wide range of positive earnings realizations. The one exception is the top earnings potential decile, where 99% of realized earnings fall in the top two outcome deciles. This may reflect the rightward skew of the earnings distribution. At the upper tail, large changes in earnings levels need not produce large changes in earnings ranks; see the figures in Appendix E.

Table 5 presents the observation probabilities for a 25-year-old white man without a high school degree. Transitory nonemployment is less common among white men than among black men. For example, a man in the bottom earnings potential decile with no criminal record will be nonemployed 29% of the time if he is white and 40% of the time if he is black. Black men are not only more likely to be persistently nonemployed, but also more likely to experience temporary nonemployment spells.

Taking stock, we see that nonemployment and incarceration pose significant risks for less educated men, especially those with low latent earnings potential. It is also

clear that the effects of incarceration are profound. Men with criminal records face markedly higher odds of nonemployment and (re-)incarceration. All of these risks are greater for black men.

Table 5: Observation probabilities, 25-year-old white men without a high school diploma

Latent State ↓			Observed Outcome											
		Jail Flag = 0							Jail Flag = 1					
	N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail	N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail
JF = 0 N	1.00													
JF = 0 Q1	0.29	0.71	0.01	0.00	0.00	0.00								
JF = 0 Q3	0.05	0.21	0.21	0.20	0.18	0.14								
JF = 0 Q5	0.02	0.03	0.30	0.56	0.10	0.01								
JF = 0 Q6	0.01	0.01	0.13	0.50	0.31	0.04								
JF = 0 Q8	0.01	0.00	0.02	0.16	0.48	0.32								
JF = 0 Q10	0.01	0.00	0.00	0.00	0.00	0.99								
JF = 0 Jail							1.00							
JF = 1 N								1.00						
JF = 1 Q1								0.42	0.58	0.00	0.00	0.00	0.00	
JF = 1 Q3								0.09	0.18	0.18	0.18	0.18	0.18	
JF = 1 Q5								0.03	0.04	0.30	0.49	0.12	0.01	
JF = 1 Q6								0.02	0.03	0.16	0.42	0.30	0.07	
JF = 1 Q8								0.01	0.00	0.01	0.12	0.54	0.32	
JF = 1 Q10								0.02	0.00	0.00	0.00	0.00	0.98	
JF = 1 Jail														1.00

Note: Rows are indexed by the latent state at age 25, columns by the observed state at the same age. JF or Jail Flag indicates previous incarceration. N indicates not employed but not currently incarcerated. For rows, Qi denotes earnings potential decile i. For columns, Qj denotes observed earnings decile j. Some transitions omitted.

5   Simulations: Incarceration, Nonemployment, and Earnings

We now turn to our model's predictions for the longer-term behavior of incarceration, employment, and earnings. We look first at the life-cycle profiles of these three variables. We then provide a sense of the long-run effect of these states in two ways: by looking at a measure of their persistence; and then by generating impulse responses to incarceration, nonemployment, and earnings shocks. Taken together, these

results address our first objective, quantifying the relationship between incarceration, employment, and earnings.

5.1 Age Profiles
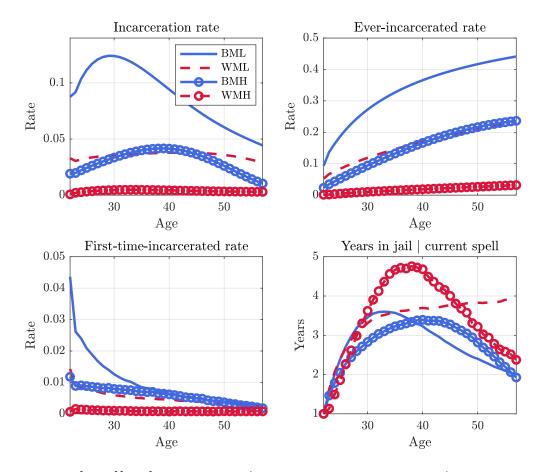
5.1.1 Incarceration

Figure 2 presents age-incarceration profiles by race for less than high school (L) and high school (H) men. The first-time incarceration rates, depicted in the bottom left panel, are monotonically declining in age, as one might expect. The fraction of the population with a history of incarceration (top right panel) thus rises most quickly at younger ages. Tables 2 and 3 showed that men with criminal records are more likely to be (re-)incarcerated in the future, and when incarcerated, more likely to spend consecutive years in jail. This is reflected in the average incarceration spell length (bottom right panel), which increases early in life. The number of repeat offenders in jail thus rises for a while, before slowly falling. This causes the total incarceration rate (top left panel) to have a hump shape.

Figure 2 also highlights the large disparities in incarceration rates by race and education. Within race, incarceration rates decrease sharply with education. Across races, incarceration rates are markedly higher for blacks than whites. Putting the two together, the rates for white men *without* a high school degree are comparable to rates for black men *with* a high school degree.

The patterns for years spent incarcerated are quite distinct from those for incarceration rates. The average incarceration spells of white men are, if anything, longer than those of blacks. Conditional on being incarcerated, middle-aged white men with a high school diploma have longer spells than those of any other group. Black men have higher incarceration rates not because they serve longer spells, but because they are far more likely to be sent to jail.[22]

Figure G.1, found in Appendix G, compares the current and ever-incarcerated rates predicted by the model to those in the data. Because we allow for nonrandom

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[22]Our finding that white defendants serve longer spells appears at odds with the tendency of black defendants to receive longer sentences in federal courts (Rehavi and Starr 2014; Light 2021). There appears to be very little difference in felony sentence lengths at the state level (Rosenmerkel et al., 2009, Table 3.6), however, and incarceration stints need not involve felony convictions at all.

Figure 2: Age-Incarceration Profiles

Note: [B,W][L,H] denote black/white, less than high school/high school.

attrition, the data and the model need not align perfectly.[23] The fit is nonetheless quite good.

5.1.2 Nonemployment

Figure 3 displays nonemployment profiles. Recall that the model has two types of nonemployment: *persistent* nonemployment, where the latent state is nonemployment, which automatically results in measured nonemployment; and *transitory* nonemployment, where the latent state is working (in particular, one of the earnings potential

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[23]Figure G.3 shows the effects of this observation bias on the incarceration and nonemployment profiles.

deciles), but the observed outcome is nonemployment.[24] These are given in the top and bottom left panels, respectively. The top right panel shows total measured nonemployment, the sum of persistent and transitory nonemployment. Figure G.2, found in Appendix G, compares the total nonemployment rates predicted by the model to those in the data. As with incarceration, the fits are good.
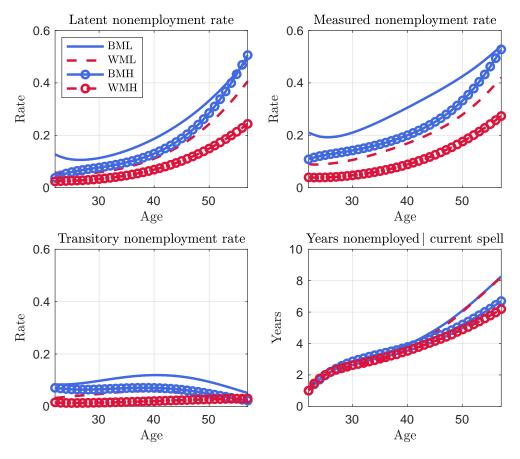
Figure 3: Nonemployment by age and type

Note: [B,W][L,H,S,C] denote black/white, less than high school/high school/some college/bachelor's degree.

The age profiles for persistent nonemployment generally rise with age, the one

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[24]Because of the annual (or biennial) frequency of the NLSY79, there is a time aggregation issue regarding how to treat individuals who are nonemployed for periods of less than a year: Under our coding, individuals who work for only part of a year are classified as employed. This is one likely reason why the dynamics of the lowest earnings potential deciles, which include many part-timers, are somewhat distinct from those higher up.

exception being a modest decline for young men without a high school degree. These upward slopes are consistent with the tendency of older workers to exit the workforce. The profiles for transitory nonemployment behave very differently, sometimes displaying a hump shape. But even when transitory nonemployment is rising, persistent nonemployment rises more quickly. As men age, an increasing fraction of their nonemployment is persistent. This is one reason why the duration of nonemployment (bottom right panel) rises with age.

The profiles for total (measured) nonemployment show that black men who did not attend college are much more likely to be nonemployed than their white counterparts. While education-related differences in nonemployment are significant, race-related differences are arguably larger. For example, the nonemployment rate for black high school graduates rises from 11% at age 22 to 53% by age 57; nonemployment for white men rises from 4% to 27%. In fact, at any age, a black man with a high school degree is more likely to be nonemployed than a white man without one.

5.1.3   Earnings

Our model's predictions for earnings (for men), disaggregated by race and education, are shown in Figure 4. The top left and bottom right panels include both incarcerated and nonincarcerated men. They show that the canonical hump shape over the life-cycle is maintained. As expected, earnings increase sharply with educational attainment, while significant racial differences within education groups remain.

The impact of incarceration on earnings can be seen by comparing the earnings of those who have never been incarcerated (top right) with those who have (bottom left). The bottom left panel shows that incarceration compresses the education gradient of earnings to a striking degree. The figure suggests that because people with an incarceration history have similar earnings, it is those with high initial earnings— whites and the more highly educated—who suffer the bigger earnings *loss*.

5.2   Persistence

One of the strengths of our statistical framework is that it allows the intertemporal persistence of earnings to vary across the earnings distribution. To construct a simple
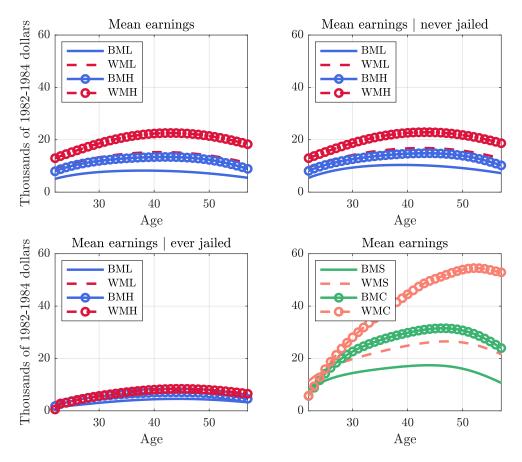
Figure 4: Age-earnings profiles for men by race and education

Note: [B,W][L,H,S,C] denote black/white, less than high school/high school/some college/bachelor's degree.

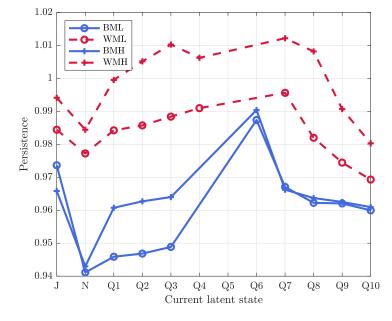state-specific measure of persistence, we begin with the deviation

$$z_{k,t+j} := \mathbb{E}[y_{t+j} \mid \ell_t = L_k] - \mathbb{E}[y_{t+j}],$$

where y denotes measured earnings, and ℓ denotes the latent state. We then measure state k-conditional persistence as:

$$\rho_{k,t} := \left(\frac{\frac{1}{5} \sum_{j=5}^{9} z_{k,t+j}}{\frac{1}{5} \sum_{j=0}^{4} z_{k,t+j}} \right)^{1/5}.$$

$\rho_{k,t}$ measures how quickly earnings return to their unconditional mean value when the age-t latent state is k. When y follows a simple AR(1), $y_{t+1} = \rho y_t + e_t$, $\rho_{k,t}$ reduces to ρ. We take five-year averages to remove the highest-frequency dynamics.[25]

Figure 5: Earnings persistence by latent state, men with a high school degree or less

Note: [B,W]M[L,H] denote black/white, men, less than high school/high school; J indicates current incarceration; N indicates not employed but not currently incarcerated; Qi denotes earnings potential decile i.

Figure 5 shows age-averaged earnings persistence by state for men who are high school dropouts or have a high school degree.[26] Across the latent states Q1-Q10, the earnings of white men are considerably more persistent. While $\rho_{k,t}$ is typically above 1 for white men with a high school degree and around .98 for white high school dropouts, for black men 0.96 is a more representative number. The earnings effects of nonemployment or jail are similarly more persistent for white men than black men. For both races, persistence is lower at the tails of the earnings potential distribution (e.g., Q1 and Q10) than in the middle.

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[25]Our persistence measure is similar in spirit to the quantile-based measure proposed by Arellano et al. (2017), which, if adapted to scaled means, would equal $\rho_{k,t} = \frac{\partial \mathbb{E}[y_{t+1} \mid \ell_t]}{\partial \ell_t}\big|_{\ell_t = L_k}$.

[26]To avoid small denominators, we estimate $\rho_{k,t}$ only for the states where $|\frac{1}{5}\sum_{j=0}^{4} z_{k,t+j}/\sigma(y_{t+j})| \geq 0.25$ for $\sigma(y_{t+j})$ the unconditional standard deviation of y_{t+j}. Values for these states are indicated by markers on the plot.

Figure 5 also highlights the importance of treating incarceration differently from other forms of nonemployment: the effects of jail are considerably more persistent than those of nonemployment, even though both states have zero earnings.

5.3   Lifetime Totals

To assess the cumulative effects of incarceration and earnings, it is useful to construct lifetime totals. We convert the stream of pre-tax earnings $\{y_t\}_{t=1}^T$ into a net present value,

$$\mathbb{E} \sum_{t=1}^T R^{1-t} y_t,$$

setting the risk-free rate R to 1.02, a standard value (e.g., McGrattan and Prescott, 2000). We will refer to this total as lifetime earnings. To avoid extrapolating beyond the NLSY79 sample period, the terminal period T corresponds to age 57. Although our measure of lifetime earnings is only partial, it covers more than three decades.

