Incarceration, Employment, and Earnings: Dynamics and Differences*

Grey Gordon† John Bailey Jones‡ Urvi Neelakantan§
Kartik Athreya¶

September 22, 2022

Abstract

We study the dynamics of incarceration, employment, and earnings. Our hidden Markov model distinguishes between first-time and repeat incarceration, between persistent and transitory nonemployment and earnings risks, and accounts for nonresponse bias. We estimate the model via maximum likelihood using the National Longitudinal Survey of Youth 1979, accounting for the large differences in incarceration rates by race, education level, and gender. First-time incarceration is associated with 32% (51%) lower expected lifetime earnings and 6 (10) fewer years of employment for Black (White) men with a high school degree. Among less-educated men, differences in incarceration and nonemployment can explain around half the Black-White lifetime earnings gap.

Keywords: earnings dynamics, incarceration, racial inequality
JEL Codes: C23, D31, J15

*This paper was previously circulated under the title "Incarceration, Earnings, and Race." We are grateful to Amanda Michaud and Abigail Wozniak for helpful comments and to Thomas Lubik and Mark Watson for early guidance. Emily Emick and Luna Shen provided excellent research assistance. This research was supported in part through computational resources provided by the BigTex High Performance Computing Group at the Federal Reserve Bank of Dallas. The views expressed here are those of the authors and should not be interpreted as reflecting the views of the Federal Reserve Bank of Richmond or the Federal Reserve System.

†Federal Reserve Bank of Richmond
‡Federal Reserve Bank of Richmond
§Federal Reserve Bank of Richmond
¶Federal Reserve Bank of Richmond

1 Introduction

The United States has the world's largest prison population and highest incarceration rate (Institute for Crime & Justice Policy Research, 2018). Between 1980 and 2016, the incarceration rate rose from 0.22% to 0.67% (Bureau of Justice Statistics, 2021). Incarcerees are disproportionately male, Black, and less educated. Within certain groups, incarceration is now pervasive: among Black male high school dropouts born between 1975 and 1979, 68% had been incarcerated at least once (Western and Pettit, 2010, Table 1).

Despite the growth in incarceration and its prevalence among certain demographic groups, much remains unknown about the relationship between incarceration, employment, and earnings.[1] Our goals in this paper are to (1) quantify the dynamic relationship between incarceration, employment, and earnings across demographic groups and (2) measure the contribution of incarceration and other forms of nonemployment to the earnings gap between Black and White men.[2] In doing so, we offer a framework that can be used to study the earnings dynamics of people with varied employment patterns—women, Black men, and irregularly-employed White men—who have received relatively little attention in the literature on earnings dynamics.

We estimate a statistical model of incarceration, employment, and earnings over the life cycle, using a flexible specification 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 long-lasting responses to episodes of incarceration. Transition probabilities depend on age, gender, race, education, and previous incarceration. Individuals in each race-gender-education group are further divided into two permanent parameter types. 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.[3]

Our estimates show that individuals—at least through the eyes of the econometrician—face enormous income risk from incarceration and long-term nonemployment. We

[1] 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."

[2] 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.

[3] Indeed, we find that White men who are nonemployed are less likely to be observed.

estimate that the lifetime earnings of a 22-year-old Black (White) male high-school graduate who has experienced first-time incarceration are $101,000 ($258,000) or 32% (51%) lower than for one who has not. For those without a high school diploma, the corresponding numbers are $105,000 and $171,000, amounting to 56% and 49% gaps for Black and White men, respectively. The large lifetime differences follow from essentially permanent reductions in flow earnings after an incarceration spell. The earnings differences from a transition to persistent nonemployment are also significant, and comparable to those from incarceration. The lifetime earnings of Black (White) male high school graduates who transition to persistent nonemployment are $118,000 ($134,000) lower than the earnings of those who do not.

Although the earnings differences for those with a history of incarceration and nonemployment are stark for both Black and White men, the *incidence* of carceral episodes differs markedly. For high school graduates, our estimates indicate that while 21% of Black men will eventually be incarcerated, only 3% of White men will. 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 8.2 years of nonemployment, 4.2 years more than White men.

To summarize, the likelihood of nonemployment and incarceration is far higher for Black men than for their White counterparts, while the expected fall in earnings is smaller. What, then, is the contribution of these forces to the lifetime earnings gap between Black and White men?[4] One way we answer this question is by eliminating incarceration and/or nonemployment and recalculating the gap.[5] In the baseline, White male high school graduates earn 58% more than Black male high school graduates over their lifetimes. Eliminating incarceration alone would reduce this to 53%, while eliminating nonemployment alone would reduce it to 39%. If both incarceration and nonemployment were ruled out of the stochastic process, the lifetime earnings of White male high school graduates would exceed those of Black males by 32%. Alternatively, a formal decomposition suggests that 41% of the lifetime earnings gap for high school graduates is associated with nonemployment and/or incarceration. This fraction is higher (63%) for high school dropouts and lower (15%) for college graduates.

Finally, our work offers a methodological innovation in the form of a rich yet rela-

[4]We focus on male high school graduates, but similar patterns hold across education levels.

[5]Eliminating incarceration would, presumably, have profound implications for the structure of wages and, indeed, society in general. When making our calculations, we ignore any such general equilibrium effects. Our goal is simply to estimate how, all else equal, predicted earnings would change statistically if incarceration or nonemployment were no longer states.

tively tractable framework for earnings processes. Our framework incorporates nonemployment, incarceration, and positive earnings, imposes few distributional assumptions, and builds on a well-established statistical literature. Whenever incarceration, or more generally any discrete outcome, is important for understanding earnings, our framework provides a flexible way to account for it. It produces an earnings process, expressed in terms of transition matrices, that fits easily in many quantitative analyses.

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 an incarceration 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 an incarceration record can fill. Moreover, consistent with the first two mechanisms, an incarceration 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 approaches. 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, in addition to having two permanent unobserved types, we condition on education, gender, race, and an individual's incarceration and earnings history. These studies generally find that incarceration depresses subsequent labor market outcomes. Among studies using administrative data, a popular strategy is to 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 there being causal effects of incarceration (Travis et al., 2014, Table 8-2).

[6] We use "incarceration record" to mean a record that includes time spent in jail or prison.

Like most models of earnings processes, our framework is statistical, and episodes of incarceration therein are not necessarily 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. We also allow for permanent unobserved parameter heterogeneity, introducing the possibility that individuals "inclined" toward incarceration have poorer lifetime earnings prospects. Finally, 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 differ 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 that follow incarceration. To our knowledge, our analysis is the first of its type.

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). Within these models, incarceration depresses earnings in various ways. For example, Guler and Michaud (2018) assume that incarceration leads to human capital depreciation and a higher proclivity for crime. Because our model is statistical, its parameters cannot be interpreted as the structural parameters of a household decision problem. On the other hand, taking a statistical approach allows us to utilize a far more flexible specification, with weaker distributional assumptions and 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 earnings among male *workers* has in fact narrowed considerably.[7] As the growth of the employment gap has coincided with the surge in incarceration, it is natural to ask whether the two are related, if only in a statistical sense.

[7] 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.

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 contributes 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. In this and other respects, our estimates generalize the process for wages, unemployment, and incarceration used by Caucutt et al. (2021) in their study of marriage markets.[8]

We also make a methodological contribution to the literature on earnings processes. 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. Section 2 introduces our statistical model, and Section 3 describes the data. We interpret our parameter estimates in Section 4. In Section 5, we discuss the model's implications for employment, incarceration, and earnings over the life-cycle and calculate the changes in lifetime earnings and employment following an episode of incarceration. In Section 6, we assess the

[8] Caucutt et al. (2021) estimate a Markov Chain for imprisonment, nonemployment, and wages when employed by combining data from several sources, including the Current Population Survey, the 2004 Survey of Inmates in State and Federal Correctional Facilities, and the NLSY79. Our model differs from theirs in three key ways. First, we use an explicit life-cycle framework with age-dependence, while they use a perpetual youth framework. Second, we distinguish between persistent latent states and transitory variation, while they use a standard Markov Chain. Third, we allow the probability that individuals become incarcerated to vary with their earnings potential, while they assume that all employed individuals face the same risk of imprisonment. Our framework also differs by allowing for permanent heterogeneity and nonrandom attrition.

contributions of incarceration and other forms of nonemployment to the racial gap in lifetime earnings. Section 7 concludes.

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.[9]

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.[10] These are then interacted with a $\{0, 1\}$ incarceration record flag, so $\mathbb{L}$ 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 incarceration record flag, so $\mathbb{M}$ 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. Note 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 is an effective way to model nonnormal shocks and variable persistence.[11] 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

[9]See also Farmer (2021). Bartolucci et al. (2010) provide an introduction.

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

[11]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.

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, $\mathbf{A}_x$:

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

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, education level, and unobserved permanent type (which enter semi-parametrically, as there are separate sets of parameters for each group).[12] The second 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 $\mathbf{B}_z$:

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

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 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.

2.2 Latent State Transitions

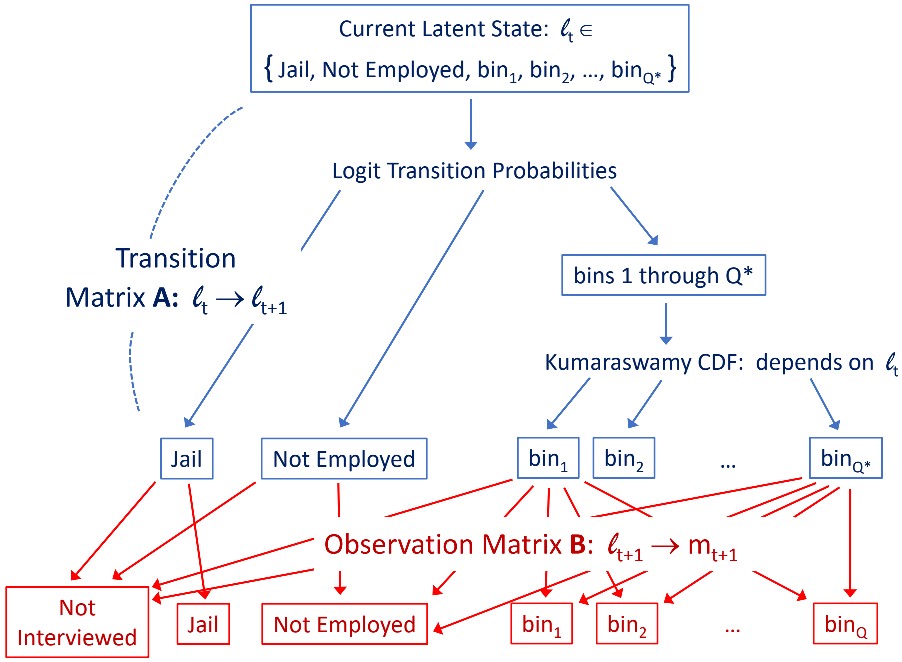
As the top half of Figure 1 shows, we populate the transition matrix $\mathbf{A}$ in two steps. First, we use a multinomial logit regression to determine the one-period-ahead probabilities of incarceration, long-term nonemployment, or potential employment (bins 1 to Q^*). We assume that an incarceration record is backward-looking and permanent: 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, $\tilde{p}_{q^*} := [p_{q^*} + p_{q^*-1}]/2$. For example, when earnings potential is 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 need not depend the number of bins.

Second, we estimate the distribution of next period's earnings potential, condi-

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

Figure 1: Earnings process transitions



tional 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 potential 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: $\alpha = \alpha(\ell_t, x_t)$ and $\beta = \beta(\ell_t, x_t)$. When the current state is the earnings potential 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 do the same. 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 show that the Kumaraswamy distribution can approximate a standard Gaussian AR(1) process quite well.

Because we use the midpoint value $\tilde{p}_{q_t^*}$ to characterize the current earnings potential 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 $\mathbf{B}$. The first step is to determine the probability that an individual is interviewed by the NLSY at time t.[13] 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 nonrandom 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 $\mathbf{A}$ and $\mathbf{B}$ 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 latent states to observed outcomes has this property.

[13]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.

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.

2.4 Initial Probabilities

We construct the initial distribution of latent states, $\mu_1(\ell_1 \mid \tilde{x}_1)$, in much the same way we found their transition probabilities. (Here, $\tilde{x}_1$ consists of race, gender, education, and the unobserved type.) 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). Finally, we estimate the probability that the individual has an incarceration record, conditional on the other latent states, using a logistic regression. The product of these two probabilities gives us our initial distribution.