Table 6 summarizes the distribution of lifetime earnings as of age 22 for all race-gender-education combinations. It also reports the average total time in years that individuals spend incarcerated, employed, or nonemployed. The top panel of the table shows results for men. While black men have lower lifetime earnings at any level, the differences are most stark for the least educated. Among those without a high school diploma, white men will on average earn $346,000 over their lives, 83% more than the $189,000 earned by black men. For those with a college degree, the gap is 51%. The differences are even larger at the 10th percentile: a gap of 250% for high school dropouts vs. 51% for college graduates. This is consistent with the findings of Bayer and Charles (2018), who show that the racial earnings gap is smaller at the top of the earnings distribution. The low absolute earnings of black high school dropouts are also notable. 25% of black men without a high school degree earn $67,000 or less over their lifetimes, and 10% earn $28,000 or less. The top panel further shows that the higher incarceration rates of black men lead them to spend considerably more time in jail, an additional two years for high school dropouts.

The second panel of Table 6 presents statistics for women. Although our focus is on men, who are far more likely to be incarcerated, there are some notable differences between the genders. Women are much more likely to be nonemployed; a black woman

Table 6: Lifetime totals by race, education, and gender

Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	189	346	306	506	378	561	631	950
Lifetime earnings p10	28	98	83	193	125	220	256	387
Lifetime earnings p25	67	174	147	323	212	321	371	500
Lifetime earnings p50	151	335	270	501	353	539	567	819
Lifetime earnings p75	276	493	427	656	505	724	811	1198
Lifetime earnings p90	417	629	598	835	670	994	1142	1912
Expected years E	21.3	27.8	26.4	31.9	28.6	31.7	30.3	33.1
Expected years J	3.2	1.3	1.1	0.1	1.2	0.2	0.2	0.0
Expected years N	11.5	7.0	8.5	4.0	6.2	4.1	5.6	2.9
Ever-J rate, old	0.44	0.23	0.24	0.03	0.17	0.05	0.06	0.02

Variable	BFL	WFL	BFH	WFH	BFS	WFS	BFC	WFC
Lifetime earnings avg.	94	158	197	240	263	295	414	461
Lifetime earnings p10	5	29	41	66	87	102	160	152
Lifetime earnings p25	22	68	79	121	134	161	234	243
Lifetime earnings p50	57	135	155	212	223	264	372	407
Lifetime earnings p75	139	227	294	329	367	407	548	614
Lifetime earnings p90	247	325	422	462	498	539	730	859
Expected years E	15.6	21.4	23.4	26.4	26.8	28.4	30.0	29.8
Expected years J	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Expected years N	20.2	14.5	12.6	9.6	9.2	7.6	6.0	6.2
Ever-J rate, old	0.06	0.03	0.01	0.01	0.02	0.01	0.01	0.01

Note: [B,W][M,F][L,H,S,C] denote black/white, male/female, less than high school/high school/some college/bachelors degree; E indicates employed; J indicates jailed or incarcerated; N indicates nonemployed but not currently incarcerated; earnings are pre-tax thousands of 1982-1984 dollars.

without a high school diploma is nonemployed for an average of nearly 20 years, a white woman for 15 years. The racial gaps are also considerably smaller for more educated groups.

5.4 GIRFs

When an individual becomes incarcerated or nonemployed, what happens to his future earnings and employment? To answer this question within the context of our nonlinear

model, we calculate generalized impulse response functions (GIRFs). To construct the GIRFs, we first identify a time-0 information set $\mathcal{F}$ such that all individuals with a common value of $\mathcal{F}$ have the same expected future outcomes. We then simulate forward a large number of individuals for t periods. This gives us, for each simulated individual i and each variable of interest x, the history $\{x_{i,t}\}_{t=1}^{T}$. Let the indicator function δ_i equal 1 when a particular shock, say incarceration, is realized at time 1. The effects of this particular shock at time $t \geq 1$ are then given by the sample analogue of

$$\Delta[x_t|\mathcal{F}] := \mathbb{E}[x_{i,t} \mid \delta_i = 1, \mathcal{F}] - \mathbb{E}[x_{i,t} \mid \mathcal{F}].$$

When we compute this, we also compute a boot-strapped standard error. In the GIRFs we present below, the conditioning set $\mathcal{F}$ always includes being age 22 at $t = 0$, being male, and initially residing in the fifth latent earnings potential decile. We calculate separate sets of GIRFs for each race-education combination and for each value of the criminal record flag.

5.4.1 Incarceration Shocks

Figure 6 plots the GIRFs generated by an incarceration episode among male high school dropouts. The first row of the figure shows that at impact, a jail shock reduces expected earnings for black (white) men by roughly \$6,000 (\$8,000). The earnings loss wears off slowly, particularly for first-time offenders. The second and third rows show that some of the earnings loss is due to higher rates of future incarceration or nonemployment.

The top panel of Table 7 reports the lifetime impacts of the jail shocks. The impact of first-time incarceration on lifetime earnings is a loss of \$103,400 for black men and \$169,700 for white men with less than a high school diploma. These are massive amounts. To put them in perspective, unconditional lifetime earnings are \$189,000 and \$346,000 for the two groups, respectively (Table 6). Thus, for those with less than a high school diploma, first-time incarceration reduces earnings by more than 45%. A large part of the decline in earnings results from the fact that first-time incarceration leads to a reduction of 36% or more in the number of years spent working due to more years spent nonemployed or in jail: 9.6 years (out of 21.3—see Table 6) and 10.1 (out of 27.8) for black men and white men, respectively, without a high school diploma.
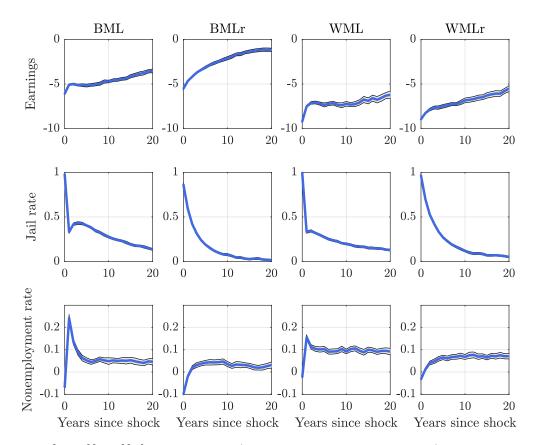
Figure 6: GIRFs for jail shocks, by race and incarceration history, men without a high
    school diploma

Note: [B,W][L,H][,r] denote black/white, less than high school/high school, no
criminal record/criminal record; Qi denotes earnings potential decile i. Earn-
ings are measured in thousands of 1982-1984 dollars.

Figure 6 and Table 7 both show that high school graduates experience larger
earnings losses after an incarceration spell than high school dropouts and that white
men experience larger losses than blacks. This in part follows mechanically from the
employment channel. If incarceration reduced male employment in every group by the
same number of years, white men and high school graduates, who earn more when
employed, would lose more income. Table 7 shows that the employment effects of
incarceration are in fact larger for white men, perhaps because they are more likely
to be employed in its absence. Moreover, the third panel of Figure 4 shows that men
with a criminal record have similar earnings across races and education levels.
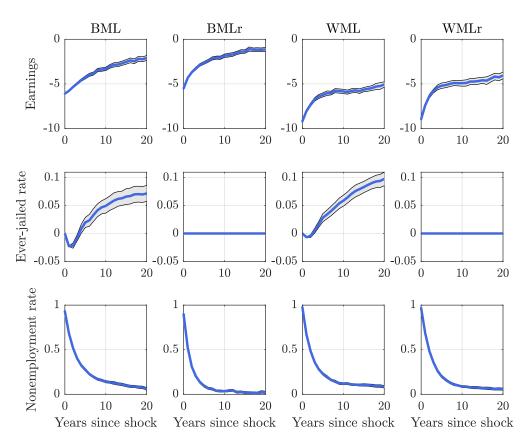
Table 7: GIRF statistics by shock, group type, and response variable

| **GIRF for a transition to jail: Q5 to J** | | | | | | | |
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.1	-9.2	-5.5	-8.9	-9.1	-12.7	-9.5	-12.6
Lifetime earnings	-103.4	-169.7	-51.0	-159.1	-121.0	-273.1	-143.7	-324.5
Future years E	-9.6	-10.1	-4.4	-7.5	-8.0	-12.1	-6.9	-14.7
Future years N	1.8	3.6	0.8	2.3	2.1	4.9	2.3	5.1
Future years J	7.7	6.5	3.5	5.2	5.9	7.1	4.7	9.6

| **GIRF for a transition to nonemployment: Q5 to N** | | | | | | | |
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.1	-9.2	-5.5	-8.9	-9.1	-12.7	-9.5	-12.6
Lifetime earnings	-78.2	-145.8	-46.8	-119.3	-109.8	-163.2	-111.3	-209.7
Future years E	-6.4	-6.8	-3.9	-6.3	-7.3	-6.9	-6.3	-9.9
Future years N	5.9	6.1	2.9	5.0	6.9	6.5	4.7	5.5
Future years J	0.4	0.7	0.9	1.2	0.5	0.4	1.6	4.4

| **GIRF for a bad latent earnings transition: Q5 to Q3** | | | | | | | |
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-3.4	0.1	-2.9	0.8	-4.0	-1.4	-4.1	-4.4
Lifetime earnings	-57.6	-118.4	-36.1	-114.7	-83.8	-177.4	-85.3	-195.0
Future years E	-2.8	-3.4	-2.0	-3.9	-2.3	-2.9	-2.5	-3.6
Future years N	2.3	2.9	1.1	2.2	2.0	2.7	1.6	2.3
Future years J	0.6	0.5	0.9	1.7	0.3	0.1	0.9	1.3

| **GIRF for a good latent earnings transition: Q5 to Q7** | | | | | | | |
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	2.8	2.0	2.0	1.4	3.1	3.9	2.6	3.7
Lifetime earnings	49.6	70.2	44.5	84.0	63.5	103.1	62.1	120.7
Future years E	2.2	1.5	2.5	2.3	1.4	0.5	1.5	0.8
Future years N	-1.5	-1.2	-1.0	-1.2	-1.2	-0.5	-0.9	-0.6
Future years J	-0.6	-0.3	-1.5	-1.1	-0.2	0.0	-0.6	-0.2

Note: [B,W][M,F][L,H][,r] denote black/white, male/female, less than high school/high school, no criminal record/criminal record; J indicates jailed or incarcerated; N indicates nonemployed but not currently incarcerated; earnings are pre-tax thousands of 1982-1984 dollars.

Comparing the results for men with and without a criminal record shows that for high school dropouts, the impact of a return to jail (indicated by an 'r' in the heading) is smaller than the impact of an initial incarceration. This is not the case

for men with a high school degree, however, where repeat offenders experience larger earnings losses. The differences across education levels likely reflect differences in recidivism. The GIRF for any incarceration stint captures the increased risk of future incarceration. For high school dropouts, the reincarceration risk is so high that at any point a realized return to jail has (somewhat) modest effects. The reincarceration risk of high school graduates, while still significant, is lower, making a return to jail more costly.

Figure 7: GIRFs for latent nonemployment shocks, by race and incarceration history, men without a high school diploma

Note: [B,W][L,H][,r] denote black/white, less than high school/high school, no criminal record/criminal record. Earnings are measured in thousands of 1982-1984 dollars.

5.4.2 Nonemployment Shocks

Figure 7 plots the GIRFs generated by a latent nonemployment shock. Although the initial impact of a nonemployment shock on earnings is identical to that of an incarceration shock, its effects wear off more quickly. The second panel of Table 7 thus shows that the lifetime earnings loss following the nonemployment shock is smaller than the one following incarceration. The lifetime impact is still quite large, ranging from $47,000 to $210,000. The reader should keep in mind that at young ages, a nontrivial portion of nonemployment is transitory; the lifetime effects reported here are for a shock to the persistent component.

Nonemployment appears to be an important pathway to incarceration. The transition matrices in Tables 2 and 3 imply that nonemployed men are especially likely to become incarcerated. Table 7 likewise shows that a spell of nonemployment raises future jail time by 0.4 to 4.4 years. To put this in perspective, note that a white high school dropout with no criminal record would on average spend 1.3 years in jail (Table 6). The additional 0.7 expected years of incarceration due to nonemployment (Table 7) is an increase of over 50%. Even after conditioning on education, race, and gender, nonemployment significantly contributes to incarceration.
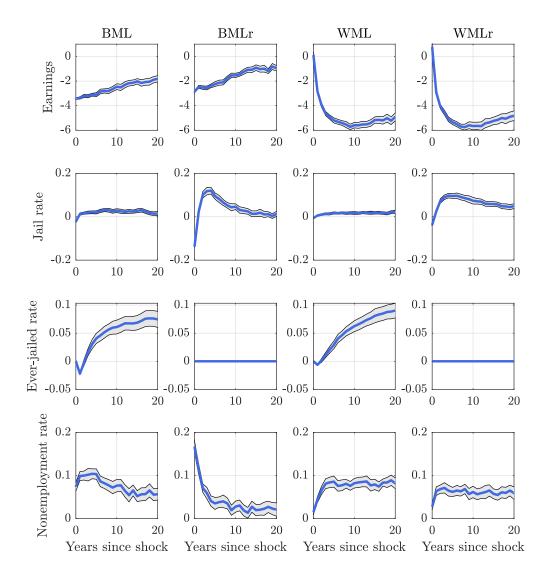
5.4.3 Q5 to Q3 Shocks and Q5 to Q7 Shocks

Tables 2 and 3 also show that men with low latent earnings potential are more likely to transition to incarceration or nonemployment. We examine these dynamics more carefully in Figures 8 and 9, which plot the effects of moving down (from decile 5 to decile 3) or up (from decile 5 to decile 7) the distribution of earnings potential.