2.5 Permanent Unobserved Heterogeneity

We assume that each individual belongs to one of two permanent types, which differ via seven parameters. Four of the parameters affect the latent state transition matrix $\mathbf{A}_x$. These are the two intercept terms in the first-stage logit—which determine whether the individual is incarcerated, persistently nonemployed or potentially employed—and the two intercept terms in the expressions for the Kumaraswamy parameters $\alpha(\cdot)$ and $\beta(\cdot)$ that determine the distribution of earnings potential. The fifth and sixth parameters affect the observation matrix $\mathbf{B}_z$. The fifth parameter is the intercept term in the logit determining whether an individual is observed; the types may differ in their propensity to continue participating in the NLSY79. The sixth parameter is the intercept term in the logit determining whether an individual with positive earnings potential is currently nonemployed. The seventh parameter affects the initial distribution μ_1. This is the intercept in the logit determining whether an individual enters our sample with an incarceration record. As a normalization we require that the intercept on employment in the logit equation used to populate $\mathbf{A}_x$ be smaller for the second type. The type-related differences are otherwise unrestricted.

The distribution of types for each individual n is found using a multinomial logit, the arguments of which are a constant and the log of the predicted probability $\widehat{\Pr}(n$

is ever incarcerated). We find this probability through a separate logit regression, where the probability of ever being incarcerated (in our NLSY79 sample period) is expressed as a function of the individual's AFQT quartile, mother's education, and indicators for whether the individual lived with both parents until age 18 and whether the mother was a teenager when the individual was born. Our choice of variables follows Merlo and Wolpin (2015). The incarceration probability thus indexes a set of factors that simultaneously affect incarceration risk and earnings outcomes in the absence of incarceration; exposure to these factors will, by changing the distribution of parameters, change the model's predictions. Because incarceration rates are low within certain education groups, we estimate separate sets of probabilities for the four race-sex groupings, with the individual's education level included as a control. Appendix A details our approach.

2.6 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 similar to the methodology for the regime-switching model presented in Hamilton (1994, chapter 22). Appendix A provides a detailed description. We estimate separate sets of transition and observation probabilities for each race-gender-education group, with two distinct parameter types within each group. We weight each individual's log-likelihood using the NLSY79 sampling weights for 1979.[14]

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 an incarceration record and estimate a simplified model of employment and earnings. To this set of parameters, we add incarceration-related parameters estimated for 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;[15] with a logistic formu-

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

[15]For White men and Black women with college degrees, and White women with a high school degree, the fraction of individuals in the NLSY79 who report an incarceration record is implausibly low, 0.03% or less. In these cases we impute the rates using data from other race and education groups.

lation, 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.

2.7 Quantiles and Conditional Means

To complete our model, we need to delineate earnings bins and assign a level of earnings to each. We estimate age-specific bin cutoffs for each race-gender-education group using quantile regressions. Using these cutoffs, we 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 has far more observations than the NLSY79.

3 Data

3.1 The NLSY79

Our primary source of data is the 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.[16] The NLSY79 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.

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 start our sample at age 22, which helps ensure that those who chose to attend college have entered the workforce.

We have four education categories: less than a high school diploma, high school

[16] When estimating our model from 1994 onward, we use biennial transition matrices generated by multiplying annual matrices.

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

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. 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 its 20s and into its 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, where 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 an "incarceration record," namely a personal history of at least one *previous* incarceration spell.[19] The fourth panel shows employment. The first row of this panel, which shows aggregate results, reveals that the earnings gaps 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 an incarceration record are 25-40pp lower than those of men without. There may also be incarceration-related differences in the earnings of those who work.

[18]Our focus on men is motivated by the fact that incarceration rates for women turn out to be vanishingly small. See Appendix D.

[19]Because our measure of an incarceration record is backward-looking, our estimation sample starts in 1980, allowing us to use the 1979 incarceration measure.

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								
All	479	499	322	209	781	1,016	603	838
Ever incarcerated	176	90	44	12	136	22	20	1

Note: [LTHS,HS,SC,CG] denote less than high school/high school/some college/college graduate. Statistics calculated using 1979 weights.

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 three 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 earnings quantiles, we use 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. 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 and limit observations to those aged between 22 and 66. We choose 66 as the upper limit since that is the normal Social Security retirement age for the NLSY79 cohort. After applying these restrictions, around 3 million individuals remain. We define earnings 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.[20] 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.

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:

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

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

We use the results of Equation (4) to predict the decile cutoffs 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 cutoffs 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

[20]The CPS elicits income information for the year prior to the survey year.

through these age-specific means. We use this to construct life-cycle profiles of within-decile mean earnings for our cohort of interest. Figures E.3 and 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. We instead highlight one of the implied transition matrices (**A**) and observation matrices (**B**).

4.1 Latent Transition Matrices

We focus our discussion of the transition matrices on Black men without a high school degree, where the dynamics of incarceration are easiest to see, but all race and education groups display similar patterns. Table 2 present the latent state transition probabilities for a 25-year-old Black man. Rows index the current state ℓ_t, while columns index the future state ℓ_{t+1}.[21] We show results for unobserved type 2, which is the most common type among Black men without a high school degree.

The first general pattern 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 with no incarceration history (IR=0) in the bottom decile of the earnings-potential distribution (Q1) has a roughly 9% chance of becoming incarcerated at age 26. The incarceration probability for an otherwise identical man in the 8th decile (Q8) is 1%.

The second is that recidivism is prevalent. A 25-year-old Black man currently in the bottom decile of earnings potential with an incarceration record has a 39% chance of being in jail the following year, an increase of 30pp 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 an incarceration 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

[21] To avoid presenting 24^2 numbers, we condense the matrix **A** along each dimension: We present transition probabilities for only a subset of the current states, reducing the number of rows; we also combine future states by summing probabilities, reducing the number of columns.

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

	Future State													
		Incarceration Record = 0							Incarceration Record = 1					
Current State ↓	N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail	N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail
IR = 0 N	0.74	0.16	0.03	0.02	0.01	0.01	0.03							
IR = 0 Q1	0.15	0.52	0.18	0.06	0.01	0.00	0.09							
IR = 0 Q3	0.05	0.26	0.54	0.11	0.00	0.00	0.04							
IR = 0 Q5	0.02	0.01	0.23	0.63	0.09	0.00	0.02							
IR = 0 Q6	0.01	0.00	0.07	0.53	0.38	0.00	0.01							
IR = 0 Q8	0.01	0.00	0.01	0.12	0.55	0.31	0.01							
IR = 0 Q10	0.00	0.00	0.00	0.02	0.08	0.89	0.01							
IR = 0 Jail								0.19	0.28	0.09	0.05	0.02	0.01	0.36
IR = 1 N								0.56	0.16	0.03	0.02	0.01	0.01	0.21
IR = 1 Q1								0.07	0.35	0.13	0.05	0.01	0.00	0.39
IR = 1 Q3								0.03	0.21	0.44	0.10	0.00	0.00	0.22
IR = 1 Q5								0.01	0.01	0.19	0.57	0.10	0.00	0.12
IR = 1 Q6								0.01	0.00	0.06	0.47	0.37	0.00	0.09
IR = 1 Q8								0.00	0.00	0.01	0.11	0.51	0.32	0.06
IR = 1 Q10								0.00	0.00	0.00	0.02	0.07	0.87	0.04
IR = 1 Jail								0.05	0.09	0.03	0.02	0.01	0.00	0.80

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

the large numbers on the diagonals indicate. For example, a 25-year-old man with no incarceration record in the top earnings potential decile has an 89% 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.

4.2 Measurement Matrices

We turn next to the probabilities mapping from the latent states to observed outcomes, embodied in the matrix **B**. Table 3 presents the observation probabilities for a 25-year-old Black man without a high school degree. Rows index the latent state, ℓ_t, and columns the observed outcome, m_t. We condense the results in much the same way as we did for the transition matrix **A**.

Perhaps the most notable feature of Table 3 is the high likelihood that a worker with

Table 3: Observation probabilities, 25-year-old Black men without a high school diploma, unobserved type 2

		Observed Outcome													
		Incarceration Record = 0							Incarceration Record = 1						
Latent State ↓		N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail	N	Q1+ Q2	Q3+ Q4	Q5+ Q6	Q7+ Q8	Q9+ Q10	Jail
IR = 0	N	1.00													
IR = 0	Q1	0.40	0.60	0.00	0.00	0.00	0.00								
IR = 0	Q3	0.16	0.24	0.55	0.05	0.00	0.00								
IR = 0	Q5	0.06	0.13	0.25	0.29	0.19	0.08								
IR = 0	Q6	0.04	0.10	0.20	0.28	0.25	0.14								
IR = 0	Q8	0.02	0.00	0.00	0.09	0.59	0.30								
IR = 0	Q10	0.01	0.00	0.00	0.00	0.00	0.99								
IR = 0	Jail							1.00							
IR = 1	N								1.00						
IR = 1	Q1								0.60	0.40	0.00	0.00	0.00	0.00	
IR = 1	Q3								0.29	0.22	0.40	0.08	0.01	0.00	
IR = 1	Q5								0.12	0.17	0.18	0.18	0.18	0.17	
IR = 1	Q6								0.08	0.18	0.18	0.19	0.19	0.18	
IR = 1	Q8								0.04	0.00	0.02	0.15	0.48	0.31	
IR = 1	Q10								0.02	0.00	0.00	0.00	0.01	0.97	
IR = 1	Jail														1.00

Note: Rows are indexed by the latent state at age 25, columns by the observed state at the same age. IR or "Incarceration Record" indicates previous incarceration. "Jail" denotes current 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.

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 incarceration record and 60% of the time if he has one. Recall that within our model 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 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.

Extrapolating from these results, 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 men with incarceration records face markedly higher odds of nonemployment and (re-)incarceration.

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 variables. We then provide a sense of the long-run implications of these states by generating impulse responses to shocks that result in incarceration and nonemployment (and, in the appendix, changes in earnings potential). Taken together, these results address our first objective, quantifying the relationship between incarceration, employment, and earnings.

5.1 Age Profiles

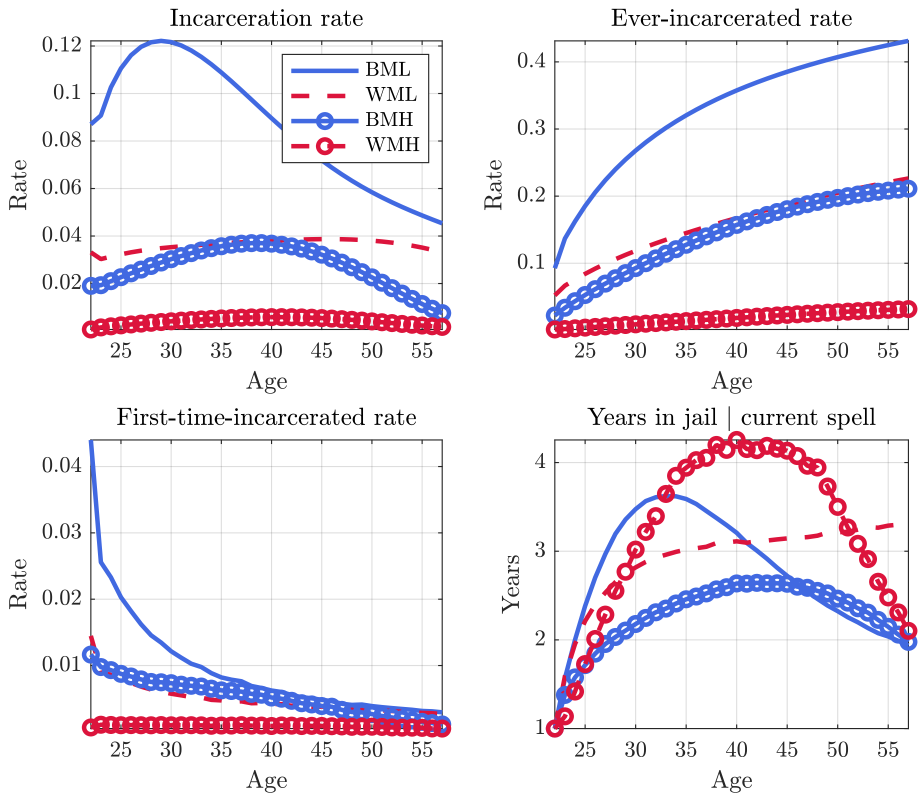
5.1.1 Incarceration

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. The fraction of the population with a history of incarceration (top right panel) thus rises fastest at younger ages. Table 2 showed that men with incarceration records are more likely to be (re-)incarcerated 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 Black men than White men. 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 distinct from those for incarceration rates. The average incarceration spells of White men are longer than those of Black men. Conditional on being incarcerated, middle-aged White men with a high school diploma have longer spells than any other group. Black men have higher incarceration rates not because they serve longer spells, but because they are far more likely to be

Figure 2: Age-Incarceration Profiles



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

incarcerated.[22]

Figure G.1 in Appendix G compares the model's predictions for current and ever-incarcerated rates to the data. Because we allow for nonrandom attrition, the data and the model need not align perfectly.[23] The fit is nonetheless quite good.