Figure 8 shows the GIRFs that result when a man's latent earnings potential falls from the fifth to the third decile. Among high school dropouts, the dynamic effects of this shock on earnings differ markedly by race. For blacks, the shock has a large initial impact that shrinks monotonically. For whites, the initial effect of the shock is small—in fact it is slightly positive—but the earnings loss expands rapidly in subsequent years. This may reflect heterogeneous age dynamics, especially in the mapping from latent states to observed outcomes (see Table 5). Table 7 shows that the cumulative earnings losses from this shock are comparable, if in most cases smaller, to those from a nonemployment shock. For example, a white high school dropout

with no criminal record who is hit by a nonemployment shock will on average suffer a lifetime earnings loss of \$146,000; the latent earnings potential shock generates an average loss of \$118,000.

Figure 8: GIRFs for a latent Q5 to Q3 shock, by race and incarceration history, men without a high school diploma

Note: [B,W][L,H][,r] denote black/white, less than high school/high school, no criminal record/criminal record. Earnings are measured in thousands of 1982-1984 dollars.
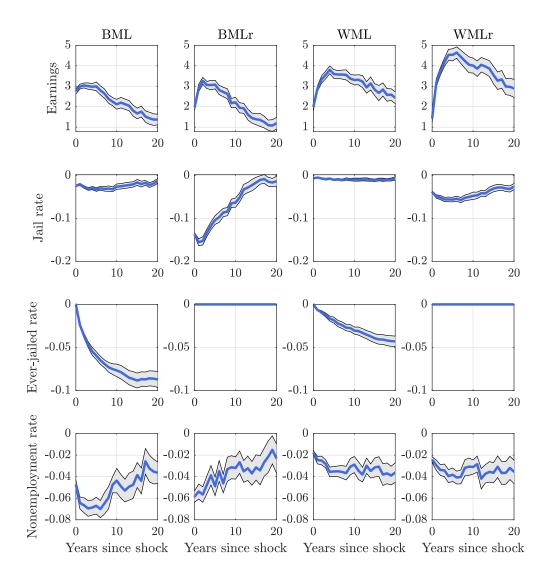
Figure 9: GIRFs for a Q5 to Q7 shock, by race and incarceration history, men without a high school diploma

Note: [B,W][L,H][,r] denote black/white, less than high school/high school, no criminal record/criminal record. Earnings are measured in thousands of 1982-1984 dollars.

Figure 8 and Table 7 also show that a decline in latent earnings potential leads to higher rates of incarceration. Here too the effects of a shock to latent earnings are similar to those of a shock to nonemployment. For a black high school dropout

with a criminal record, a negative earnings shock implies an additional 0.9 years in jail, while a nonemployment shock also implies an additional 0.9 years. A negative earnings shock also implies higher future nonemployment, although the increases are smaller than those following the nonemployment shock itself.

Figure 9 shows the GIRFs for a positive transition, an increase in latent earnings potential from the fifth to the seventh decile. While the GIRFs for an increase in earnings potential qualitatively mirror those for a decrease in earnings potential, quantitatively the effects are often asymmetric. This can be seen most easily in Table 7, where, for example, the increase in years of employment after a positive earnings shock is smaller than the decrease in years of employment after a negative earnings shock. This sort of asymmetry, assumed away in many statistical models of earnings, arises naturally in our flexible Hidden Markov Model specification.

6 Accounting for the Black-White Earnings Gap

We have seen that incarceration and nonemployment shocks have large and persistent effects on earnings, and that black individuals are in general more likely to be incarcerated or nonemployed than whites. It is thus natural to ask how the racial earnings gap would change if we eliminated racial differences in incarceration and nonemployment. The first way we answer this question is by constructing counterfactual simulations where episodes of incarceration and/or nonemployment no longer occur and comparing the racial gaps generated by these counterfactual exercises to those generated by the full model.

The first and second panels of Table 8 report summary statistics for the benchmark model and the no-incarceration counterfactual, respectively. For high school dropouts, the benchmark model produces a gap in mean lifetime earnings of \$157,000 (\$346,000 − \$189,000). In the absence of incarceration, this gap falls to \$145,000 (\$366,000 − \$221,000), a decline of 7.6%. The contribution of incarceration to the racial earnings gap is relatively small for two main reasons. The first reason is that even though incarceration is far more prevalent among blacks, its effects, when measured in levels, are larger for whites. For example, Table 7 shows that among dropouts and high school graduates, the loss of lifetime earnings following an incarceration

shock is roughly twice as large for white men as it is for black men. The second is mechanical: We have expressed the gaps in levels rather than proportional changes. For example, in the benchmark model, the gap for high school dropouts equals 83% of black earnings (157/189). When incarceration is eliminated, the fraction falls to 66% (145/220). As a proportion of a fraction, this is a reduction of 21%, as opposed to the 7.6% reduction in levels.

An informative exercise is to compare the change in average earnings induced by eliminating incarceration to the change in average years of work. For black high school dropouts, removing incarceration causes years of employment to increase 14.6%, from 21.3 to 24.4. Lifetime earnings increase by a similar amount, 16.9%. Given that low-earnings individuals are more likely to become incarcerated, one might expect the elimination of incarceration to have a larger effect on aggregate employment than aggregate earnings. One reason this does not happen is that incarceration has a scarring effect on earnings. As Tables 2-5 show, men with criminal records are, when employed, more likely to experience low earnings.

The third panel of Table 8 shows results for the no-nonemployment counterfactuals. In the absence of nonemployment, the gap for dropouts actually rises, to $157,000. The proportional gap moves in the opposite direction, however, falling to 59%. The bottom panel shows results for the full employment counterfactual. Eliminating both incarceration and nonemployment causes the gap to shrink substantially, to $128,000, about 40% (128/322) of black earnings. This is about 18% smaller than the benchmark gap for dropouts in levels, and as a fraction of black earnings, smaller by 52%.

The effects of eliminating incarceration and nonemployment are, as expected, smaller for more highly educated men. By way of example, for high school graduates, the original lifetime earnings gap is $200,000, 65% of the lifetime earnings of black men. Eliminating incarceration reduces the gap to $188,000 (59% of black lifetime earnings); eliminating nonemployment reduces the gap to $172,000 (44%); at full employment, the gap falls to $152,000 (37%). The effects are also smaller at the top of the lifetime earnings distribution. For high school dropouts, the lifetime earnings gap at the 90th percentile is $212,000, or 51% of the black earnings total of $417,000. At full employment, the gap falls to $163,000, or 31% of black earnings.

The counterfactual exercises in Table 8 provide one way to measure the effects

Table 8: Summary statistics by race and education, benchmark model and counterfactual experiments

| | **Benchmark** | | | | | | | |
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	189	346	306	506	378	561	631	950
Lifetime earnings p10	28	98	83	193	125	220	256	387
Lifetime earnings p50	151	335	270	501	353	539	567	819
Lifetime earnings p90	417	629	598	835	670	994	1142	1912
Expected years E	21.3	27.8	26.4	31.9	28.6	31.7	30.3	33.1
Expected years J	3.2	1.3	1.1	0.1	1.2	0.2	0.2	0.0
Expected years N	11.5	7.0	8.5	4.0	6.2	4.1	5.6	2.9
Ever-J rate, old	0.44	0.23	0.24	0.03	0.17	0.05	0.06	0.02
	No incarceration							
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	221	366	321	509	401	567	644	954
Lifetime earnings p10	40	120	95	199	156	229	275	388
Lifetime earnings p50	197	357	289	503	378	543	578	823
Lifetime earnings p90	450	636	612	837	691	999	1152	1917
Expected years E	24.4	29.3	27.6	32.1	30.1	32.0	30.7	33.2
Expected years N	11.6	6.7	8.4	3.9	5.9	4.0	5.3	2.8
	No nonemployment							
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	268	425	388	560	460	652	768	1095
Lifetime earnings p10	76	180	156	260	218	333	346	451
Lifetime earnings p50	253	422	364	542	442	609	666	929
Lifetime earnings p90	491	675	673	894	758	1093	1410	2103
Expected years E	30.4	34.2	34.2	35.8	34.4	35.8	35.8	36.0
Expected years J	5.6	1.8	1.8	0.2	1.6	0.2	0.2	0.0
Ever-J rate, old	0.46	0.22	0.24	0.02	0.15	0.03	0.05	0.02
	No incarceration or nonemployment							
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	322	450	412	564	487	657	780	1098
Lifetime earnings p10	166	226	189	265	247	337	357	450
Lifetime earnings p50	297	439	384	544	463	612	676	931
Lifetime earnings p90	519	682	685	896	779	1097	1418	2106
Expected years E	36.0	36.0	36.0	36.0	36.0	36.0	36.0	36.0

Note: [B,W][M,F][L,H,S,C] denote black/white, male/female, less than high school/high school/some college/college graduate; E means employed; J means jailed or incarcerated; N means nonemployed; earnings are pre-tax thousands of 1982-1984 dollars.

of incarceration and/or nonemployment on the racial earnings gap. An alternative approach is the following decomposition. Let $m^T = \{m_t\}_{t=1}^T$ denote a history of bin

realizations—jail, nonemployment, and earnings deciles—and let $p(m^T, \text{race}), \text{race} \in \{W, B\}$, denote the probability function for these histories. (The function $p_t(\cdot)$ also depends on gender and education, which we will ignore for now.) Let $y_t(m_t, \text{race})$ denote the time-t earnings associated with outcome bin m_t, with lifetime earnings given by $PDV(m^T, \text{race}) := \sum_{t=1}^{T} R^{1-t} y_t(m_t, \text{race})$. It follows that for either race, any summary statistic (mean, median, etc.) for lifetime earnings can be written as $\varsigma(y(\cdot, \text{race}), p(\cdot, \text{race}))$ or, more compactly, as $\varsigma(y^{\text{race}}, p^{\text{race}})$.[27]

The racial gap in earnings is then given by:

$$\varsigma(y^W, p^W) - \varsigma(y^B, p^B) = \left[\varsigma(y^W, p^W) - \varsigma(y^B, p^W) \right] + \left[\varsigma(y^B, p^W) - \varsigma(y^B, p^B) \right] \quad (5)$$

$$= \left[\varsigma(y^W, p^B) - \varsigma(y^B, p^B) \right] + \left[\varsigma(y^W, p^W) - \varsigma(y^W, p^B) \right]. \quad (6)$$

The first bracketed term in equations (5) and (6) measures the effects of racial differences in earnings, holding fixed the distribution of outcome bins. The second bracketed term measures the effects of racial differences in the distribution of outcome bins, holding fixed the earnings values associated with each outcome bin. The second term can be viewed as capturing the effects of racial gaps in incarceration and nonemployment, although it captures distributional differences of every sort.[28] The ratio of this term to the entire gap provides a relative measure. Equations (5) and (6) are equally valid; in practice, we calculate the ratio both ways and take the average.

We apply this decomposition to lifetime earnings in Table 9, which presents the share of the lifetime earnings gap attributable to racial differences in the distribution of outcome bins.[29] The first row shows that for male high school dropouts, 64% of the difference in average lifetime earnings is attributable to differences in the distribution of outcome bins, much of which is due to differences in incarceration or nonemployment. By way of comparison, recall that for high school dropouts, eliminating incarceration and nonemployment in their entirety reduces the levels gap by 18% and the fractional gap by 52%.

Continuing along the first row, the ratios for high school graduates, men with some

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[27]To fix ideas, for means we have $\varsigma(y^{\text{race}}, p^{\text{race}}) = \sum_{m^T} PDV(m^T, \text{race}) \, p(m^T, \text{race})$.

[28]This decomposition does not allow us to separately measure the effects of incarceration and nonemployment.

[29]The numbers underlying Table 9 can be found in Appendix H.

college education, or college graduates, are 46%, 48%, and 21%, respectively. The decomposition exercises thus suggest that, for most education levels, racial differences in nonemployment and incarceration constitute a significant portion of the earnings gap. The remaining rows of Table 9 show results for various lifetime earnings percentiles. In general, the ratios are larger at lower percentiles, suggesting that differences in employment histories matter more at the bottom of the earnings distribution.

Table 9: Decomposition: Fraction of lifetime earnings gap explained by differences in the distribution across bins

Variable	ML	MH	MS	MC
Lifetime earnings avg.	63.7	46.1	47.5	20.5
Lifetime earnings p10	76.6	61.0	59.3	29.2
Lifetime earnings p50	72.4	55.0	50.4	15.9
Lifetime earnings p90	47.3	22.8	48.0	31.2

Note: [M][L,H,S,C] denote male, less than high school/high school/some college/college graduate. Analysis follows equations (5) and (6), as described in the text.

7 Conclusion

Despite the prevalence and growth of incarceration in the United States, much remains unknown about the relationship between incarceration, employment, earnings, and demographics. In this paper, we exploit the rich panel structure of the NLSY79, one of the few datasets that tracks incarceration, to estimate the dynamics of incarceration, employment, and earnings. We deploy a Hidden Markov Model that distinguishes between first-time and repeat incarceration, allows for both persistent and transitory employment and earnings shocks, and allows for nonresponse bias.