5.1.2 Nonemployment

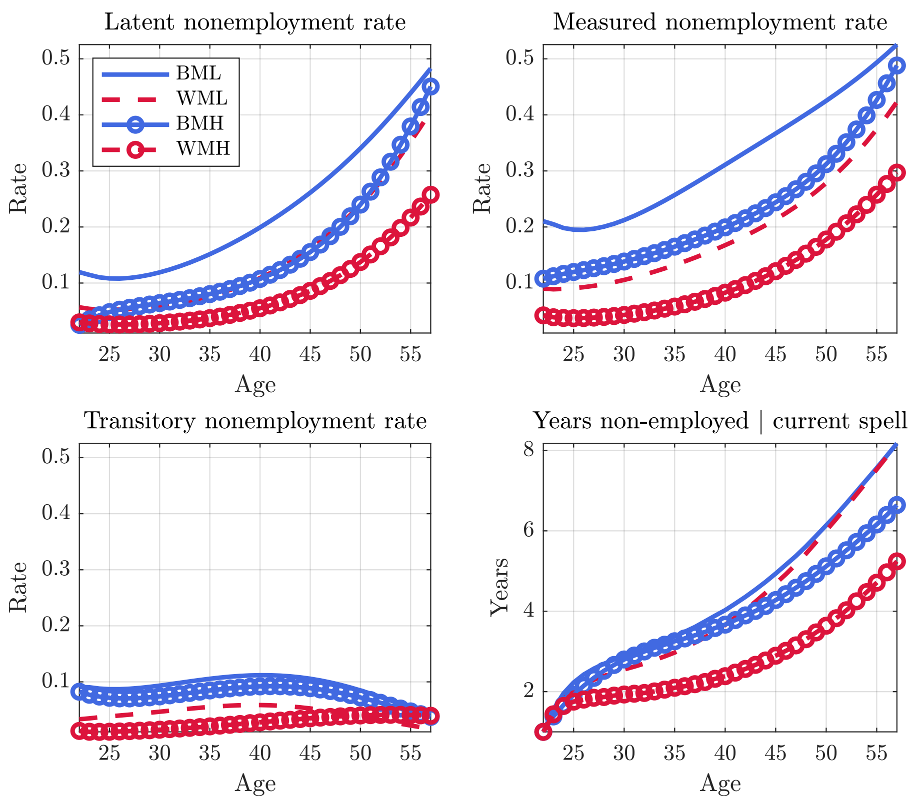
Figure 3 displays nonemployment profiles. Recall that the model has two types of nonemployment: *persistent* nonemployment, where the latent state is nonemployment,

[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. Moreover, our definition of incarceration, being based on responses to the NLSY's residence question, includes episodes such as misdemeanor sentences or pre-trial detention that do not involve felony sentences at all. It may be the case that the inclusion of misdemeanor sentencing, paired with higher rates of misdemeanor sentencing for Black defendants, explains the finding of shorter spells for Black defendants.

[23]Figure G.4 shows the estimated effects of this observation bias on the incarceration and nonemployment profiles.

which automatically results in measured nonemployment; and *transitory* nonemployment, where the latent state is one of the earnings potential 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.3 in Appendix G compares the total nonemployment rates predicted by the model to those in the data. As with incarceration, the fits are good; however, nonresponse bias is sometimes important.

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 profiles for persistent nonemployment rise with age, the 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

[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-time workers, are somewhat distinct from those higher up.

transitory nonemployment behave differently, sometimes displaying a hump shape. But even when transitory nonemployment is rising, persistent nonemployment rises faster. 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. Both transitory and persistent nonemployment display gaps. 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 50% by age 57; nonemployment for White men rises from 3% to 30%. In fact, at any age, a Black man with a high-school diploma is more likely to be nonemployed than a White man without one.

5.1.3 Type-related differences

In general, the results shown in this paper are averages taken across the group-specific parameter types. Table 4 shows that, within each group, the types behave quite differently. At age 50, type 2 individuals are less likely to be employed and more likely to have acquired an incarceration record. In most groups they are more likely to go unobserved, suggesting that nonemployed men are underrepresented in the NLSY79. The two exceptions to this pattern, Black men without a high school degree and Black men with some college experience, are also the two groups with the smallest type-related differences in employment.

5.1.4 Earnings

Our model's predictions for men's earnings, disaggregated by race and education, are shown in Figure 4. The top left and bottom right panels include both incarcerated and nonincarcerated men. They exhibit the canonical hump shape over the life-cycle. As expected, earnings increase sharply with educational attainment, while significant racial differences within education groups remain. As Figure G.2 in the Appendix shows, our model's predictions for earnings generally match the data well.

Earnings differences between the incarcerated and never-incarcerated can be seen by comparing the top right panel with the bottom left. The bottom left panel shows that the education gradient of earnings among the incarcerated is compressed to a striking degree. It follows that because people with an incarceration history have similar earnings, the earnings gaps between the incarcerated and never-incarcerated are

Table 4: Type-specific summary statistics by race and education for men

	Black Men				White Men			
	LTHS	HS	SC	CG	LTHS	HS	SC	CG
Fraction employed, age 50 (%)								
Type 1	53.5	74.8	73.5	87.7	71.7	89.9	84.1	95.2
Type 2	51.7	49.9	72.6	61.4	64.1	62.3	61.6	72.0
Average	52.0	66.7	72.8	82.1	68.6	81.7	78.8	88.6
Fraction with an incarceration record, age 50 (%)								
Type 1	26.0	14.4	12.4	3.5	14.9	1.4	4.1	NA
Type 2	43.6	30.8	15.8	8.4	28.4	5.8	4.2	NA
Average	40.7	19.7	14.8	4.6	20.5	2.7	4.1	NA
Fraction unobserved, age 50 (%)								
Type 1	56.5	6.4	61.6	4.0	6.2	7.4	6.8	4.8
Type 2	6.2	37.0	4.8	59.6	51.6	79.3	88.0	78.2
Average	14.4	16.3	22.2	15.9	25.0	28.7	25.8	25.8
Distribution of types								
Type 1	16.3	67.5	30.7	78.5	58.5	70.4	76.6	71.4
Type 2	83.7	32.5	69.3	21.5	41.5	29.6	23.4	28.6

Note: [LTHS,HS,SC,CG] denote less than high school/high school/some college/college graduate. NA indicates that transitions into and out of incarceration were not estimated for the group in question because of their low frequency. For subsequent analyses with this group, we impute incarceration probabilities as described in the Appendix F.

largest among those with high initial earnings – Whites and the more highly educated.

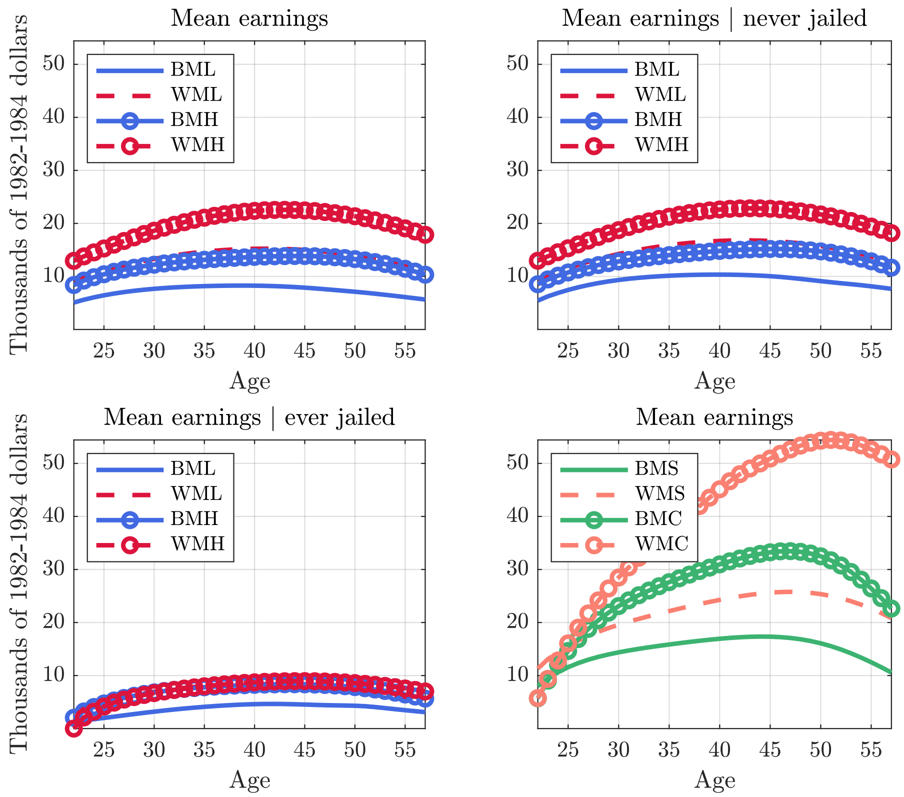
5.2 Lifetime Totals

We are also interested in cumulative earnings differences over the lifetime between different groups. To calculate these, we convert the stream of pre-tax earnings $\{y_t\}_{t=1}^T$ into a net present value, $\sum_{t=1}^T R^{1-t} y_t$, 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. Our measure of lifetime earnings, though partial, covers more than three decades.

Table 5 summarizes the distribution of lifetime earnings as of age 22 for all race-education combinations for men.[25] It also reports the average years that individuals spend incarcerated, employed, or nonemployed. While Black men have lower lifetime earnings at any education level, the differences are starkest for the least educated.

[25] Appendix D reports the results for women.

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.

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 47%. The differences are even larger at the 10th percentile: a gap of 238% for high school dropouts vs. 31% 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 \$29,000 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.

5.3 GIRFs

As we condition on incarceration or nonemployment, what happens to the associated predictions for earnings and employment? To answer this question within the context of our nonlinear model, we calculate generalized impulse response functions (GIRFs).

Table 5: Lifetime totals by race and education for men

Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	189	346	319	505	376	550	651	955
Lifetime earnings p10	29	98	91	203	124	207	291	381
Lifetime earnings p25	67	174	157	329	210	309	395	498
Lifetime earnings p50	150	333	285	497	349	525	574	817
Lifetime earnings p75	277	492	441	650	506	715	836	1215
Lifetime earnings p90	423	630	620	824	672	984	1157	1929
Expected years E	21.3	27.8	26.9	31.9	28.5	30.9	31.4	32.9
Expected years J	3.1	1.3	1.0	0.2	1.2	0.2	0.2	0.0
Expected years N	11.5	6.9	8.2	4.0	6.4	4.9	4.4	3.1
Ever incarcerated by age 57	0.43	0.23	0.21	0.03	0.17	0.04	0.06	0.02

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

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 if individual i realizes a particular shock, say incarceration, at time 1. The mean effects of this shock at time $t \geq 1$ are then given by the sample analogue of

$$\Delta\mathbb{E}[x_t|\mathcal{F}] \coloneqq \mathbb{E}[x_{i,t} \,|\, \delta_i = 1, \mathcal{F}] - \mathbb{E}[x_{i,t} \,|\, \delta_i = 0, \mathcal{F}].$$

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

5.3.1 Interpretation

The GIRFs are estimates of how expected life trajectories change when the individual experiences a shock such as incarceration. To understand whether these predictions have causal content, consider the Neyman-Rubin potential outcome $x_{i,t}(\delta_i^*)$— the value $x_{i,t}$ would take if the observed outcome δ_i had taken the value δ_i^* instead. Using $G(\cdot)$ to denote distributions, the causal effect of the shock can be defined as the hypothetical difference[26]

$$G(x_{i,t}(1) \,|\, \mathcal{F}) - G(x_{i,t}(0) \,|\, \mathcal{F}),$$

while the data allow us to estimate

$$G(x_{i,t}(1) \,|\, \delta_i = 1, \mathcal{F}) - G(x_{i,t}(0) \,|\, \delta_i = 0, \mathcal{F}).$$

The empirical estimate is causal under the assumption that that the unobserved counterfactual outcomes equal their observed counterparts:

$$G(x_{i,t}(1) \,|\, \delta_i = 0, \mathcal{F}) = G(x_{i,t}(1) \,|\, \delta_i = 1, \mathcal{F}) \text{ and } G(x_{i,t}(0) \,|\, \delta_i = 1, \mathcal{F}) = G(x_{i,t}(0) \,|\, \delta_i = 0, \mathcal{F}).$$

Recall that $\mathcal{F}$ includes, in addition to age, sex, race and education, the prior period's latent state and the individual's permanent type. Our results will be causal only if $\mathcal{F}$ encodes all of the relevant information available at time 0 and the effects of its elements are specified correctly. Moreover, $\mathcal{F}$ cannot control for transitory selection. It might be the case, for example, that even if $\mathcal{F}$ contains all the information available at $t = 0$, people who enter incarceration do so because their earnings prospects unexpectedly deteriorate at $t = 1$. In the end, we believe exercises such as the GIRFs are informative, but remain agnostic as to their interpretation.

A related identification issue is that incarceration is the culmination of a multi-step process involving the commission of a crime, apprehension, trial and sentencing.[27] "Incarceration shocks" could take place at any of these stages. Our empirical measures, however, tell us only whether an individual currently resides in a jail or prison. As we turn our attention to the GIRFs for the incarceration shocks, this caveat, and the ones preceding it, should be kept in mind.

5.3.2 Incarceration Shocks

Figure 5 plots the GIRFs generated by an incarceration episode among male high school dropouts. The first row shows that at impact, a jail shock lowers the model's mean earnings prediction for Black (White) men by roughly \$6,000 (\$9,000). The predicted earnings loss wears off slowly, particularly for first-time offenders. The second and third rows show that some of the loss reflects a higher predicted likelihood of future incarceration or nonemployment.

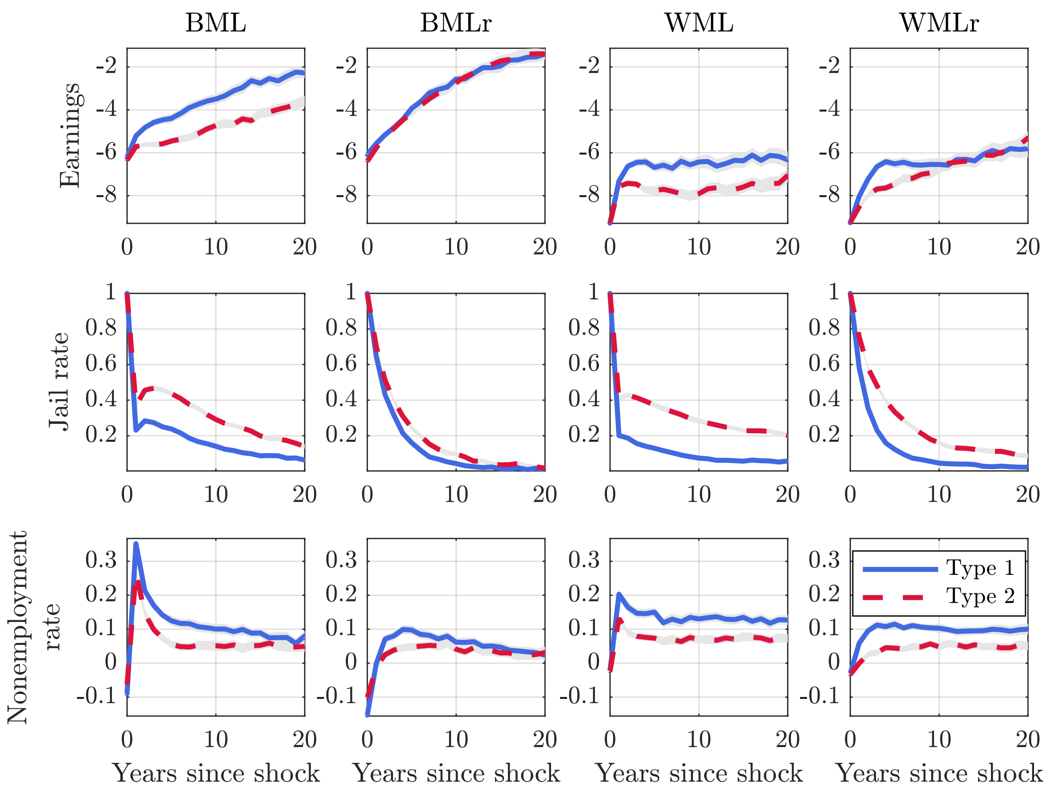
The top panel of Table 6 reports the lifetime change in predicted earnings in the wake of jail shocks. First-time incarceration is associated with a reduction in lifetime

[26] In potential outcomes parlance, this is a weighted average of the treatment effects for both the treated and the untreated.

[27] We are grateful to a referee for raising this point.

earnings of $104,800 for Black men and $170,700 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 5). A large part of the change in earnings stems from a expected reduction of 35% or more in the number of years spent working due to more years spent nonemployed or in jail: 9.8 years (out of 21.3—see Table 5) and 9.7 (out of 27.8) for Black and White men, respectively, without a high school diploma.

Figure 5: 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 incarceration record/incarceration record; Qi denotes earnings potential decile i. Earnings are measured in thousands of 1982-1984 dollars.

Figure 5 and Table 6 both show that the drops in predicted earnings after an incarceration spell are larger for high school graduates than for high school dropouts and that predicted losses are larger for White men than Black men. 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 6 shows that the fall

Table 6: 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	-6.3	-9.3	-6.3	-9.3	-9.2	-12.7	-10.2	-12.6
Lifetime earnings	-104.8	-170.7	-65.5	-155.4	-101.3	-257.5	-145.9	-252.4
Future years E	-9.8	-9.7	-5.3	-7.3	-5.6	-9.9	-5.6	-10.5
Future years N	2.1	3.9	1.1	2.7	1.3	3.8	2.1	2.6
Future years J	7.7	5.8	4.2	4.6	4.3	6.0	3.5	7.9
GIRF for a transition to nonemployment: Q5 to N								
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.3	-9.3	-5.6	-9.1	-9.2	-12.8	-10.0	-12.6
Lifetime earnings	-87.9	-141.3	-53.2	-116.2	-118.3	-134.1	-98.0	-86.8
Future years E	-7.1	-6.8	-4.3	-6.3	-7.2	-5.1	-5.6	-5.7
Future years N	6.5	6.2	3.1	5.3	7.2	4.8	5.6	3.2
Future years J	0.6	0.6	1.2	1.0	0.0	0.2	0.0	2.5

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

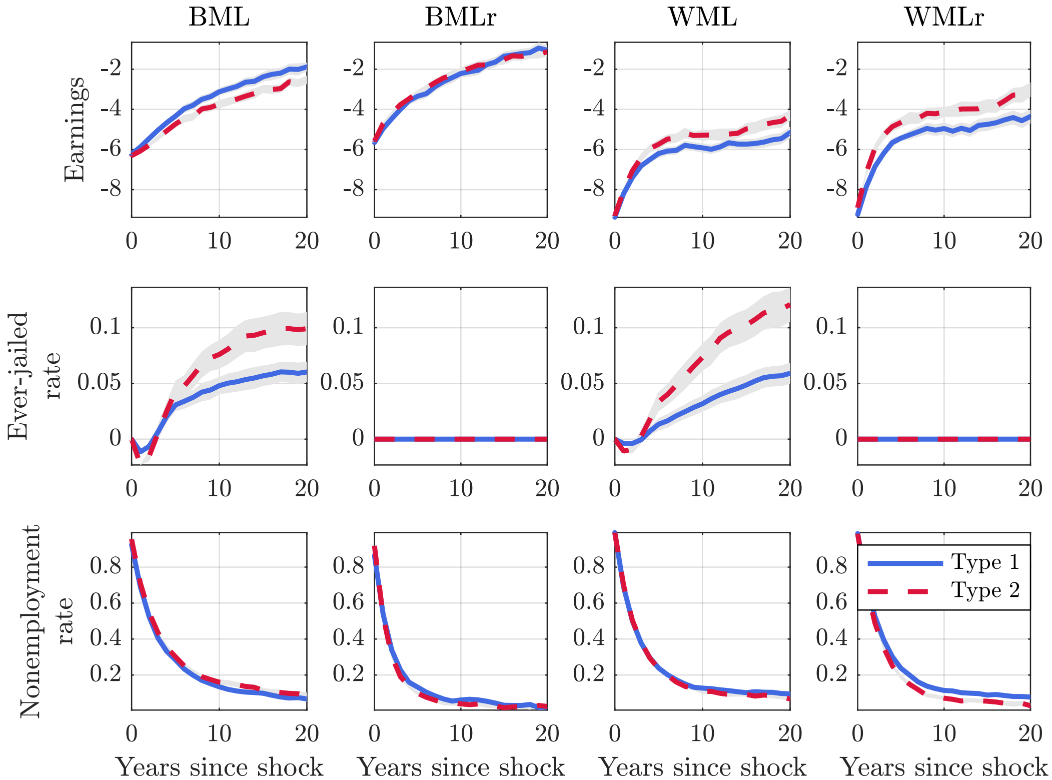
in expected employment following a spell of incarceration is in fact larger for White men, perhaps because they are more likely to be employed in its absence. Moreover, the bottom left panel of Figure 4 shows that men with an incarceration record have similar earnings across races and education levels.

Comparing the results for men with and without an incarceration record shows that, for high school dropouts, the lifetime earnings loss from first-time incarceration is greater than from a return to jail (indicated by an ‘r’ in the heading). As can be seen in Table 6, this is not the case for men with a high school degree where repeat offenders see 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, leading to a larger drop in predicted earnings.

5.3.3 Nonemployment Shocks

Figure 6 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 6 thus

Figure 6: 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 incarceration record/incarceration record. Earnings are measured in thousands of 1982-1984 dollars.

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 \$53,200 to \$141,300. 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 matrix in Table 2 implies that nonemployed men are especially likely to become incarcerated. Table 6 likewise shows that a spell of nonemployment raises future jail time from 0.6 to 1.2 years for those without a high school diploma. To put this in perspective, note that a White high school dropout with no incarceration record would on average spend 1.3 years in jail (Table 5). The additional 0.6 expected years of incarceration due to nonemployment (Table 6) is an increase of 46%. Even after conditioning on education, race, and gender, nonemployment significantly contributes to incarceration.

5.3.4 Earnings Shocks

Table 2 also shows that men with low latent earnings are more likely to transition to incarceration or nonemployment. Appendix H examines the predicted effects of moving up and down the earnings distribution in more detail.[28] Consistent with Table 2, moving from the fifth to the third earnings potential decile leads to higher incarceration rates (especially among those with a history of incarceration) and lower employment and earnings. The effects of moving from the fifth to the seventh decile have the opposite sign, although in many cases different magnitudes.

6 Accounting for the Black-White Earnings Gap

We have seen that incarceration and nonemployment shocks signal large and persistent changes in 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 for the NLSY79 cohort would change if we (somehow) eliminated racial differences in the rates of incarceration and nonemployment, while leaving all other aspects of the statistical environs unchanged.

The first way we answer this question is by constructing counterfactual simulations where episodes of incarceration and/or nonemployment no longer occur. We compare the racial gaps generated by these counterfactuals to those from the full model.[29]

The first and second panels of Table 7 report summary statistics for the benchmark model and the counterfactual no-incarceration process, 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 \$144,000 ($\$365,000-\$221,000$), a decline of 8.3%. The contribution of incarceration to the racial earnings gap is relatively small for two main reasons. The first is that even though incarceration is far more prevalent among Black men, the revisions in conditional mean earnings, when measured in levels, are *larger* for White men. For example, Table 6 shows that among dropouts and high school graduates, the reduction in predicted

[28]The GIRFs in Appendix H show that in some cases the immediate response to moving to a lower latent earnings potential bin is an increase in (average) realized earnings. In Appendix I we show that such a response is consistent with the restrictions we impose on the observation matrix. We also present results from an alternative specification that does not generate this outcome. Imposing this restriction does not change our main findings, and it at times significantly worsens our model's fit.

[29]In addition to the identification concerns outlined in Section 5.3.2, these exercises do not account for the general equilibrium effects that would accompany the elimination of incarceration or nonemployment. Our results should be interpreted instead as summarizing the individual-level consequences of these changes, all else equal, and even then only in a statistical sense.

Table 7: 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	319	505	376	550	651	955
Lifetime earnings p10	29	98	91	203	124	207	291	381
Lifetime earnings p50	150	333	285	497	349	525	574	817
Lifetime earnings p90	423	630	620	824	672	984	1157	1929
Expected years E	21.3	27.8	26.9	31.9	28.5	30.9	31.4	32.9
Expected years J	3.1	1.3	1.0	0.2	1.2	0.2	0.2	0.0
Expected years N	11.5	6.9	8.2	4.0	6.4	4.9	4.4	3.1
Ever incarcerated by age 57	0.43	0.23	0.21	0.03	0.17	0.04	0.06	0.02
No incarceration								
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	221	365	333	510	399	555	664	958
Lifetime earnings p10	40	119	98	208	153	216	307	382
Lifetime earnings p50	195	355	303	501	373	529	585	819
Lifetime earnings p90	457	638	632	828	692	988	1166	1932
Expected years E	24.4	29.3	27.7	32.1	29.9	31.2	31.8	32.9
Expected years N	11.6	6.7	8.3	3.9	6.1	4.8	4.2	3.1
No nonemployment								
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	270	424	400	556	462	662	737	1115
Lifetime earnings p10	80	179	156	262	219	341	333	458
Lifetime earnings p50	252	417	380	538	441	614	627	959
Lifetime earnings p90	499	677	685	883	764	1104	1354	2105
Expected years E	30.7	34.1	34.2	35.8	34.4	35.8	35.6	36.0
Expected years J	5.3	1.9	1.8	0.2	1.6	0.2	0.4	0.0
Ever incarcerated by age 57	0.44	0.22	0.24	0.02	0.15	0.03	0.07	0.01
No incarceration or nonemployment								
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	323	447	427	562	488	667	749	1116
Lifetime earnings p10	165	221	206	269	246	346	345	457
Lifetime earnings p50	296	435	400	542	462	617	636	961
Lifetime earnings p90	528	683	696	889	784	1107	1365	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.