The estimated effects of first-time incarceration on earnings are substantial, reducing lifetime earnings by at least a third and—for some subgroups—a half. This reduction in lifetime earnings is due both to the extensive margin, through fewer years employed, and the intensive margin, through lower earnings while working. A positive link between nonemployment and jail is also apparent: Low latent earnings

imply higher incarceration risk. All of the shocks we consider have highly persistent effects.

Relative to their white counterparts, black men earn less and are more likely to be nonemployed or incarcerated. Decomposition exercises with our model show that among less-educated men, differences in incarceration and nonemployment can explain a significant portion of the black-white gap in lifetime earnings. A promising avenue for future research, which we are currently pursuing, is to use our estimates in a consumption-savings model that can quantify the role of incarceration (among other factors) in the large wealth differences observed across race, gender, and education groups.

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For Online Publication: Appendices

A   Specification Details

Let $\ell_{n,t} \in \mathbb{L} = \{L_0, L_1, ..., L_{I-1}\}$ denote individual n's underlying, latent labor market state at date t, and let $m_{n,t} \in \mathbb{M} = \{M_0, M_1, ..., M_{J-1}\}$ denote the earnings outcome observed by the researcher. The set of latent states, $\mathbb{L}$, consists of incarceration, long-term nonemployment, and Q^* earnings *potential* bins. This set of outcomes is then interacted with a $\{0, 1\}$ criminal record flag, so that $\mathbb{L}$ contains $2(Q^* + 2)$ elements. The set of observed outcomes, $\mathbb{M}$, consists of incarceration, nonemployment (short- or long-term), Q positive earnings bins, and not interviewed/missing. The nonmissing outcomes are also interacted with the criminal record flag, so that $\mathbb{M}$ contains $2Q + 5$ elements.

Let p_q, $q = 0, 1, ..., Q$ denote the probability cutoffs for the earnings bins. In practice, we partition earnings into deciles, so that $p_q \in \{0.0, 0.1, ..., 0.8, 1\}$ and $Q = 10$. We also assume that the bins for latent earnings potential are the same as those for observed earnings, so that $Q^* = Q$. To streamline the notation, we will proceed under this assumption.

Our model is based on two key assumptions. The first is that $\ell_{n,t}$ is conditionally Markov, with the $I \times I$ transition matrix, $\mathbf{A}_x$:

$$\mathbf{A}_{j,k \,|\, x} = \Pr(\ell_{n,t+1} = L_k \,|\, \ell_{n,t} = L_j, \, x_{n,t}) = \Pr(\ell_{n,t+1} = L_k \,|\, \mathcal{F}_t), \qquad (7)$$

where $x_{n,t}$ is a vector of exogenous variables, and $\mathcal{F}_t$ denotes the time-t information set. The second is that the distribution of the observed outcome $m_{n,t}$ depends on only the contemporaneous realization of $\ell_{n,t}$. We can place the probabilities that map $\ell_{n,t}$ to $m_{n,t}$ in the $I \times J$ matrix $\mathbf{B}_z$:

$$\mathbf{B}_{j,k \,|\, z} = \Pr(m_{n,t} = M_k \,|\, \ell_{n,t} = L_j, \, z_{n,t}) = \Pr(m_{n,t} = M_k \,|\, \mathcal{F}_{t-1}, \ell_{n,t}). \qquad (8)$$

The final element of our model is the $1 \times I$ row vector $\mu_1(l_{n,1}|x_{n,1})$, which gives the unconditional distribution of the initial latent state $\ell_{n,1}$.

We estimate separate sets of transition and observation probabilities for each

race-gender-education combination. We now turn to describing how these probability matrices are populated. To simplify the notation, we drop the individual index n, and suppress the dependence on race, gender, and education.

Our framework has many similarities to Arellano et al. (2017), who also rely heavily on quantiles. A fundamental difference is that they work with conditional quantiles, in order to construct inverse conditional CDFs, while we work with unconditional quantiles, in the spirit of copulas. In Arellano et al.'s (2017) framework, the conditional distribution of quantile ranks is always uniform, and thus independent of the current latent state, because the quantiles themselves are conditional and thus depend on the latent state. In contrast, we have a single set of cross-sectional (given race, gender, education, and age) quantiles for all values of the latent state; in our framework, the quantiles are independent of the current latent state, but the distribution of outcomes across quantile ranks depends on the current latent state.

A.1 Latent State Transitions

We define a person as having a criminal record if he has been incarcerated in any *previous* period. Once a person is incarcerated, he will have a criminal record in all subsequent periods. Figure 1 illustrates the remainder of the process for populating the matrices $\mathbf{A}$ and $\mathbf{B}$. As the top half of this figure shows, we find the elements of the transition matrix $\mathbf{A}_x$ in two steps. First, we use a multinomial logit regression to determine the one-period-ahead probabilities of incarceration (IC), long-term nonemployment (NE), or employment ($\mathcal{Q}^*$):

$$\Pr\left(\ell_{t+1} \in k \,|\, \ell_t = j,\, x_t\right) = \lambda_{j,k} \bigg/ \sum_{m \in \{NE, \mathcal{Q}^*, IC\}} \lambda_{j,m}, \tag{9}$$

$$j \in \mathbb{L}, \quad k \in \{NE, \mathcal{Q}^*, IC\},$$

$$\lambda_{j,NE} \equiv 1, \quad \forall j,$$

$$\lambda_{j,m} = \exp\left(\mathbf{x}(a_t, \ell_t)\boldsymbol{\zeta}_m\right), \quad m \in \{\mathcal{Q}^*, IC\},$$

where $\{\boldsymbol{\zeta}_m\}_{m \in \{\mathcal{Q}^*, IC\}}$ are coefficient vectors for future states. Nonemployment is the benchmark state. In an abuse of notation, $\mathbf{x}(a_t, \ell_t)$ denotes the explanatory variables in the logit regression. The elements of this vector include a polynomial in current

age (a_t), indicators for the current state, and interactions:

$$\mathbf{x}(a_t, \ell_t) = \left[\begin{array}{ccccccccccc} 1 & a_t & \frac{a_t^2}{100} & \mathcal{I}_t^{NE} & \mathcal{I}_t^{NE}a_t & \tilde{p}_j & \tilde{p}_j a_t & \tilde{p}_j^2 & \tilde{p}_j^2 a_t & \mathcal{I}_t^{IC} & \mathcal{I}_t^{CR} \end{array} \right],$$

where: a_t denotes the individual's age at calendar year t; $\mathcal{I}_t^{NE}$ and $\mathcal{I}_t^{IC}$ are 0-1 indicators for long-term nonemployment or incarceration, respectively; $\mathcal{I}_t^{\mathcal{Q}} = 1 - \mathcal{I}_t^{NE} - \mathcal{I}_t^{IC}$ indicates positive earnings; $\mathcal{I}_t^{CR}$ is the 0-1 indicator for a criminal record (previous incarceration); and $\tilde{p}_j$ gives the individual's (approximate) earnings rank. In particular, when state j corresponds to earnings bin q_j, $\tilde{p}_j = [p_{q_j} + p_{q_j-1}]/2$. By way of example, when earnings are partitioned into deciles, $\tilde{p}_j \in \{0.05, 0.15, ..., 0.85, 0.95\}$. When j indicates incarceration or persistent nonemployment, $\tilde{p}_j$ is set to 0. Because we treat $\tilde{p}_j$ as continuous rather than categorical, the number of variables in the logistic regression is invariant to the number of bins.

Second, we estimate the distribution of next period's earnings potential, conditional on being employed, across the bins. To do this, we assume that the conditional distribution of ranks follows the Kumaraswamy (1980) distribution. Like the Beta distribution, the Kumaraswamy distribution is a flexible function defined over the $[0, 1]$ interval; however, its cdf is much simpler:

$$K(p;\, \alpha, \beta) = \Pr(y \leq p;\, \alpha, \beta) = 1 - (1 - p^\alpha)^\beta.$$

The parameters α and β are both strictly positive. It follows that if bin q covers quantiles p_{q-1} to p_q,

$$\begin{aligned}
\Pr\left(\ell_{t+1} = \text{bin } q \mid \ell_t = j, x_t\right) = {} & \Pr\left(\ell_{t+1} \in \mathcal{Q}^* \mid \ell_t = j, x_t\right) \quad (10) \\
& \times \left[K\left(p_q; \alpha\big(\mathbf{x}(a_t, \ell_t)\big), \beta\big(\mathbf{x}(a_t, \ell_t)\big)\right) - K\left(p_{q-1}; \alpha\big(\mathbf{x}(a_t, \ell_t)\big), \beta\big(\mathbf{x}(a_t, \ell_t)\big)\right) \right], \\
& j \in \mathbb{L}, \quad q \in \{1, 2, ..., Q\}, \\
\alpha\big(\mathbf{x}(a_t, \ell_t)\big) = {} & \exp\big(\mathbf{x}(a_t, \ell_t)\boldsymbol{\zeta}_a\big), \\
\beta\big(\mathbf{x}(a_t, \ell_t)\big) = {} & \exp\big(\mathbf{x}(a_t, \ell_t)\boldsymbol{\zeta}_b\big).
\end{aligned}$$

$K\big(0;\, \alpha, \beta\big) = 0$ and $K\big(1;\, \alpha, \beta\big) = 1$ by definition. The Kumaraswamy parameters α and β are functions of the current state and the vector $\mathbf{x}$; $\boldsymbol{\zeta}_a$ and $\boldsymbol{\zeta}_b$ are the associated coefficient vectors. Because we use the midpoint value $\tilde{p}_{q_j}$ to characterize the current

earnings bins, as the number of bins grows large, our discretized distribution converges to a continuous one. It is natural to view both the binning of the data and the expressions for $\alpha\big(\mathbf{x}(a_t, \ell_t)\big)$ and $\beta\big(\mathbf{x}(a_t, \ell_t)\big)$ as semiparametric approximations that will become more complicated as the sample size grows.

Recall that once a person is incarcerated, he will have a criminal record for the rest of his life. As a result, $\mathbf{A}$ will be approximately block diagonal (as in Tables 2 and 3). The first $Q+1$ rows of this matrix denote cases where at time t the individual has no criminal record ($\mathcal{I}_t^{CR} = 0$) and is not currently incarcerated; his current state is long-term nonemployment (state 0) or one of the earnings potential bins. Such a person will not have a criminal record at time $t+1$; even if he becomes incarcerated at $t+1$, he will not have a prior conviction at that point. The first $Q+1$ rows thus have (potentially) nonzero values in the first $Q+2$ columns and zeros for the remainder. (Given that we start our indexing at 0, this corresponds to rows 0 through Q and columns 0 through $Q+1$.) The final $Q+2$ rows are for people who have a criminal record at time t, $\mathcal{I}_t^{CR} = 1$. These rows will have zeros in the first $Q+2$ columns and (potentially) nonzero values for the remainder. This leaves one row to consider, namely the one for a person who at time t has no criminal record—he has not been incarcerated in the past—but is currently in jail. This person will have a criminal record at time $t+1$, so row $Q+1$ is configured like the rows for those with a criminal record at time t. The transition probabilities for this person will differ, however, from that of a person who at time t is both in jail and in possession of a criminal record. To sum, the matrix $\mathbf{A}$ has a $(Q+1) \times (Q+2)$ block in the upper left corner, a $(Q+3) \times (Q+2)$ block in the lower right corner, and zeros everywhere else.

A.2 Observation Probabilities

Let O_t indicate whether the individual was interviewed in the current survey wave. The set of observed outcomes, $\mathbb{M}$, consists of the set of latent states, $\mathbb{L}$, and missing ($O_t = 0$). It is of course not necessary that $\mathbb{M}$ and $\mathbb{L}$ align so closely, but it simplifies the analysis. With this assumption, $\mathbb{M}$ contains $2(Q+2)+1 = 2Q+5$ elements, and the observation matrix $\mathbf{B}$ is $(2Q+4) \times (2Q+5)$.

To populate $\mathbf{B}$, we first find the probability that the individual is not interviewed

at time t, using a logit specification:

$$\mathbf{B}_{j,0\,|\,z} = \Pr\left(O_t = 0 \,|\, \ell_t = j,\, z_t\right) = 1 - \frac{\exp\left(\mathbf{z}_0(a_t, \ell_t, O_{t-1})\boldsymbol{\gamma}_0\right)}{1 + \exp\left(\mathbf{z}_0(a_t, \ell_t, O_{t-1})\boldsymbol{\gamma}_0\right)}, \quad j \in \mathbb{L}, \quad (11)$$

where

$$\mathbf{z}_0(a_t, \ell_t, O_{t-1}) = \begin{bmatrix} 1 & a_t & \frac{a_t^2}{100} & \mathcal{I}_t^{NE} & \mathcal{I}_t^{CR} & O_{t-1} \end{bmatrix}.$$

The interview probability depends on the presence of earnings but not their rank.