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 65% (144/221). As a proportion of a ratio, this is a reduction of 21.7% (1-65/83), as opposed to the 7.6% reduction in levels.

An informative exercise is to compare the change in average earnings induced by eliminating incarceration from the model to the change in average years of work. Under this alternative, for Black high school dropouts, the number of years employed increases 14.6%, from 21.3 to 24.4. Implied 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 the incarceration state to have a larger effect on model-predicted aggregate employment vs. earnings. One reason this does not happen is that incarceration has a (statistically) scarring effect on earnings. As Tables 2-3 show, men with incarceration records are, when employed, more likely to experience low earnings.

The third panel of Table 7 shows results for the no-nonemployment counterfactual. In the absence of nonemployment as a possible state, the gap for dropouts actually rises, to \$157,000. The proportional gap moves in the opposite direction, however, falling to 57%. The bottom panel shows that eliminating both the incarceration and nonemployment states reduces the gap substantially, to \$124,000, or 38% (124/323) of Black earnings. This is 21% smaller than the benchmark gap for dropouts in levels and smaller by 54% (1-38/83) in relative terms.

The roles played by the incarceration and nonemployment states are, as expected, less important for more highly educated men. For example, for high school graduates, the original lifetime earnings gap is \$186,000, 58% of the lifetime earnings of Black men. Without incarceration as a state, the gap falls to \$177,000 (53% of Black lifetime earnings); abstracting from nonemployment reduces the gap to \$156,000 (39%); without both, the gap falls to \$135,000 (32%). The changes are also smaller at the top of the lifetime earnings distribution. For high school dropouts, the lifetime earnings gap at the 90th percentile is \$207,000, or 49% of the Black earnings total of \$423,000. Without the incarceration and nonemployment states, the gap falls to \$155,000, or 29% of Black earnings.

The counterfactual exercises in Table 7 provide one way to measure the potential effects of incarceration and/or nonemployment on the racial earnings gap, albeit a statistical measure predicated on invariant behaviors. An alternative—although still statistical—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 $p(m^T, \text{race}), \text{race} \in \{\text{W}, \text{B}\}$, denote the probability function for these histories. (The function $p(\cdot)$ also depends on gender, education, and unobserved type, 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 $PDV(m^T, \text{race}) \coloneqq \sum_{t=1}^{T} R^{1-t} y_t(m_t, \text{race})$. 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 $\varsigma(y^{\text{race}}, p^{\text{race}})$.[30] The racial gap in earnings is then given by:

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

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

The first bracketed term in equations (5) and (6) measures the contribution of racial differences in earnings, holding fixed the distribution of outcome bins. The second bracketed term measures the contribution 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 contribution of racial gaps in incarceration and nonemployment, although it captures distributional differences of every sort.[31] The ratio of this term to the entire gap provides a relative measure. Equations (5) and (6) are equally valid; we calculate the ratio both ways and take the average.

Table 8: Decomposition: Fraction of lifetime earnings gap explained by differences in the distribution across outcome bins

Variable	ML	MH	MS	MC
Lifetime earnings avg.	63.4	41.0	45.2	14.8
Lifetime earnings p10	76.5	59.2	55.4	-10.3
Lifetime earnings p50	72.5	50.3	48.7	11.9
Lifetime earnings p90	45.5	9.5	46.4	30.7

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.

We apply this decomposition to lifetime earnings in Table 8, which presents the share of the lifetime earnings gap attributable to racial differences in the distribution of outcome bins.[32] The first row shows that for male high school dropouts, 63% 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 comparison, recall that for high school dropouts, ruling out states of incarceration

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

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

[32] The numbers underlying Table 8 can be found in Appendix J.

and nonemployment in their entirety would alter the model-implied earnings-levels gap by 21% and the fractional gap by 54%.

Continuing along the first row, the ratios for high school graduates, men with some college education, or college graduates, are 41%, 45%, and 15%, 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 8 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.

7 Conclusion

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. We estimate separate processes for each race-sex-education group and allow for permanent unobserved heterogeneity within each group.

Our estimates imply that first-time incarceration signals a fall in lifetime earnings of at least a third and—for some subgroups—a half. Mechanically, this reduction operates both through fewer years employed and 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.

Black men earn less and are more likely to be nonemployed or incarcerated than White men. Decomposition exercises with our model show that among less-educated men, differences in incarceration and nonemployment can account for a significant portion of the Black-White gap in lifetime earnings.

A key contribution of our paper is to provide a flexible statistical framework for studying the earnings dynamics of those with irregular labor market attachment, a group that has received relatively little attention. Not only does our methodology allow us to capture varying levels of labor market attachment, it also accommodates nonrandomness and persistence in missing data, which are of first-order importance for incarceration and nonemployment. Finally, by producing a Markov chain, our framework fits easily into computational models, and as such can be used as an input or target for structural work. A limitation of our study is that the estimates are based on a single birth cohort; care must be taken when applying them to other time periods.

A promising avenue for future research, which we are currently pursuing, is to use our estimated earnings process in a consumption-savings model to quantify the role of incarceration (among other factors) in the large wealth differences across race, gender, and education groups. This framework can also be used to estimate how household spending and balance sheets respond to episodes of incarceration and nonemployment.

References

Abowd, J. M. and D. Card (1989): "On the Covariance Structure of Earnings and Hours Changes," *Econometrica*, 57, 411–445.

Altonji, J. G., A. A. Smith Jr, and I. Vidangos (2013): "Modeling Earnings Dynamics," *Econometrica*, 81, 1395–1454.

Arellano, M., R. Blundell, and S. Bonhomme (2017): "Earnings and Consumption Dynamics: A Nonlinear Panel Data Framework," *Econometrica*, 85, 693–734.

Bartolucci, F., A. Farcomeni, and F. Pennoni (2010): "An Overview of Latent Markov Models for Longitudinal Categorical Data," *arXiv preprint arXiv:1003.2804*.

——— (2012): *Latent Markov Models for Longitudinal Data*, Chapman and Hall/CRC.

Bayer, P. and K. K. Charles (2018): "Divergent Paths: A New Perspective on Earnings Differences Between Black and White Men Since 1940," *Quarterly Journal of Economics*, 133, 1459–1501.

Bonhomme, S. and J.-M. Robin (2009): "Assessing the Equalizing Force of Mobility using Short Panels: France, 1990–2000," *Review of Economic Studies*, 76, 63–92.

——— (2010): "Generalized Non-Parametric Deconvolution with an Application to Earnings Dynamics," *Review of Economic Studies*, 77, 491–533.

Bureau of Justice Statistics (2021): "Key Statistics," Tech. rep., Bureau of Justice Statistics.

Caucutt, E. M., N. Guner, and C. Rauh (2021): "Incarceration, Unemployment, and the Racial Marriage Divide," Tech. rep., BSE, Working Paper 1300.

De Nardi, M., G. Fella, and G. Paz-Pardo (2020): "Nonlinear Household Earnings Dynamics, Self-insurance, and Welfare," *Journal of the European Economic Association*, 18, 890–926.

Farmer, L. E. (2021): "The discretization filter: A simple way to estimate nonlinear state space models," *Quantitative Economics*, 12, 41–76.

Fella, G. and G. Gallipoli (2014): "Education and Crime over the Life Cycle," *Review of Economic Studies*, 81, 1484–1517.

Fu, C. and K. I. Wolpin (2018): "Structural Estimation of a Becker-Ehrlich Equilibrium Model of Crime: Allocating Police across Cities to Reduce Crime," *Review of Economic Studies*, 85, 2097–2138.

Guler, B. and A. Michaud (2018): "Dynamics of Deterrence: A Macroeconomic Perspective on Punitive Justice Policy," CHCP working papers, 2018-6, Centre for Human Capital and Productivity, University of Western Ontario.

Guvenen, F. (2009): "An Empirical Investigation of Labor Income Processes," *Review of Economic dynamics*, 12, 58–79.

Guvenen, F., F. Karahan, S. Ozkan, and J. Song (2020): "What Do Data on Millions of US Workers Reveal about Life-Cycle Earnings Risk?" Tech. rep., University of Toronto.

Hamilton, J. D. (1989): "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica*, 357–384.

——— (1994): *Time Series Analysis*, Princeton University Press.

Heckman, J. J., J. E. Humphries, and N. S. Mader (2011): "The GED," in *Handbook of the Economics of Education*, Elsevier, vol. 3, 423–483.

Hu, Y., R. Moffitt, and Y. Sasaki (2019): "Semiparametric Estimation of the Canonical Permanent-Transitory Model of Earnings Dynamics," *Quantitative Economics*, 10, 1495–1536.

Institute for Crime & Justice Policy Research (2018): "World Prison Brief," Tech. rep.

Jones, M. C. (2009): "Kumaraswamy's Distribution: A Beta-Type Distribution with Some Tractability Advantages," *Statistical Methodology*, 6, 70–81.

Kling, J. R. (2006): "Incarceration Length, Employment, and Earnings," *American Economic Review*, 96, 863–876.

Kumaraswamy, P. (1980): "A Generalized Probability Density Function for Double-Bounded Random Processes," *Journal of Hydrology*, 46, 79–88.

Light, M. T. (2021): "The Declining Significance of Race in Criminal Sentencing: Evidence from US Federal Courts," *Social Forces*.

Lochner, L. (2004): "Education, Work, and Crime: A Human Capital Approach," *International Economic Review*, 45, 811–843.

Loeffler, C. E. (2013): "Does Imprisonment Alter the Life Course? Evidence on Crime and Employment from a Natural Experiment," *Criminology*, 51, 137–166.

McGrattan, E. R. and E. C. Prescott (2000): "Is the Stock Market Overvalued?" *Federal Reserve Bank of Minneapolis Quarterly Review*, 24, 20–40.

Meghir, C. and L. Pistaferri (2004): "Income Variance Dynamics and Heterogeneity," *Econometrica*, 72, 1–32.

Merlo, A. and K. I. Wolpin (2015): "The transition from school to jail: Youth crime and high school completion among black males," *European Economic Review*, 79, 234–251.

Mueller-Smith, M. (2015): "The Criminal and Labor Market Impacts of Incarceration," Unpublished.

Neal, D. and A. Rick (2014): "The Prison Boom and the Lack of Black Progress after Smith and Welch," NBER working paper no. 20283, National Bureau of Economic Research.

Pager, D. (2008): *Marked: Race, Crime, and Finding Work in an Era of Mass Incarceration*, University of Chicago Press.

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

Rosenmerkel, S. P., M. R. Durose, and D. Farole Jr (2009): "Felony Sentences in State Courts, 2006-statistical tables," *US Department of Justice, Bureau of Justice Statistics*, 1–45.

Ruggles, S., S. Flood, R. Goeken, J. Grover, E. M. J. Pacas, and M. Sobek (2020): "IPUMS USA: Version 10.0 [Dataset]," Https://doi.org/10.18128/D010.V10.0.

Scott, S. L. (2002): "Bayesian Methods for Hidden Markov Models: Recursive Computing in the 21st Century," *Journal of the American Statistical Association*, 97, 337–351.

Survey Research Center (1992): "A Panel Study of Income Dynamics: Procedures and Tape Codes, 1989 Interviewing Year; Wave XXII: A Supplement," Tech. rep., Institute for Social Research, University of Michigan.

Travis, J., B. Western, and F. S. Redburn, eds. (2014): *The Growth of Incarceration in the United States: Exploring Causes and Consequences*, The National Academies Press.

Trivedi, P. K. and D. M. Zimmer (2007): *Copula Modeling: An Introduction for Practitioners*, Now Publishers Inc.

Western, B. and B. Pettit (2010): "Incarceration & Social Inequality," *Daedalus*, 139, 8–19.

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 $\{0, 1\}$ incarceration 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 incarceration record flag, so that $\mathbb{M}$ contains $2Q + 5$ elements.

Each individual belongs to one of G permanent but unobserved parameter types, indexed by g. In practice, we set $G = 2$. As a matter of notation, we will index types by superscripts, suppressing them when convenient.

Let p_q, $q = 0, 1, ..., Q$ denote the probability cutoffs for the earnings bins. We partition earnings into deciles, so that $p_q \in \{0.0, 0.1, ..., 0.9, 1\}$ 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, $\mathbf{A}^g_x$:

$$\begin{aligned}\mathbf{A}^g_{j,k\,|\,x} &= \Pr(\ell_{n,t+1} = L_k \,|\, \ell_{n,t} = L_j,\ \text{type} = g,\ x_{n,t}) \\ &= \Pr(\ell_{n,t+1} = L_k \,|\, \mathcal{F}_t),\end{aligned} \tag{7}$$

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 $\mathbf{B}^g_z$:

$$\begin{aligned}\mathbf{B}^g_{j,k\,|\,z} &= \Pr(m_{n,t} = M_k \,|\, \ell_{n,t} = L_j,\ \text{type} = g,\ z_{n,t}) \\ &= \Pr(m_{n,t} = M_k \,|\, \mathcal{F}_{t-1}, \ell_{n,t}).\end{aligned} \tag{8}$$

Conditional on type, our statistical model is completed by the $1 \times I$ row vector

$\mu_1^g(l_{n,1}|x_{n,1})$, which gives the distribution of the initial latent state $\ell_{n,1}$.

Incorporating parameter heterogeneity requires us to specify how $\mathbf{A}_x^g$, $\mathbf{B}_z^g$ and μ_1^g vary across types. The final element of our framework is the $G \times 1$ vector $\tau(y_n)$, which gives individual i's probability distribution over types, which is a function of the initial conditions vector y_n.

We estimate separate sets of transition and observation probabilities for each race-gender-education combination. There are multiple parameter types within each combination. To reduce clutter, we will suppress the dependence on race, gender, and education in the exposition below.

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.

We turn now to describing how $\mathbf{A}_x^g$, $\mathbf{B}_z^g$ and μ_1^g are populated. We will proceed sequentially, first describing how the model works for a given value of g, then identifying the parameters that vary with g, and finally describing how the type probabilities for each individual, $\tau(y_n)$, are determined.

A.1 Latent State Transitions

At this point, we will cease the indexing of individual (n) and type (g).

We define a person as having an incarceration record if he has been incarcerated in any *previous* period. Once a person is incarcerated, he will have an incarceration 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 potential 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:

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

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 potential; $\mathcal{I}_t^{IR}$ is the 0-1 indicator for an incarceration record (previous incarceration); and $\tilde{p}_j$ gives the individual's (approximate) earnings rank. In particular, when state j corresponds to earnings potential bin q_j^*, $\tilde{p}_j = [p_{q_j^*} + p_{q_j^*-1}]/2$. For 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 can be 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^*},

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

$K\big(0;\, \alpha,\beta\big) = 0$ 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 potential bin, 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 an incarceration record for the rest of his life. As a result, $\mathbf{A}$ will be approximately block diagonal (as in Table 2). The first $Q+1$ rows of this matrix denote cases where at time t the individual has no incarceration record ($\mathcal{I}_t^{IR} = 0$) 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 an incarceration 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 an incarceration record at time t, $\mathcal{I}_t^{IR} = 1$. 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 incarceration record—he has not been incarcerated in the past—but is currently in jail. This person will have an incarceration record at time $t+1$, so row $Q+1$ is configured like the rows for those with an incarceration 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 an incarceration 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:

$$\begin{aligned}\mathbf{B}_{j,0\,|\,z} &= \Pr\big(O_t = 0 \,|\, \ell_t = j,\, z_t\big) \\ &= 1 - \frac{\exp\big(\mathbf{z}_0(a_t, \ell_t, O_{t-1})\boldsymbol{\gamma}_O\big)}{1+\exp\big(\mathbf{z}_0(a_t, \ell_t, O_{t-1})\boldsymbol{\gamma}_O\big)}, \quad j \in \mathbb{L}, \end{aligned} \tag{11}$$

where

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

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 incarceration 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 incarceration records are reported accurately. With these assumptions, we get

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

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

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, $q \in \mathcal{Q}$, 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 **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

$$\mathbf{z}_1(a_t, \ell_t) = \left[\begin{array}{ccccccccc} 1 & a_t & \frac{a_t^2}{100} & \tilde{p}_j & \tilde{p}_j a_t & \tilde{p}_t^2 & \tilde{p}_t^2 a_t & \mathcal{I}_t^{IR} & \mathcal{I}_t^{IR} a_t \end{array}\right].$$

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

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

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

$$L^\star\left(p, \tilde{p};\, \sigma\right) = \frac{\exp(\sigma(p - \tilde{p}))}{1 + \exp(\sigma(p - \tilde{p}))} \Big/ \left[\frac{\exp(\sigma(1 - \tilde{p}))}{1 + \exp(\sigma(1 - \tilde{p}))} - \frac{\exp(-\sigma\tilde{p})}{1 + \exp(-\sigma\tilde{p})}\right], \tag{16}$$

$$\sigma_{\mathbf{z}_1} = \left|\mathbf{z}_1(a_t, \ell_t)\boldsymbol{\gamma}_E\right|. \tag{17}$$

Our decision to center the distribution $L^\star\left(p, \tilde{p}_j;\, \sigma\right)$ 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 $\sum_q \Pr\left(\text{bin } q \,|\, \ell_j,\, O = 1,\, z\right) = \Pr\left(\mathcal{Q} \,|\, \ell_j,\, O = 1,\, z\right), \forall j$.

Multiplying the probabilities in equations (14) and (15) by the observation probability 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, using a multinomial logit transformation. Conditional on having positive earnings, we find the distribution across the earnings potential bins using the Kumaraswamy distribution $K\big(p;\, \alpha_0, \beta_0\big)$; 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 an incarceration record, conditional on the other latent states. Here we use a logistic distribution, allowing the probability of an incarceration 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 Type-Related Variation

The probability matrices $\mathbf{A}_x^g$, $\mathbf{B}_z^g$ and μ_1^g vary across g via seven type-specific parameters. Four of these parameters affect the transition matrix $\mathbf{A}_x^g$. These are the two intercept terms in the first-stage logit—the initial elements of $\zeta_{\mathcal{Q}^*}$ and ζ_{IC} in equation (9)—and the two intercept terms in the expressions for the Kumaraswamy parameters $\alpha(\cdot)$ and $\beta(\cdot)$—the initial elements of ζ_a and ζ_b in equation (10). The fifth and sixth parameters affect the observation matrix $\mathbf{B}_z^g$. The fifth parameter is the intercept term in the logit determining whether an individual is observed – the first element of $\boldsymbol{\gamma}_O$ in equation (11). The sixth parameter is the intercept term in the logit determining whether an individual with positive earnings potential ($\ell_{it} \in \mathcal{Q}^*$) is currently nonemployed – the first element of $\boldsymbol{\gamma}_{\mathcal{Q}}$ in equation (14). The seventh parameter affects the initial distribution μ_1^g. This is the intercept in the logit determining whether an individual enters our sample with an incarceration record.

As a matter of convenience, we express each type-related parameter as the sum of its type-1 value and a type-specific deviation for types 2 and higher: to fix ideas, the parameter ξ^g would be written as $\xi^1 + \delta_\xi^g$, with $\delta_\xi^1 \equiv 0$. This formulation becomes useful when we use the shifters for the latent state transition probabilities—$\delta_{\zeta_{\mathcal{Q}^*}}^g$, for example—to shift the corresponding coefficients in the first stage of populating the initial distribution vector μ_1^g. (We impose this restriction in order to reduce the number of type-specific parameters.) In our current two-type specification, we choose the normalization that the intercept on employment is smaller for the second type, so that $\delta^2_{\zeta_{Q^*}}$ is negative.

Finally, the distribution of types for individual n, $\tau(y_n)$, is found using a multinomial logit:

$$\Pr\left(\text{type} = g \,|\, y_i\right) = \lambda_{n,g} \Big/ \sum_{h\in\{1,2,\dots,G\}} \lambda_{n,h}, \quad g \in \{1,2,\dots,G\}, \tag{18}$$
$$\lambda_{n,1} \equiv 1, \quad \forall n,$$
$$\lambda_{n,g} = \exp(y_i\psi_g), \quad \forall n, g > 1.$$

The vector y_i has two elements: a constant, and the log of the predicted probability $\widehat{\Pr}(i \text{ is ever-incarcerated})$. We find this probability through a separate logit regression, where the probability of ever being incarcerated is expressed as a function of the individual's AFQT quartile, mother's education and indicators for whether the individual lived with both parents until age 18, and whether the mother was a teenager when the individual was born.[33] We estimate separate sets of probabilities for each race-sex grouping, including controls for the individual's own education level.

A.5 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 2021):

1. Begin with the $1 \times I$ vector of initial latent state probabilities, μ_1. Our model starts at age 22. Observations from younger ages are dropped.[34]

2. Letting j_1 index the realization of m_1, calculate the $1\times I$ vector $\eta_1 = \mu_1 \odot \left(\iota_{j_1}\mathbf{B}_1'\right)$, 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.

[33] The control variables are all categorical, and include a "missing" category.

[34] Some individual histories have gaps such that the first time the individual is observed in our sample is after age 22. In those cases we use the model to update μ_t until that later age is reached.

3. For $t = 1, 2, ..., T-1$, calculate $\eta_{t+1} = \dfrac{1}{\eta_t \mathbf{1}}\big(\eta_t \mathbf{A}_t\big) \odot \big(\iota_{j_{t+1}} \mathbf{B}'_{t+1}\big)$.[35] 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 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, creating the risk of underflow errors. We thus calculate the log-likelihood as the sum of the logged probabilities, $\sum_t \ln(\eta_t \mathbf{1})$, rather than the log of the product, $\ln\Big(\prod_t (\eta_t \mathbf{1})\Big)$.

Steps 1-4 are repeated for each value of g. The unconditional likelihood for individual n is

$$\Pr(m_{n,1}, m_{n,2}, ..., m_{n,T_n} \,|\, y_n) = \sum_{g=1}^{G} \tau_g(y_n) \prod_{t=1}^{T_n} (\eta^g_{n,t} \mathbf{1}),$$

where $\tau_g(y_n)$ gives the probability that individual n belongs to type g. The concerns about underflow errors described above lead us to calculate the unconditional log-likelihood as

$$\begin{aligned} &\ln\big(\Pr(m_{n,1}, m_{n,2}, ..., m_{n,T_n} \,|\, y_n)\big) = \\ &\quad \sum_{t=1}^{T_n} \ln(\eta^1_{n,t}\mathbf{1}) \;+\; \ln\left(\sum_{g=1}^{G} \tau_g(y_n)\, \exp\left[\sum_{t=1}^{T_n} \ln(\eta^g_{n,t}\mathbf{1}) \;-\; \sum_{t=1}^{T_n} \ln(\eta^1_{n,t}\mathbf{1})\right]\right). \end{aligned}$$

The second term of this formulation exploits the fact that the ratio of any two type-specific likelihoods, each of which is less than 1, will be larger in magnitude than either of the individual likelihoods themselves (and so will be less subject to underflows).

B The Kumaraswamy Approximation

By assuming that the distribution of earnings ranks is Kumaraswamy with parameters $\alpha(\mathbf{x}(a_t, \ell_t)), \beta(\mathbf{x}(a_t, \ell))$, there will always be some approximation error (unless that

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

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 Kumaraswamy 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

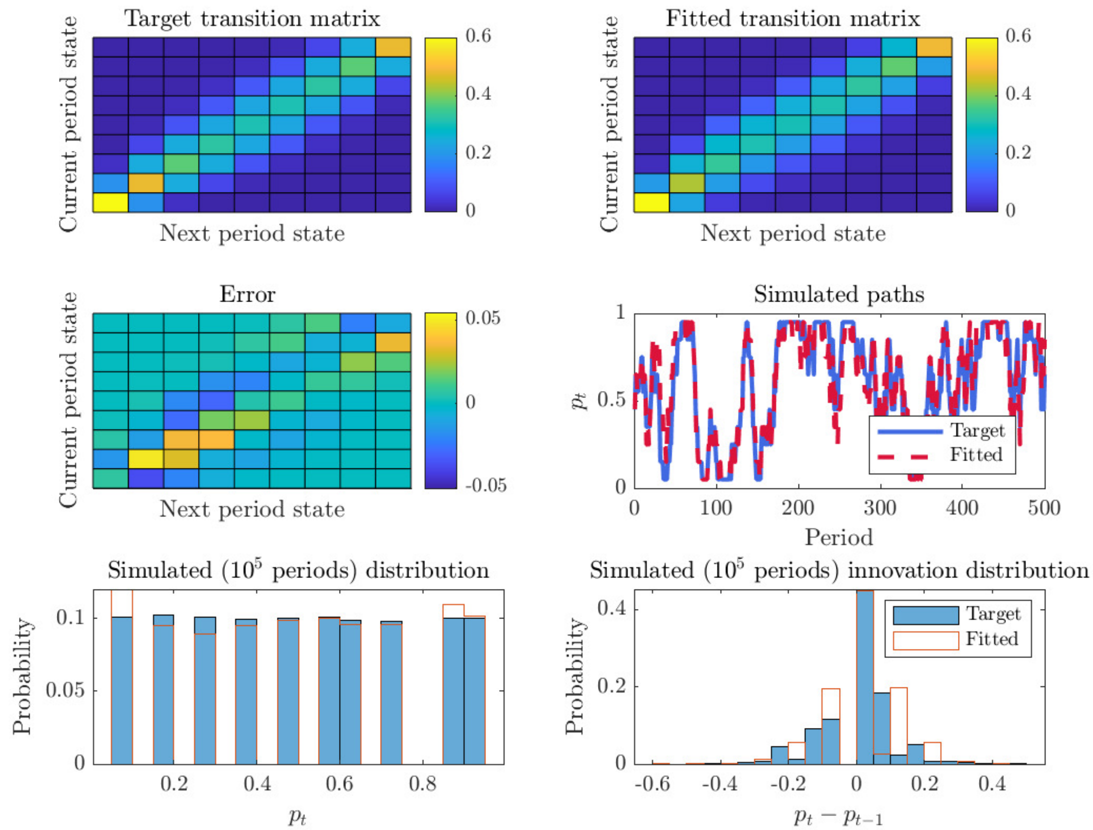
$$\begin{aligned}\mathcal{L}(\theta) = \sum_{b=1}^{10} \sum_{q=1}^{10} & N^S(\ell_{t+1} = \text{bin } q \text{ and } \ell_t = \text{bin } b) \\ & \times \ln\left(\Pr^K(\ell_{t+1} = \text{bin } q \,|\, \ell_t = \text{bin } b\,;\, \theta)\right),\end{aligned}$$

where $N^S(\cdot)$ denotes simulation counts, and $\Pr^K(\cdot)$ 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.