Next, we find the distribution of states for individuals who are interviewed. We assume that the individual's criminal record is measured accurately, so that the latent incarceration state maps 1-for-1 into observed incarceration. Likewise, we assume that the latent nonemployment state maps 1-for-1 into observed nonemployment, consistent with our view that the state represents long-term unemployment. We assume further that criminal records are reported accurately. With these assumptions, we get

$$\mathbf{B}_{j,j+1\,|\,z} = \frac{\exp\left(\mathbf{z}_0(a_t, \ell_t, O_{t-1})\boldsymbol{\gamma}_0\right)}{1 + \exp\left(\mathbf{z}_0(a_t, \ell_t, O_{t-1})\boldsymbol{\gamma}_0\right)}, \quad j \in \{0, Q+1, Q+2, 2Q+3\}, \quad (12)$$

$$\mathbf{B}_{j,k\,|\,z} = 0, \quad j \in \{0, Q+1, Q+2, 2Q+3\},\ k \notin \{0, j+1\}. \quad (13)$$

To populate the remaining elements of $\mathbf{B}$, we assume that when the latent state ℓ_t is the earnings potential bin q the individual's observed outcome may be any observed earnings bin, $q_k \in \mathcal{Q}$, or nonemployment. Nonemployment realized in these circumstances is purely transitory, and has no effect on the individual's latent earnings prospects. Transitory incarceration shocks are ruled out, and the corresponding elements of $\mathbf{B}$ are set to zero. Our approach for finding these probabilities is similar to the one employed for the latent states. First, we find the probability that the individual will be nonemployed or working, using a logit:

$$\Pr\left(m_t \in k \,|\, \ell_t = j,\, O_t = 1,\, z_t\right) = \lambda_{j,k} \,\Big/\! \sum_{h \in \{NE,\mathcal{Q}\}} \lambda_{j,h}, \tag{14}$$

$$j \in \{\text{bin } 1, \text{bin } 2, ..., \text{bin } Q\} \times \{0,1\},$$
$$k \in \{NE, \mathcal{Q}\},$$
$$\lambda_{j,NE} \equiv 1, \quad \forall j,$$
$$\lambda_{j,\mathcal{Q}} = \exp\left(\mathbf{z}_1(a_t, \ell_t)\boldsymbol{\gamma}_{\mathcal{Q}}\right),$$

with the conditioning vector $\mathbf{z}_1$ given by

$$\mathbf{z}_1(a_t, \ell_t) = \begin{bmatrix} 1 & a_t & \frac{a_t^2}{100} & \tilde{p}_j & \tilde{p}_j a_t & \tilde{p}_t^2 & \tilde{p}_t^2 a_t & \mathcal{I}_t^{CR} & \mathcal{I}_t^{CR} a_t \end{bmatrix}.$$

Note that $M_0 = NE$ is again the benchmark state. We continue to assume that criminal records are reported accurately.

Next, the probabilities for the individual earnings bins are found using a univariate logit distribution:

$$\Pr\left(m_t = \text{bin } q \,|\, \ell_t = j,\, O_t = 1,\, z_t\right) = \Pr\left(m_t \in \mathcal{Q} \,|\, \ell_t = j,\, O_t = 1,\, z_t\right)$$
$$\times \left[L^\star\left(p_q, \tilde{p}_j;\, \sigma_{\mathbf{z}_1}\right) - L^\star\left(p_{q-1}, \tilde{p}_j;\, \sigma_{\mathbf{z}_1}\right)\right], \tag{15}$$
$$j \in \{\text{bin } 1, \text{bin } 2, ..., \text{bin } Q\} \times \{0,1\},$$
$$q \in \{1, 2, ..., Q\},$$

$$L^\star\left(p, \tilde{p};\, \sigma\right) = \frac{\exp(\sigma(p - \tilde{p}))}{1 + \exp(\sigma(p - \tilde{p}))} \Big/ \left[\frac{\exp(\sigma(1 - \tilde{p}))}{1 + \exp(\sigma(1 - \tilde{p}))} - \frac{\exp(-\sigma\tilde{p})}{1 + \exp(-\sigma\tilde{p})}\right], \tag{16}$$
$$\sigma_{\mathbf{z}_1} = \exp\left(\mathbf{z}_1(a_t, \ell_t)\boldsymbol{\gamma}_E\right).$$

Our decision to center the distribution $L^\star\left(p, q_j;\, \sigma\right)$ around the latent earnings rank $\tilde{p}_j$ is an identifying assumption. Given that the logistic density is symmetric around zero, our assumption implies that if the earnings bins are also symmetric, the most likely observed earnings level is the current latent state. The denominator in equation (16) ensures that $\sum_q \Pr\left(\text{bin } q \,|\, \ell_j,\, O = 1,\, z_t\right) = \Pr\left(\mathcal{Q} \,|\, \ell_j,\, O = 1,\, z_t\right)$, $\forall j$.

Multiplying the probabilities in equations (14) and (15) by the observation prob-

ability given in (12) completes the process.

A.3   Initial Probabilities

We construct the initial distribution of latent states, $\mu_1(\ell_1|\tilde{x}_1)$, in much the same way we found their transition probabilities. First, we find the probability that the individual is incarcerated, nonemployed (long-term), or in one of the positive earnings potential bins. Conditional on having positive earnings, we find the distribution across the earnings potential bins using the Kumaraswamy distribution $K(p; \alpha_0, \beta_0)$; the calculations parallel those in equation (10). The parameters α_0 and β_0 are scalars to be estimated. The final step is to estimate the probability that the individual has a criminal record, conditional on the other latent states. Here we use a logistic distribution, allowing the probability of a criminal record to depend on $\mathcal{I}_0^{NE}$, $\mathcal{I}_0^{IC}$, and q_0. The product of these two probabilities gives us our initial distribution.

A.4   Likelihood

We estimate our model using maximum likelihood. Suppose that an individual has the sequence of observed outcomes $\{m_t\}_{t=1}^T$. The likelihood of this sequence can be found via forward recursion (Bartolucci et al. 2010; Scott 2002; see also Hamilton 1994, chapter 22, and Farmer 2020):

1. Begin with the $1 \times I$ vector of initial latent state probabilities, μ_1.

2. Letting j_1 index the realization of m_1, calculate the $1 \times I$ vector $\eta_1 = \mu_1 \odot (\iota_{j_1} \mathbf{B}_1')$, where $\odot$ denotes the Hadamard product, element by element multiplication. Here ι_j is the $1 \times J$ row vector with 1 at position j and zeros elsewhere; the product $\iota_{j_1} \mathbf{B}_1'$ returns (transposed) column j_1 of $\mathbf{B}_1$. Element i of η_1 thus gives the joint time-1 probability of latent state i and the observed outcome m_1.

3. For $t = 1, 2, ..., T - 1$, calculate $\eta_{t+1} = \dfrac{1}{\eta_t \mathbf{1}}(\eta_t \mathbf{A}_t) \odot (\iota_{j_{t+1}} \mathbf{B}_{t+1}')$.[30] The $1 \times I$ vector η_{t+1} gives the joint probability distribution of the latent state ℓ_{t+1} and the outcome observed at time $t + 1$ (m_{t+1}), conditional on all outcomes observed

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[30]When the NLSY79 moves to two-year frequency, we simply multiply successive transition matrices.

through time t. The sum $\eta_t \mathbf{1}$ is the probability of the outcome observed at time t, conditional on all prior observed outcomes. The ratio $\frac{\eta_t}{\eta_t \mathbf{1}}$ thus gives the distribution of the latent states at time t, conditional on all outcomes observed through time t, and $\mathbf{A}_t$ updates the distribution to time $t+1$. The right-hand term of the Hadamard product accounts for m_{t+1}.

4. Calculate the cumulative probability, $\Pr(m_1, m_2, ..., m_T) = \prod_{t=1}^{T}(\eta_t \mathbf{1})$.

As Scott (2002) observes, if T is large, the product in item (4) may be very small. We thus find the sum of the logged probabilities rather than the log of the product.

B   The Kumaraswamy Approximation

By assuming that the distribution of earnings ranks is Kumarswarmy with parameters $\alpha(\mathbf{x}(a_t, \ell_t)), \beta(\mathbf{x}(a_t, \ell))$, there will always be some approximation error (unless that happens to be the exact distribution). In this section, we investigate how much error there is. We begin by running a long simulation of an AR(1) for earnings,

$$z_t = \rho_z z_{t-1} + \sigma_z \varepsilon_t, \quad \varepsilon_t \sim N(0, 1),$$

constructing bins (which define our latent state ℓ) and a transition matrix from the simulation, and then fitting the simulated data with our Kumaraswarmy approximation. We then conduct a number of tests to assess the goodness of fit between our target and fitted transition matrix.

In terms of details, we use $\rho_z = 0.95$, in line with most estimates, and fix $\sigma_z = 1$, which is just a normalization since we work in quantile space. We use 10 bins with the 9 cutoffs $\{0.1, 0.2, ..., 0.9\}$. We let $\mathbf{x}$ (for α and β) be a cubic in $\tilde{p}_q$, the bin midpoints. This leaves us with 8 parameters (4 for both α and β). In choosing the parameters, we use maximum likelihood. In particular, letting θ denote the coefficient vector, the log-likelihood is

$$\mathcal{L}(\theta) = \sum_{b=1}^{10} \sum_{q=1}^{10} N^S(\ell_{t+1} = \text{bin } q \text{ and } \ell_t = \text{bin } b) \cdot \ln\left(\Pr^K(\ell_{t+1} = \text{bin } q \mid \ell_t = \text{bin } b; \theta)\right),$$

where $N^S(\cdot)$ denotes simulation counts, and $\mathrm{Pr}^K(\cdot)$ denotes probabilities generated by our Kumaraswamy specification.

The top left and right panels of Figure B.1 contain the target and fitted transition matrices, respectively. The current state is given by rows, while the next period state is given by columns. Brighter colors represent large probability transitions, while dark blue colors are close to zero. Visually, one can see the fitted and target matrix are quite close to each other. The difference between the fitted and target transition rates is presented in the middle left panel labeled "Error." The errors are quite close to zero, but can be as high as 0.05 or as low as -0.05 in some points. Notably, these high and low errors occur close to one another, allowing for the possibility that they average out in some sense. As discussed immediately below, this idea is confirmed by long simulations of the transition matrices.
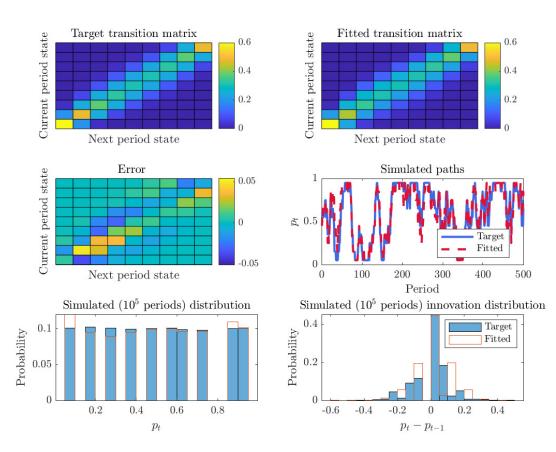
Figure B.1: Error from the Kumaraswamy approximation

The middle right panel plots a 500-period simulation using both the target and fitted transition matrix. To do this, we start both simulations with the same initial state and then use the same sequence of $U[0, 1]$ realizations to draw from $F(\ell_{t+1}|\ell_t)$. This is a quite demanding test as it allows for errors to accumulate over time. And, indeed, some slight errors can be seen. However, in practice the errors do *not* accumulate, with mistakes low or high corrected shortly. This is consistent with the balance of high and low errors in the fitted transition matrices.

When we do an even longer (100,000) period simulation to look at the target and fitted invariant distribution (bottom left panel) and innovation distribution (bottom right panel), we again see some error. However, again these errors seem to be balanced. E.g., while the probability of being in the lowest state is too high in the fitted distribution, the probability of being in the penultimate lowest bin is too small. Similar statements can be made in terms of the innovation distribution. Hence, while the Kumaraswamy approximation is not perfect, it seems to do a good job of approximating earnings dynamics provided they are reasonably captured by a persistent, AR(1) process. Stated differently, if the earnings dynamics conditional on job-to-job transitions roughly follow the most common assumption in the literature—a persistent AR(1) process with normal innovations—then our Kumaraswamy functional form allows for a good approximation of earnings dynamics.

C   Earnings and Employment Measures

In this appendix, we describe how we measure employment and earnings in the data.

C.1   NLSY79

We measure earnings as the sum of wage income, salary income and the labor portion of farm and business income, with the latter found using the approach found in the Panel Study of Income Dynamics (PSID) (Survey Research Center, 1992). We will refer to individuals with no farm or business income as "workers." The NLSY79 reports both total hours and total weeks of work. We include military hours in the total: These are fairly small, as we do not use the NLSY79's military subsample.

In general, employed individuals have positive (80 or more) hours of work, positive (2 or more) weeks of work, and positive ($250 or more in 1980 dollars) earnings. When the three measures contradict, we define employment as follows.

1. If a person has positive earnings **and either** positive hours **or** positive weeks, she is employed.

2. A person with no hours **and** no weeks of work is nonemployed, regardless of earnings.

3. A **worker** with no earnings is nonemployed, regardless of hours or weeks.

4. A **nonworker** with positive hours **and** positive weeks is employed, regardless of earnings.

5. If a **nonworker** has no earnings **and either** no hours **or** no weeks, she is nonemployed.

C.2   CPS

Consistent with our approach in the NLSY, our CPS earnings measure includes not just wage and salary income, but also the labor component of farm and business income, again applying the PSID (Survey Research Center, 1992) methodology.

The CPS reports both the number of weeks worked in the prior year and the usual number of hours worked each week. We consider individuals who worked for less than two weeks to be nonemployed, along with those who worked less than 80 hours over the entire year (i.e., the product of usual hours worked each week and the number of weeks worked was less than 80). Workers (no business or farm income) with less than $250 (in 1980 dollars) of earnings are also considered to be nonemployed.

D Summary Statistics for Women

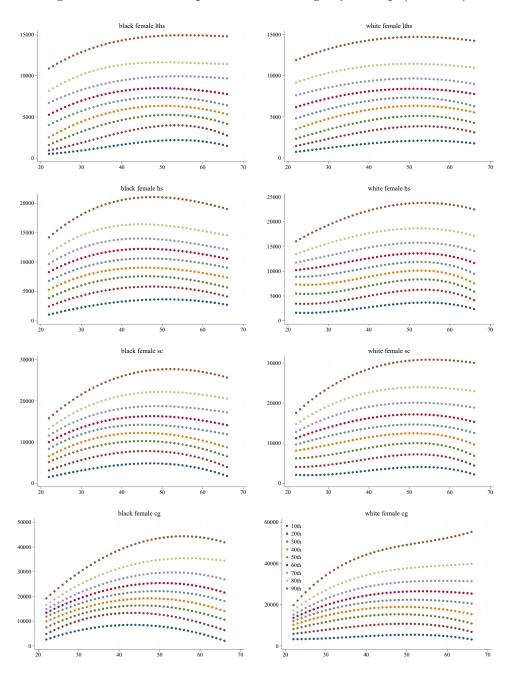This section presents CPS summary statistics for women in Table D.1.

Table D.1: Summary Statistics by Race and Education for Women, NLSY79

	Black Women				White Women			
	LTHS	HS	SC	CG	LTHS	HS	SC	CG
Earnings (in $1,000s)								
Mean	3.23	7.34	9.69	14.79	5.69	9.09	11.09	17.19
10th percentile	0	0	0	0	0	0	0	0
25th percentile	0	0	0.64	4.56	0	0.63	2.22	4.56
50th percentile	0	5.77	8.80	13.54	2.70	7.92	9.60	14.29
75th percentile	5.20	11.96	14.87	21.74	9.32	13.64	16.13	23.37
90th percentile	11.11	17.74	22.01	30.01	15.01	20.11	23.33	34.60
Currently Incarcerated (%)								
All ages	0.79	0.10	0.12	0	0.17	0.01	0.07	0.02
22-29	0.42	0.03	0.04	0	0.11	0.00	0.01	0.02
30-39	1.49	0.11	0.16	0	0.41	0.02	0.19	0.02
40-49	0.60	0.21	0.19	0	0	0.03	0.04	0.01
50 and older	0.27	0.18	0.10	0	0	0	0	0
Previously Incarcerated (%)								
All ages	2.82	0.45	0.80	0	1.48	0.03	0.30	0.29
22-29	0.55	0	0.15	0	0.73	0.01	0.05	0.20
30-39	4.06	0.24	0.67	0	1.41	0	0.20	0.26
40-49	4.49	1.24	1.63	0	2.60	0.07	0.77	0.41
50 and older	3.56	1.24	1.84	0	2.77	0.14	0.67	0.44
Fraction Employed (%)								
All	38.39	61.22	67.62	76.60	53.80	65.38	69.87	76.87
Previously incarcerated	25.78	18.81	47.87	N/A	23.89	19.96	42.56	96.08
Not previously incarcerated (%)	38.76	61.41	67.74	76.66	54.22	65.37	69.94	76.80
Mean Values								
Year of birth	1960.2	1960.4	1960.2	1960.3	1960.4	1960.1	1960.2	1960.3
Age	31.24	31.04	30.85	30.80	29.57	28.99	28.99	30.59
Fraction of female population (%)	3.36	3.78	4.73	3.04	12.10	27.19	20.34	25.45
Observations	6,206	7,464	8,768	5,788	8,665	16,584	12,160	16,086
Individuals	325	392	452	301	660	1,058	724	934

Note: [LTHS,HS,SC,CG] denote less than high school/high school/some college/college graduate.

E Decile Cutpoints and Within-Decile Means

This section gives the estimated decile cutpoints in Figures E.1 and E.2, and the estimated within-decile means in Figures E.3 and E.4.

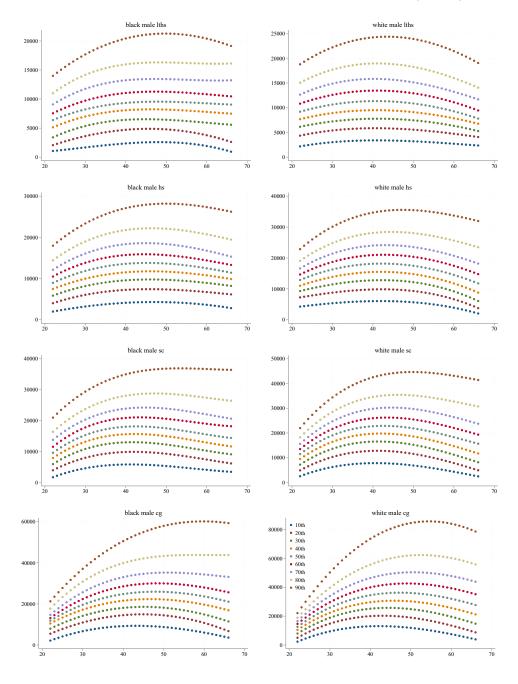Figure E.1: Decile Cutpoints for Earnings by Group (Females)

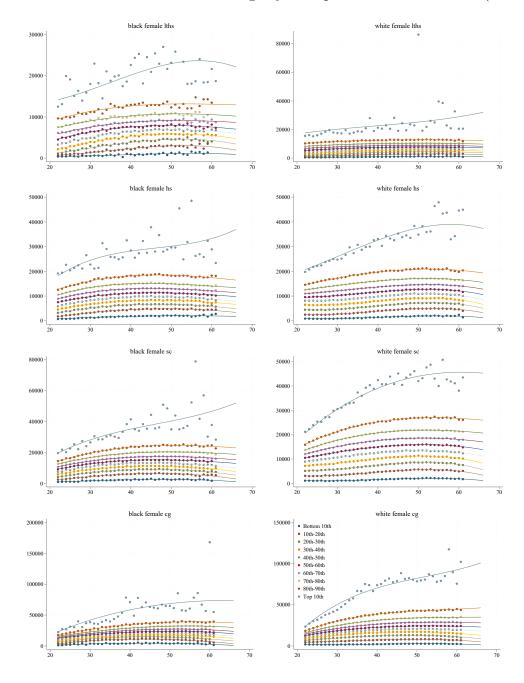# Figure E.2: Decile Cutpoints for Earnings by Group (Males)

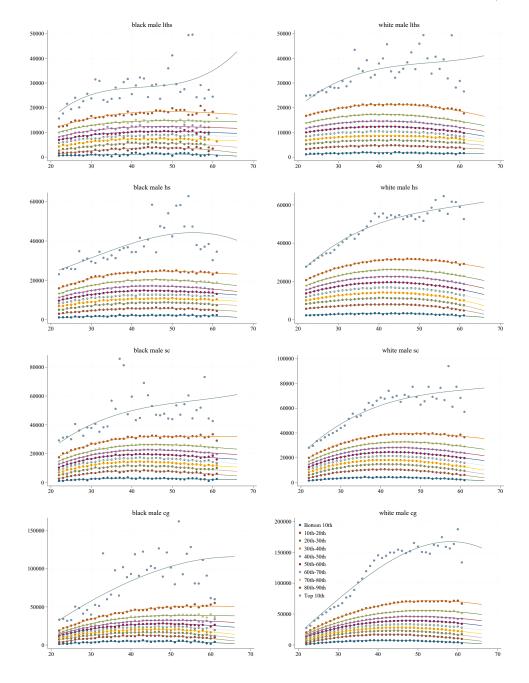Figure E.3: Within-Decile Mean Earnings by Group: Data and Estimates (Females)

Figure E.4: Within-Decile Mean Earnings by Group: Data and Estimates (Males)

F Coefficient Estimates

Tables F.1 and F.2 show coefficient estimates for, respectively, men and women. The associated standard errors are found using the information matrix.

For a number of groups—white men with a college degree, white women with at least a high school diploma, and black women with either a high school or a college degree—the incidence of incarceration is so low that their incarceration-related parameters cannot be estimated accurately. In these cases, we use the data to estimate a simplified model that omits incarceration. To this set of parameters, we add incarceration-related parameters estimated for other, similar groups, namely white men with some college education, or white women without a high school diploma, or black women with some college experience. These coefficients are identified by an entry of "NA" in the standard error slot.

When making these imputations, we adjust the intercepts for the incarceration probabilities to match the probabilities observed in the NLSY for the group. The logic of our adjustments is the following. Consider a simple static logistic model, where

$$u = \frac{1}{1 + E + IC},$$
$$e = \frac{E}{1 + E + IC},$$
$$ic = \frac{IC}{1 + E + IC},$$

give the probabilities of being nonemployed, employed, or incarcerated, respectively. Suppose the incarceration constant for group i is known to be $\ln(IC_i)$, and we want to build off this constant to impute $\ln(IC_j)$ for group j. If we know the probabilities ic_i, ic_j, u_i, u_j, we have

$$ic_i = \exp(\ln(IC_i)) \cdot u_i,$$
$$ic_j = \exp(\ln(IC_j)) \cdot u_j,$$

which can be rearranged to yield

$$\exp\left(\frac{\ln(IC_j)}{\ln(IC_i)}\right) = \frac{ic_j}{ic_i} \cdot \frac{u_i}{u_j},$$

$$\Rightarrow \ln(IC_j) = \ln(IC_i) + \big(\ln(ic_j) - \ln(ic_i)\big) - \big(\ln(u_j) - \ln(u_i)\big). \qquad (17)$$

Letting $\ln(IC)$ be the intercept for the incarceration-related expression, the latter two terms of (17) comprise our adjustment. In practice, we calculate ic and u by averaging across all sample periods, and we estimate ic as the average probability of criminal record, which is somewhat less noisy than incarceration itself. A further complication is that for white men and black women with a college degree, and white women with a high school degree, the fraction of individuals with a criminal record is very low, 0.03% or less. In these cases, we have a second layer of imputation, for the fraction ic itself. Black female college graduates are assigned the criminal record fraction observed for black female high school graduates; white female high school graduates are assigned the fraction for white female college graduates; and white male college graduates are given the fraction for white men with some college, scaled downward using the fractions observed for black men. All of these imputations are admittedly *ad hoc*, but the groups to which they are applied have very low rates of incarceration, implying that the imputations have small quantitative effects.

One final complication is that at the baseline estimates for white men with some college education and black men with college degrees, older men cycle between nonemployment and the bottom earnings decile on annual basis. Because the NLSY79 switches to a biennial frequency after 1994, such behavior is consistent with the data, as individuals have a high probability of returning to their initial state two years later. To prevent such behavior, we either set a time trend coefficient to zero, or use estimates from a local maximum where the time trend is small.