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

Figure B.1: Error from the Kumaraswamy approximation



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 Results for Women

Table D.1 presents NLSY79 summary statistics for women.

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								
All	325	392	452	301	660	1,058	724	934
Ever incarcerated	15	6	7	0	19	3	7	3

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

Table D.2: Lifetime totals by race and education for women

Variable	BFL	WFL	BFH	WFH	BFS	WFS	BFC	WFC
Lifetime earnings avg.	91	164	197	243	264	298	418	479
Lifetime earnings p10	14	30	41	71	89	107	148	172
Lifetime earnings p25	33	69	79	130	135	174	228	252
Lifetime earnings p50	75	144	154	224	225	275	382	414
Lifetime earnings p75	131	240	294	345	366	415	565	638
Lifetime earnings p90	192	331	421	447	498	526	736	919
Expected years E	15.2	21.6	23.5	26.2	26.7	28.1	29.7	29.7
Expected years J	0.2	0.1	0.0	0.0	0.0	0.0	0.0	0.0
Expected years N	20.6	14.4	12.5	9.8	9.2	7.9	6.3	6.3
Ever incarcerated by age 57	0.06	0.03	0.01	0.00	0.02	0.00	0.01	0.00

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

Table D.2 summarizes the distribution of lifetime earnings as of age 22 for all race-education combinations for women. Although our focus is on men, who are far more likely to be incarcerated, there are some notable differences between genders. Women are much more likely to be nonemployed; a Black woman without a high school diploma is nonemployed for an average of nearly 20 years, a White woman for 15 years. Racial gaps are also considerably smaller for more educated groups.

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)

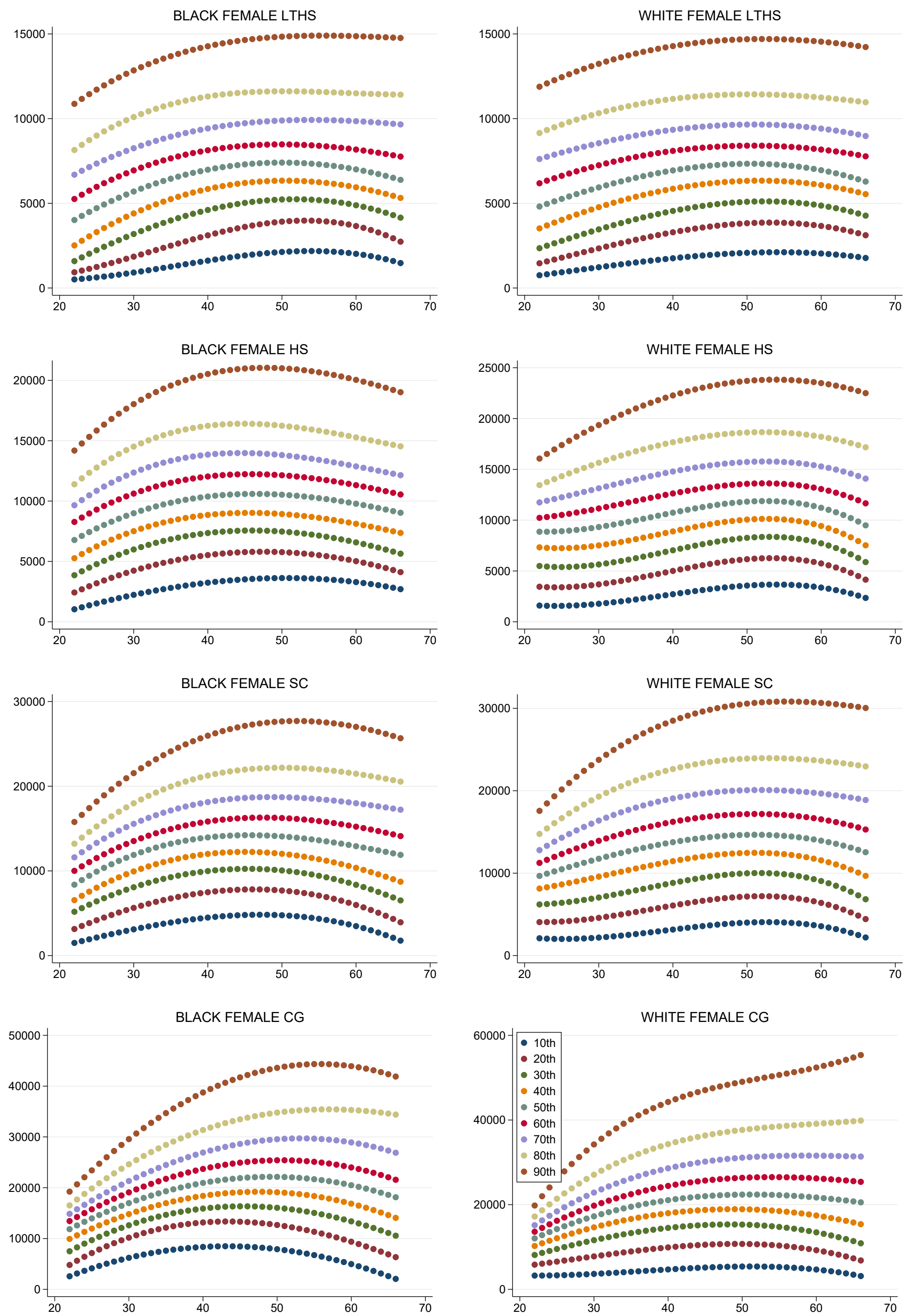


Figure E.2: Decile Cutpoints for Earnings by Group (Males)

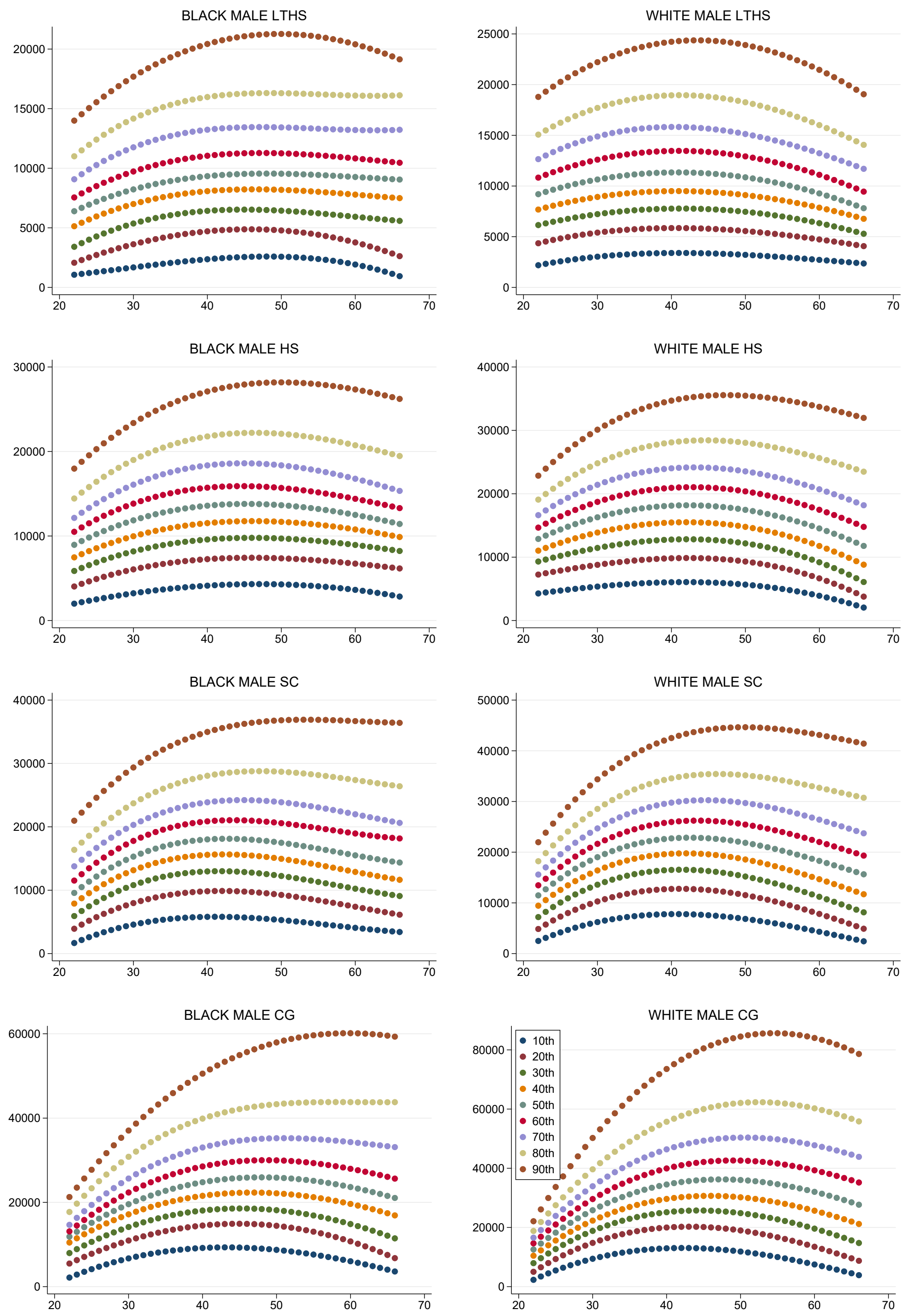


Figure E.3: Within-Decile Mean Earnings by Group: Data and Estimates (Females)