Table F.1: Parameter Estimates, Men

	Black Men								White Men							
	Less than HS		HS Diploma		Some College		Bachelors +		Less than HS		HS Diploma		Some College		Bachelors +	
	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)
Probability of a Positive Latent Earnings Ability State Next Year																
Constant	2.26	1.30	2.53	1.29	1.88	1.74	4.01	2.15	2.94	1.08	3.45	1.16	2.80	0.97	1.86	0.82
Age	-0.03	0.07	0.01	0.07	0.01	0.09	-0.10	0.13	0.01	0.06	-0.06	0.06	-0.05	0.05	0.01	0.05
Age²/100	0.00	0.09	-0.11	0.08	-0.08	0.11	0.09	0.17	-0.08	0.07	0.00	0.08	0.02	0.07	-0.01	0.07
Not employed	-1.18	0.74	-4.44	0.78	-3.30	0.78	-2.97	0.46	-2.54	0.66	-2.96	0.59	-1.44	0.47	0.02	0.29
Not employed x age	-0.05	0.02	0.03	0.02	0.02	0.02	0.00	NA	-0.04	0.02	-0.03	0.01	-0.03	0.01	-0.08	0.01
$\bar{p}$	6.06	1.22	7.62	1.25	11.11	1.67	9.17	2.34	3.35	1.07	12.38	1.32	11.90	1.30	8.97	1.05
$\bar{p}^2$	-1.38	1.40	-4.49	1.33	-8.04	1.78	-7.64	2.12	-0.38	1.05	-9.15	1.32	-9.22	1.39	-7.18	1.09
In jail	-0.30	0.41	-0.79	0.52	-1.03	0.59	7.85	3.6e05	0.10	0.55	-2.27	1.04	-1.17	2.12	-1.17	NA
Criminal record	0.34	0.16	0.20	0.18	-0.01	0.23	-0.40	1.4e02	-0.22	0.12	0.30	0.67	-0.32	0.33	-0.32	NA
Probability of Incarceration Next Period																
Constant	1.52	1.45	-1.83	1.99	0.74	3.59	0.00	2.0e02	0.02	1.27	0.35	13.19	0.06	12.40	-0.95	NA
Age	-0.09	0.08	0.11	0.11	-0.10	0.21	-0.14	10.34	0.01	0.07	-0.12	0.76	-0.11	0.74	-0.11	NA
Age²/100	0.03	0.11	-0.25	0.14	0.04	0.28	0.20	12.34	-0.07	0.09	0.07	1.01	0.04	1.11	0.04	NA
Not employed	-2.84	0.53	-3.17	0.65	-1.99	0.69	-6.34	5.8e02	-4.00	0.54	-1.63	1.24	-1.56	1.88	-1.56	NA
$\bar{p}$	1.24	0.64	0.06	0.67	0.79	1.53	-2.51	1.2e02	-1.32	0.59	0.01	1.55	-0.11	6.29	-0.11	NA
In jail	1.28	0.40	1.53	0.44	1.66	0.53	12.19	3.6e05	2.50	0.49	2.21	1.33	2.99	2.24	2.99	NA
Criminal record	2.25	0.17	1.93	0.21	2.47	0.37	0.35	2.5e02	1.56	0.14	2.79	1.27	2.11	0.79	2.11	NA
Latent Earnings Decile, Kumaraswamy Parameter α																
Constant	-1.65	0.37	-1.71	0.32	-2.83	0.34	-2.79	0.43	-1.09	0.21	1.13	0.13	-3.02	0.15	-4.66	0.13
Age	0.06	0.02	0.07	0.01	0.12	0.02	0.12	0.02	0.04	0.01	0.00	0.00	0.11	0.01	0.17	0.01
Age²/100	-0.06	0.02	-0.06	0.02	-0.11	0.02	-0.11	0.02	-0.03	0.01	0.00	0.01	-0.07	0.01	-0.13	0.01
Not employed	-0.79	0.47	-0.92	0.36	-1.36	0.65	-2.97	1.19	-0.36	0.20	-3.02	0.46	-4.48	3.35	-2.05	0.65
$\bar{p}$	6.51	0.98	5.90	0.86	6.52	0.98	5.47	1.22	5.94	0.59	2.55	0.34	9.27	0.44	9.47	0.47
$\bar{p} \times$ age	0.02	0.02	0.02	0.02	0.00	0.02	0.01	0.03	0.03	0.02	0.04	0.01	-0.06	0.01	-0.04	0.01
$\bar{p}^2$	-5.01	0.98	-4.24	0.86	-4.13	0.98	-3.38	1.32	-3.25	0.61	-0.73	0.29	-6.26	0.48	-6.84	0.50
$\bar{p}^2 \times$ age	0.00	0.03	0.00	0.02	0.00	0.02	0.00	0.03	-0.03	0.02	-0.03	0.01	0.05	0.01	0.04	0.01
Criminal record	0.02	0.03	-0.03	0.04	0.08	0.05	0.07	36.90	-0.08	0.03	-0.01	0.06	0.12	0.16	0.12	NA
Latent Earnings Decile, Kumaraswamy Parameter β																
Constant	0.26	0.37	-0.04	0.96	-2.58	1.09	-1.70	1.33	1.27	0.61	8.48	1.04	-3.85	0.53	1.20	0.37
Age	0.02	0.05	0.05	0.05	0.15	0.06	0.13	0.08	0.00	0.03	0.00	0.04	0.14	0.03	-0.12	0.02
Age²/100	0.00	0.07	-0.02	0.07	-0.11	0.09	-0.11	0.09	0.01	0.05	0.03	0.05	0.06	0.05	0.26	0.04
Not employed	-0.51	0.36	-1.51	0.33	-0.92	0.44	-2.75	0.56	-0.89	0.20	-9.31	0.69	-0.99	0.57	-0.72	0.23
$\bar{p}$	-3.28	3.20	-4.94	2.96	-6.13	3.60	-18.01	3.82	-5.79	2.40	-7.34	3.23	3.21	2.25	-28.95	1.45
$\bar{p} \times$ age	0.67	0.10	0.63	0.10	0.79	0.12	1.10	0.14	0.83	0.07	0.60	0.08	0.59	0.07	1.64	0.05
$\bar{p}^2$	1.64	3.37	3.73	3.06	6.90	3.72	18.21	4.07	5.30	2.62	0.00	2.97	0.94	2.31	31.34	1.61
$\bar{p}^2 \times$ age	-0.72	0.10	-0.70	0.10	-0.90	0.12	-1.20	0.14	-0.90	0.07	-0.67	0.08	-0.83	0.07	-1.80	0.06
Criminal record	-0.01	0.12	-0.21	0.16	0.55	0.27	0.65	2.2e02	-0.42	0.14	-0.07	0.55	0.62	1.16	0.62	NA
Probability that Individual Is Interviewed																
Constant	2.24	1.04	2.53	1.02	4.25	1.32	5.57	2.40	2.45	0.62	2.20	0.74	3.01	0.94	3.91	0.93
Age	-0.12	0.06	-0.14	0.06	-0.23	0.07	-0.34	0.13	-0.13	0.03	-0.16	0.04	-0.21	0.05	-0.25	0.05
Age²/100	0.12	0.07	0.14	0.07	0.24	0.10	0.44	0.16	0.12	0.04	0.15	0.05	0.23	0.07	0.27	0.07
Not employed	0.25	0.19	0.05	0.17	-0.32	0.27	-1.95	0.31	0.44	0.17	-1.06	0.14	-1.05	0.18	-1.44	0.17
Criminal record	0.01	0.09	0.00	0.17	0.06	0.19	0.38	99.19	0.13	0.08	0.00	0.38	0.39	1.28	0.39	NA
Observed prior wave	3.50	0.07	3.59	0.06	3.57	0.09	4.33	0.15	3.55	0.04	4.55	0.04	4.58	0.05	4.80	0.05

Table F.1: Parameter Estimates, Men (continued)

	Black Men								White Men							
	Less than HS		HS Diploma		Some College		Bachelors +		Less than HS		HS Diploma		Some College		Bachelors +	
	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)
Probability that Latent Working State Generates Positive Earnings																
Constant	2.22	1.17	0.29	1.08	-5.83	2.41	-4.88	2.22	4.10	1.16	-0.01	1.23	13.71	5.75	19.84	8.61
Age	-0.16	0.06	-0.08	0.06	0.23	0.12	0.28	0.15	-0.26	0.07	0.04	0.06	-0.51	0.21	-0.67	0.28
Age^2/100	0.28	0.08	0.29	0.09	0.24	0.16	-0.23	0.25	0.44	0.10	0.10	0.08	0.69	0.21	0.77	0.24
$\bar{p}$	13.10	4.68	28.07	4.88	50.00	10.33	29.44	12.80	24.79	4.86	30.25	5.14	0.00	16.00	-0.02	24.37
$\bar{p}\times$ age	-0.25	0.13	-0.73	0.15	-1.67	0.37	-0.60	0.31	-0.50	0.14	-0.73	0.15	-0.01	0.44	-0.05	0.58
$\bar{p}^2$	-5.87	5.19	-20.85	5.50	-41.08	10.19	-20.09	13.28	-19.66	5.33	-25.71	4.94	0.09	12.55	0.00	18.86
$\bar{p}^2\times$ age	0.14	0.14	0.63	0.16	1.42	0.34	0.40	0.29	0.46	0.15	0.64	0.14	-0.01	0.34	0.00	0.45
Criminal record	-0.82	0.13	-0.59	0.23	-0.73	0.57	-1.82	2.2e02	-0.58	0.13	-0.43	1.29	-1.14	2.21	-1.14	NA
Distribution of Observed Earnings, Dispersion Parameter σ																
Constant	17.96	19.30	-17.26	12.95	0.00	15.75	-0.02	24.24	3.57	6.47	18.10	4.73	-39.38	2.84	-0.01	2.93
Age	1.86	0.66	2.41	0.43	2.22	0.53	-2.59	0.82	1.50	0.23	1.14	0.17	2.80	0.14	1.03	0.15
Age^2/100	-0.78	0.40	-1.06	0.25	-1.17	0.42	3.25	0.65	0.73	0.23	1.25	0.14	-1.72	0.19	-3.26	0.20
$\bar{p}$	-33.73	71.39	25.00	49.58	-2.73	60.47	50.00	88.06	0.30	30.54	-39.51	23.11	-12.11	22.78	-3.09	18.73
$\bar{p}\times$ age	-7.08	2.22	-6.01	1.54	-5.99	1.79	3.06	2.48	-10.49	0.98	-11.22	0.72	-9.63	0.77	7.22	0.49
$\bar{p}^2$	0.00	68.60	7.92	47.42	0.00	60.19	29.48	85.71	5.94	32.11	50.00	22.95	50.00	29.49	-50.00	19.88
$\bar{p}^2\times$ age	8.07	2.17	5.18	1.46	6.22	1.79	-5.93	2.48	11.23	1.03	11.09	0.72	11.20	0.99	-6.68	0.51
Criminal record	-9.31	0.97	-4.27	0.89	-22.93	1.61	1.54	1.9e03	2.27	0.80	-11.55	2.26	-22.59	9.63	-22.59	NA
Initial Distribution																
Working	1.82	0.25	3.22	0.38	3.12	0.92	3.83	1.1e02	2.76	0.21	3.71	0.35	3.15	0.26	2.15	0.12
In jail	-0.37	0.28	-0.68	0.56	-0.81	4.59	-0.51	2.5e02	-0.57	0.28	-3.58	83.88	-2.80	8.05	-3.81	NA
Kumaraswamy α	0.12	0.12	0.22	0.10	0.25	0.12	-0.13	0.35	0.26	0.07	0.28	0.14	-0.37	0.14	-0.83	0.12
Kumaraswamy β	0.23	0.13	0.50	0.10	0.60	0.13	0.96	0.66	0.30	0.07	0.27	0.09	-0.04	0.10	0.35	0.09
Probability of a Criminal Record, Initial Distribution																
Constant	-1.25	0.69	-2.20	1.25	-2.86	1.41	-6.01	2.3e02	-2.19	0.51	-3.13	6.1e03	-14.10	24.83	-15.12	NA
Not employed	-6.36	1.73e02	-0.73	1.96	-4.02	727.76	4.10	6.4e02	0.32	0.93	0.00	6.1e03	10.53	25.17	10.53	NA
In jail	1.25	0.79	1.76	1.63	10.70	9.60e03	4.46	1.2e03	2.45	0.69	0.00	4.7e03	16.68	33.92	16.68	NA
$\bar{p}$	-4.04	2.03	-7.52	6.19	-3.05	3.39	0.00	1.8e03	-3.35	1.19	-50.00	1.2e05	10.89	27.67	10.89	NA

Note: "NA" indicates that the coefficient in question was not estimated, but was based on coefficients for another race-gender-education group. "NaN" indicates that numerical gradients could not be calculated. Coefficients bounded by ± 50.
†Coefficient fixed at zero.

Table F.2: Parameter Estimates, Women

	Black Women								White Women							
	Less than HS		HS Diploma		Some College		Bachelors +		Less than HS		HS Diploma		Some College		Bachelors +	
	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)
Probability of a Positive Latent Earnings Ability State Next Year																
Constant	-4.44	1.46	-0.80	1.02	-0.11	1.71	2.58	0.97	-1.21	0.63	-0.78	0.49	1.77	0.67	4.70	0.60
Age	0.28	0.08	0.12	0.05	0.05	0.12	-0.05	0.05	0.11	0.03	0.10	0.03	0.01	0.04	-0.16	0.03
Age^2/100	-0.37	0.10	-0.17	0.07	-0.08	0.16	0.03	0.07	-0.15	0.05	-0.14	0.04	-0.03	0.05	0.20	0.04
Not employed	0.55	1.02	-1.06	0.64	-0.73	0.41	-1.94	0.54	-0.21	0.37	-1.24	0.27	-2.76	0.37	-2.55	0.31
Not employed x age	-0.10	0.02	-0.05	0.02	-0.04	0.01	-0.01	0.01	-0.06	0.01	-0.04	0.01	-0.01	0.01	-0.02	0.01
$\bar{p}$	9.65	2.66	8.44	1.35	10.03	1.20	9.61	1.23	5.71	0.67	7.69	0.54	8.09	0.79	8.09	0.60
$\bar{p}^2$	-7.20	2.60	-5.55	1.42	-7.25	1.29	-6.85	1.49	-2.90	0.67	-5.35	0.54	-6.08	0.84	-6.30	0.64
In jail	-0.91	6.57	-1.78	NA	-1.78	3.7e02	-1.78	NA	-1.27	4.05	-1.27	NA	-1.27	NA	-1.27	NA
Criminal record	0.40	0.57	0.39	NA	0.39	20.17	0.39	NA	-0.62	0.61	-0.62	NA	-0.62	NA	-0.62	NA
Probability of Incarceration Next Period																
Constant	-7.57	17.64	-12.82	NA	-12.01	3.9e02	-12.03	NA	-11.60	22.95	-12.79	NA	-12.49	NA	-12.28	NA
Age	0.31	1.16	0.45	NA	0.45	19.38	0.45	NA	0.42	1.50	0.42	NA	0.42	NA	0.42	NA
Age^2/100	-0.49	2.15	-0.63	NA	-0.63	25.58	-0.63	NA	-0.67	2.08	-0.67	NA	-0.67	NA	-0.67	NA
Not employed	-3.44	11.18	-2.18	NA	-2.18	1.2e02	-2.18	NA	-0.56	5.78	-0.56	NA	-0.56	NA	-0.56	NA
$\bar{p}$	-2.13	20.44	-5.73	NA	-5.73	7.3e02	-5.73	NA	-0.15	7.84	-0.15	NA	-0.15	NA	-0.15	NA
In jail	2.74	4.32	0.25	NA	0.25	6.1e02	0.25	NA	-18.49	1.1e09	-18.49	NA	-18.49	NA	-18.49	NA
Criminal record	2.19	2.77	3.87	NA	3.87	1.7e02	3.87	NA	3.88	2.26	3.88	NA	3.88	NA	3.88	NA
Latent Earnings Decile, Kumaraswamy Parameter α																
Constant	0.27	0.63	-1.81	0.29	-2.31	0.31	-2.26	0.22	-0.63	0.33	-1.25	0.15	-2.57	0.16	-2.29	0.12
Age	0.05	0.03	0.06	0.01	0.07	0.01	0.10	0.01	0.01	0.01	0.04	0.01	0.08	0.01	0.10	0.01
Age^2/100	-0.09	0.04	-0.03	0.02	-0.05	0.01	-0.10	0.01	-0.05	0.01	-0.03	0.01	-0.08	0.01	-0.10	0.01
Not employed	-2.58	1.07	-0.70	0.34	-1.15	0.35	-1.95	0.47	-1.40	0.56	-2.31	0.32	-6.24	2.72	-1.67	0.22
$\bar{p}$	-8.14	2.25	7.29	0.95	7.45	1.06	3.00	0.80	0.17	1.24	6.34	0.41	6.09	0.60	2.78	0.37
$\bar{p}\times$ age	0.15	0.06	0.00	0.02	0.00	0.02	0.09	0.02	0.23	0.03	0.01	0.01	0.04	0.01	0.10	0.01
$\bar{p}^2$	10.55	2.25	-3.88	1.03	-4.59	1.05	0.00	0.93	0.94	1.21	-4.78	0.41	-3.86	0.63	-0.01	0.40
$\bar{p}^2 \times$ age	-0.11	0.06	-0.01	0.03	0.00	0.02	-0.10	0.02	-0.19	0.03	0.01	0.01	-0.03	0.02	-0.10	0.01
Criminal record	-0.83	2.7e05	0.01	NA	0.01	1.3e05	0.01	NA	-0.34	0.48	-0.34	NA	-0.34	NA	-0.34	NA
Latent Earnings Decile, Kumaraswamy Parameter β																
Constant	2.88	1.30	0.47	0.83	0.03	0.75	-0.88	0.80	3.75	0.66	2.14	0.41	-0.50	0.37	-2.18	0.33
Age	0.05	0.06	-0.02	0.05	-0.01	0.04	0.10	0.05	-0.18	0.03	-0.07	0.02	0.06	0.02	0.15	0.02
Age^2/100	-0.10	0.09	0.09	0.07	0.06	0.06	-0.11	0.06	0.18	0.04	0.10	0.03	-0.06	0.03	-0.16	0.03
Not employed	-3.34	0.85	-0.25	0.27	-0.12	0.25	-1.32	0.25	0.04	0.24	-1.31	0.13	-1.90	0.36	-1.39	0.13
$\bar{p}$	-16.74	4.75	-0.33	4.15	-7.57	2.94	-18.77	2.58	-16.26	2.51	-2.89	1.36	-8.07	1.20	-16.45	1.12
$\bar{p}\times$ age	0.24	0.12	0.70	0.11	0.89	0.09	1.08	0.08	1.04	0.08	0.63	0.04	0.65	0.04	0.99	0.04
$\bar{p}^2$	13.98	5.25	1.54	4.59	8.11	3.18	20.71	2.99	14.63	2.65	0.03	1.48	8.36	1.32	18.74	1.21
$\bar{p}^2 \times$ age	-0.12	0.13	-0.81	0.12	-0.98	0.09	-1.21	0.09	-1.06	0.08	-0.63	0.05	-0.74	0.04	-1.14	0.04
Criminal record	2.51	5.0e05	7.94	NA	7.94	1.7e06	7.94	NA	-0.08	2.56	-0.08	NA	-0.08	NA	-0.08	NA
Probability that Individual Is Interviewed																
Constant	2.66	1.38	4.83	1.63	2.42	1.25	3.86	1.70	4.03	1.00	2.44	0.66	2.26	0.94	2.06	0.76
Age	-0.15	0.07	-0.28	0.09	-0.15	0.07	-0.22	0.09	-0.19	0.05	-0.16	0.04	-0.16	0.05	-0.14	0.04
Age^2/100	0.16	0.09	0.32	0.11	0.16	0.09	0.25	0.12	0.18	0.06	0.15	0.05	0.15	0.07	0.13	0.05
Not employed	0.04	0.23	-0.31	0.19	-0.16	0.22	-0.23	0.30	-0.27	0.11	-0.48	0.10	-0.20	0.17	-0.59	0.12
Criminal record	0.49	4.86	1.78	NA	1.78	3.6e02	1.78	NA	1.87	6.39	1.87	NA	1.87	NA	1.87	NA
Observed prior wave	4.13	0.10	4.46	0.08	4.19	0.07	4.18	0.08	3.95	0.05	4.59	0.04	4.70	0.05	4.91	0.05

67

Table F.2: Parameter Estimates, Women (continued)

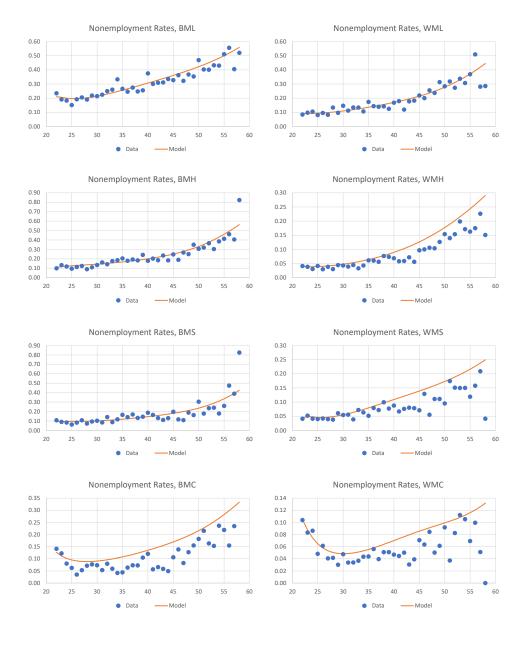|	Black Women								White Women							
	Less than HS		HS Diploma		Some College		Bachelors +		Less than HS		HS Diploma		Some College		Bachelors +	
	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)	coeff.	(s.e)
Probability that Latent Working State Generates Positive Earnings																
Constant	-3.78	1.68	-2.36	1.21	3.49	2.28	-1.57	3.07	-3.23	1.22	-1.21	0.99	4.69	1.44	4.18	1.23
Age	0.02	0.08	0.07	0.07	-0.12	0.10	0.00	0.19	-0.01	0.06	-0.06	0.06	-0.39	0.11	-0.28	0.09
Age^2/100	0.14	0.11	0.02	0.10	0.33	0.13	0.58	0.32	0.48	0.11	0.36	0.09	0.81	0.20	0.65	0.16
$\bar{p}$	24.04	8.40	26.92	5.96	16.34	9.07	50.00	16.77	31.93	5.34	35.01	3.54	46.71	9.39	30.25	5.73
$\bar{p}\times$ age	-0.45	0.23	-0.51	0.16	-0.56	0.25	-1.64	0.55	-1.09	0.17	-0.83	0.11	-1.04	0.26	-0.71	0.17
$\bar{p}^2$	-13.95	9.50	-19.61	6.29	-9.89	8.66	-39.38	16.46	-16.23	5.68	-23.75	3.62	-36.56	9.14	-17.76	5.57
$\bar{p}^2\times$ age	0.29	0.25	0.39	0.16	0.40	0.23	1.29	0.52	0.74	0.16	0.59	0.10	0.82	0.25	0.41	0.15
Criminal record	1.69	6.36	3.76	NA	3.76	4.6e04	3.76	NA	0.72	17.00	0.72	NA	0.72	NA	0.72	NA
Distribution of Observed Earnings, Dispersion Parameter σ																
Constant	28.19	25.41	7.50	11.98	5.61	5.57	39.08	19.14	44.34	9.84	7.67	10.17	-2.82	3.85	-0.38	15.50
Age	0.93	0.85	1.71	0.42	0.85	0.22	1.04	0.60	-1.44	0.40	1.47	0.35	-0.80	0.17	-2.90	0.49
Age^2/100	-0.81	0.70	0.85	0.32	0.15	0.23	-0.04	0.40	1.42	0.42	0.63	0.22	0.36	0.21	-0.47	0.24
$\bar{p}$	0.23	81.13	3.08	60.24	-47.75	39.18	-50.00	72.88	-50.00	32.67	1.63	39.57	50.00	26.20	-35.80	59.96
$\bar{p}\times$ age	-6.18	2.12	-13.18	1.87	-8.52	1.24	-5.85	2.13	3.03	0.87	-6.94	1.26	4.80	0.77	11.82	1.84
$\bar{p}^2$	0.05	74.48	-0.24	66.25	50.00	49.46	0.01	73.60	-38.69	37.26	50.00	39.76	50.00	29.07	0.28	57.47
$\bar{p}^2\times$ age	6.26	1.97	14.61	2.06	10.86	1.55	7.37	2.20	-2.80	1.01	5.92	1.26	-5.82	0.79	-10.62	1.76
Criminal record	-43.54	5.00	-32.07	NA	-32.07	1.4e02	-32.07	NA	-30.41	64.83	-30.41	NA	-30.41	NA	-30.41	NA
Initial Distribution																
Working	0.54	0.33	1.19	0.20	1.22	0.25	1.81	0.27	1.26	0.28	2.11	0.13	2.84	0.24	3.21	0.24
In jail	-46.21	NaN	-11.23	NA	-10.42	4.3e04	-10.44	NA	-11.45	2.4e04	-12.64	NA	-12.34	NA	-12.13	NA
Kumaraswamy α	-0.01	0.26	-0.07	0.16	-0.44	0.19	-0.06	0.11	-0.09	0.21	0.22	0.06	-0.36	0.09	-0.41	0.06
Kumaraswamy β	0.81	0.26	0.32	0.15	0.22	0.12	1.24	0.18	0.25	0.12	0.42	0.05	0.24	0.07	0.73	0.06
Probability of a Criminal Record, Initial Distribution																
Constant	-24.10	6.3e07	-22.17	NA	-21.36	41.28	-21.38	NA	-4.05	41.28	-5.24	NA	-4.93	NA	-4.73	NA
Not employed	-0.16	NaN	-0.62	NA	-0.62	57.54	-0.62	NA	-0.28	57.54	-0.28	NA	-0.28	NA	-0.28	NA
In jail	-21.71	NaN	-27.20	NA	-27.20	NaN	-27.20	NA	-15.88	NaN	-15.88	NA	-15.88	NA	-15.88	NA
$\bar{p}$	0.61	NaN	-0.46	NA	-0.46	2.0e02	-0.46	NA	-5.33	2.0e02	-5.33	NA	-5.33	NA	-5.33	NA

Note: "NA" indicates that the coefficient in question was not estimated, but was based on coefficients for another race-gender-education group. "NaN" indicates that numerical gradients could not be calculated. Coefficients bounded by ± 50.

G   Model Fits and Observation Bias

This appendix gives the model fits for incarceration (Figure G.1) and nonemployment (Figure G.2), as well as the bias induced by conditioning on observed outcomes (Figure G.3).

Figure G.1: Incarceration Rates, Model and Data, Men

Figure G.2: Nonemployment Rates, Model and Data, Men

Figure G.3: Model-predicted Incarceration and Nonemployment Rates, with and without Observation Bias, Men

H Decomposition Analysis, Details

This appendix provides the numbers underlying the decomposition exercise in Section 6.

Table H.1: Summary statistics by race and education, decomposition exercises

Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Benchmark								
Lifetime earnings avg.	189	346	306	506	378	561	631	950
Lifetime earnings p10	28	98	83	193	125	220	256	387
Lifetime earnings p50	151	335	270	501	353	539	567	819
Lifetime earnings p90	417	629	598	835	670	994	1142	1912
Expected years E	21.3	27.8	26.4	31.9	28.6	31.7	30.3	33.1
Expected years J	3.2	1.3	1.1	0.1	1.2	0.2	0.2	0.0
Expected years N	11.5	7.0	8.5	4.0	6.2	4.1	5.6	2.9
Ever-J rate, old	0.44	0.23	0.24	0.03	0.17	0.05	0.06	0.02
Earnings bin values switched across races								
Lifetime earnings avg.	236	279	402	386	465	456	871	683
Lifetime earnings p10	38	75	116	140	158	175	342	288
Lifetime earnings p50	190	272	357	380	436	437	770	598
Lifetime earnings p90	516	504	776	647	820	806	1618	1329
Expected years E	21.3	27.8	26.4	31.9	28.6	31.7	30.3	33.1
Expected years J	3.2	1.3	1.1	0.1	1.2	0.2	0.2	0.0
Expected years N	11.5	7.0	8.5	4.0	6.2	4.1	5.6	2.9
Ever-J rate, old	0.44	0.23	0.24	0.03	0.17	0.05	0.06	0.02
Earnings shocks switched across races								
Lifetime earnings avg.	279	236	386	402	456	465	683	871
Lifetime earnings p10	75	38	140	116	175	157	288	342
Lifetime earnings p50	272	190	380	357	437	436	598	770
Lifetime earnings p90	504	515	647	775	806	819	1328	1618
Expected years E	27.8	21.3	31.9	26.4	31.7	28.6	33.1	30.3
Expected years J	1.3	3.2	0.1	1.1	0.2	1.2	0.0	0.2
Expected years N	7.0	11.5	4.0	8.5	4.1	6.2	2.9	5.6
Ever-J rate, old	0.23	0.44	0.03	0.24	0.05	0.17	0.02	0.06

Note: [B,W][M,F][L,H,S,C] denote black/white, male/female, less than high school/high school/some college/college graduate; E means employed; J means jailed or incarcerated; N means nonemployed; earnings are pre-tax thousands of 1982-1984 dollars.