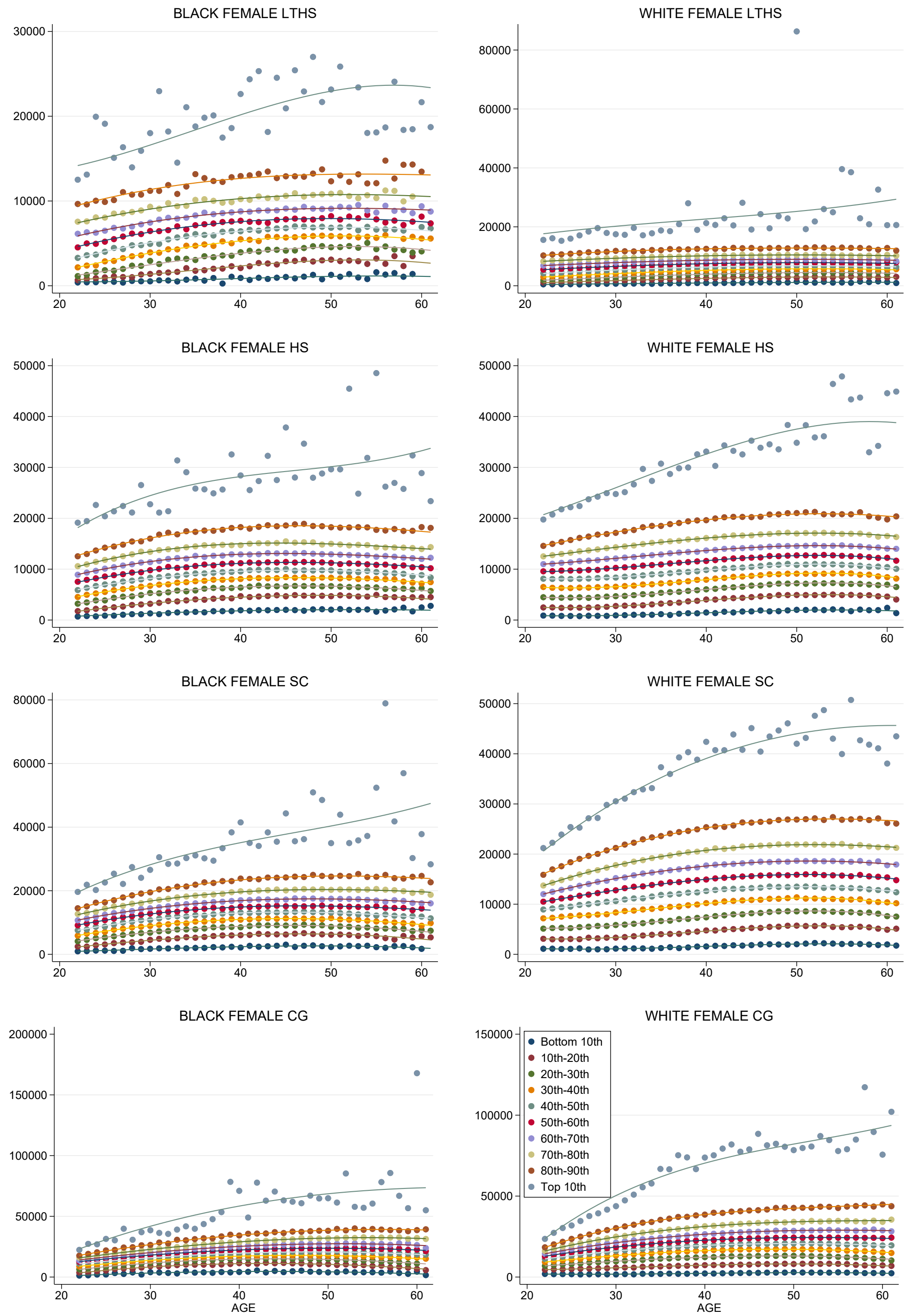
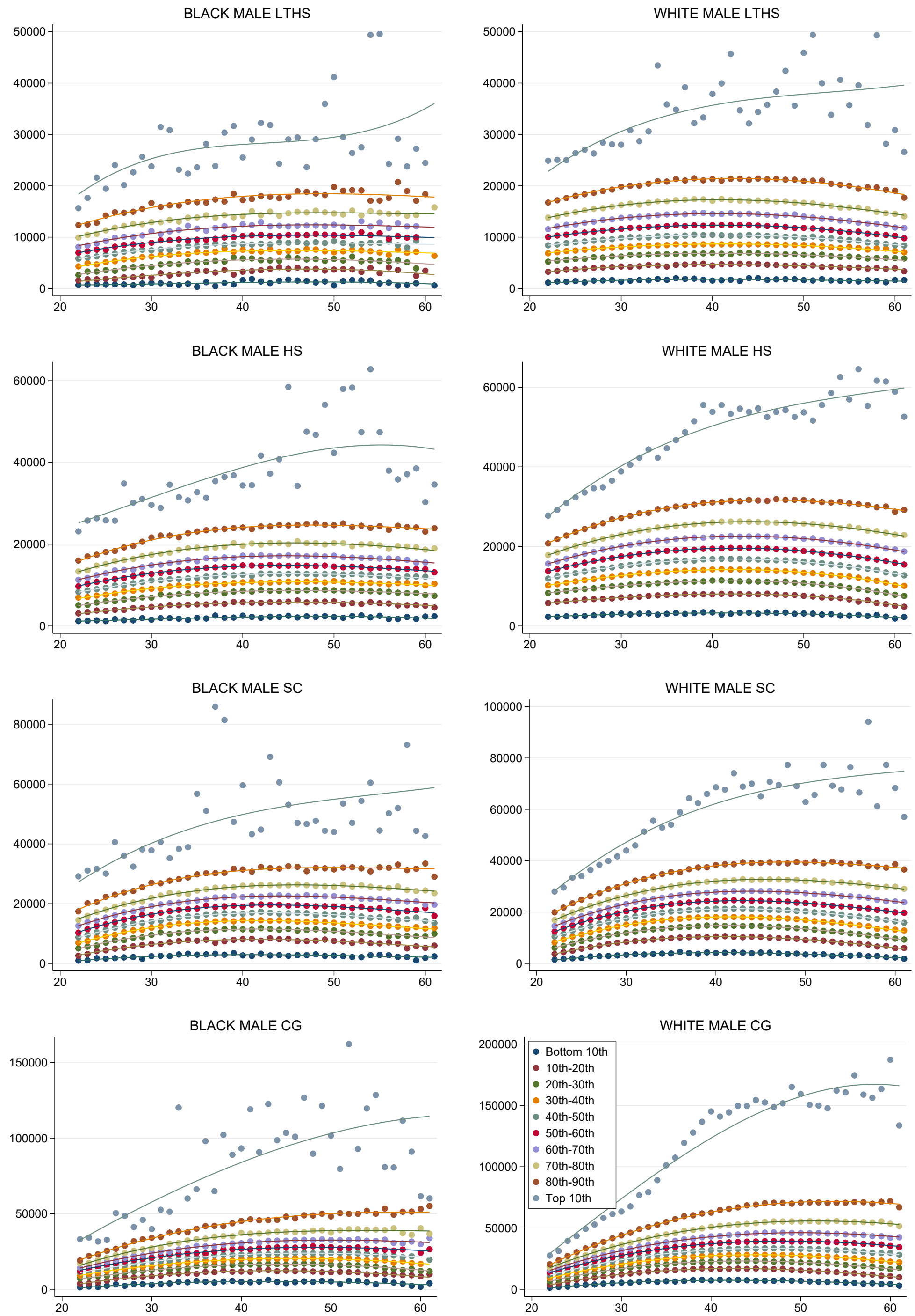


Figure E.4: Within-Decile Mean Earnings by Group: Data and Estimates (Males)



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

$$\begin{aligned} u &= \frac{1}{1+E+IC}, \\ e &= \frac{E}{1+E+IC}, \\ ic &= \frac{IC}{1+E+IC}, \end{aligned}$$

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

$$\begin{aligned} ic_i &= \exp(\ln(IC_i)) \cdot u_i, \\ ic_j &= \exp(\ln(IC_j)) \cdot u_j, \end{aligned}$$

which can be rearranged to yield

$$\begin{aligned} &\exp\left(\frac{\ln(IC_j)}{\ln(IC_i)}\right) = \frac{ic_j}{ic_i} \cdot \frac{u_i}{u_j}, \\ &\Rightarrow\ \ln(IC_j) = \ln(IC_i) + \big(\ln(ic_j) - \ln(ic_i)\big) - \big(\ln(u_j) - \ln(u_i)\big). \qquad (19) \end{aligned}$$

Letting $\ln(IC)$ be the intercept for the incarceration-related expression, the latter two terms of (19) 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 an incarceration record, which is somewhat less noisy than incarceration itself.

The adjustment also includes a term to account for cross-group differences in preference type probabilities. Suppose that the probability than an individual in group i belongs to preference type 2 is p_i, and the corresponding probability for group j is p_j. Suppose further the intercept term for a group i, type-2 individual differs from the type-1 intercept by δ_i^{IC}. If we apply δ_i^{IC} to group j, then we need to adjust the intercept term for group j by the amount $(p_i - p_j)\delta_i^{IC}$.

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 an incarceration 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 incarceration 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.

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 State Next Period																
Constant	2.97	1.26	2.63	1.45	2.14	1.83	3.84	2.30	2.79	1.08	2.24	1.12	2.67	0.93	1.75	0.77
Age	-0.07	0.07	0.02	0.07	-3.8e-3	0.09	0.02	0.11	0.02	0.06	0.02	0.06	-0.04	0.05	0.06	0.05
Age^2/100	0.05	0.09	-0.12	0.09	-0.07	0.12	-0.15	0.13	-0.10	0.07	-0.12	0.08	0.01	0.07	-0.10	0.06
Not employed	-1.35	0.75	-4.33	0.96	-3.51	0.79	-7.94	1.53	-2.57	0.67	-1.37	0.65	-1.06	0.45	-0.36	0.33
Not employed $\times$ age	-0.05	0.02	0.03	0.02	0.03	0.02	0.13	NA	-0.04	0.02	-0.02	0.02	-0.04	0.01	-0.05	0.01
$\tilde{p}$	6.79	1.27	8.37	1.40	11.40	1.73	6.69	2.80	3.68	1.12	14.14	1.44	11.89	1.31	7.75	1.02
$\tilde{p}^2$	-2.12	1.42	-4.49	1.49	-8.38	1.83	-5.38	2.69	-0.70	1.09	-10.40	1.44	-9.17	1.40	-5.37	1.07
In jail	-0.49	0.38	1.17	1.09	-1.02	0.74	11.51	3.6e6	0.06	0.54	-1.39	1.47	-1.29	2.39	-1.29	NA
Criminal record	0.33	0.15	0.24	0.20	0.01	0.27	-0.54	19.60	-0.19	0.13	0.39	1.02	-0.32	0.37	-0.32	NA
Type = 2	-0.19	0.17	-0.57	0.19	-0.04	0.21	-0.83	0.34	-0.06	0.11	-1.21	0.13	-0.78	0.17	-1.36	0.09
Probability of Incarceration Next Period																
Constant	1.47	1.43	-2.42	2.23	1.31	3.96	-1.27	1.7e2	-0.27	1.31	-3.97	12.85	-1.80	23.59	-2.76	NA
Age	-0.12	0.08	0.14	0.12	-0.13	0.23	3.4e-3	8.18	-3.0e-3	0.07	0.07	0.74	0.01	1.37	0.01	NA
Age^2/100	0.06	0.11	-0.30	0.16	0.08	0.30	-0.07	9.55	-0.06	0.09	-0.19	0.98	-0.12	1.95	-0.12	NA
Not employed	-2.57	0.46	-25.26	3.2e7	-2.10	0.79	-4.47	97.11	-4.19	0.56	-0.62	2.24	-1.58	3.21	-1.58	NA
$\tilde{p}$	1.51	0.63	0.30	0.67	0.64	1.62	-2.20	1.0e2	-1.48	0.60	2.58	2.56	-0.09	4.38	-0.09	NA
In jail	1.24	0.36	2.74	1.06	1.69	0.62	16.19	3.6e6	2.18	0.49	3.37	2.50	2.96	2.14	2.96	NA
Criminal record	2.22	0.17	1.76	0.26	2.46	0.39	0.61	1.4e2	1.53	0.16	2.93	1.28	2.03	1.62	2.03	NA
Type = 2	0.50	0.31	0.62	0.27	0.07	0.56	-0.04	15.42	0.97	0.19	0.05	1.38	-1.06	1.87	-1.06	NA
Latent Earnings Decile, Kumaraswamy Parameter alpha																
Constant	-1.96	0.37	-1.77	0.31	-2.86	0.34	-2.79	0.40	-1.09	0.21	1.15	0.13	-3.03	0.14	-4.68	0.12
Age	0.07	0.02	0.07	0.01	0.12	0.02	0.12	0.02	0.04	0.01	2.3e-3	4.7e-3	0.12	0.01	0.18	4.8e-3
Age^2/100	-0.06	0.02	-0.07	0.01	-0.12	0.02	-0.11	0.02	-0.03	0.01	2.2e-4	0.01	-0.08	0.01	-0.14	0.01
Not employed	-0.85	0.47	-0.83	0.37	-1.58	0.81	-1.89	0.67	-0.44	0.21	-2.75	0.39	-0.51	0.59	-1.63	0.48
$\tilde{p}$	6.92	1.01	5.63	0.87	5.94	0.96	5.26	1.10	6.03	0.59	2.48	0.34	8.63	0.41	8.85	0.44
$\tilde{p}\times$ age	-1.7e-4	0.03	0.03	0.02	0.01	0.02	0.01	0.03	0.02	0.02	0.04	0.01	-0.06	0.01	-0.03	0.01
$\tilde{p}^2$	-5.73	1.01	-4.01	0.85	-3.52	0.97	-3.13	1.16	-3.32	0.61	-0.66	0.30	-5.66	0.45	-6.31	0.47
$\tilde{p}^2\times$ age	0.03	0.03	-0.01	0.02	-0.01	0.02	-2.7e-3	0.03	-0.02	0.02	-0.04	0.01	0.04	0.01	0.03	0.01
Criminal record	-0.01	0.03	-0.06	0.04	0.09	0.05	0.04	2.54	-0.07	0.03	-0.05	0.14	0.10	0.16	0.10	NA
Type = 2	0.06	0.03	0.02	0.02	0.02	0.03	-0.20	0.05	-0.04	0.02	0.02	0.01	-0.02	0.02	-0.02	0.01
Latent Earnings Decile, Kumaraswamy Parameter beta																
Constant	0.82	0.91	-0.04	0.95	-2.90	1.10	-1.86	1.26	1.15	0.61	8.71	1.01	-5.36	0.57	1.11	0.38
Age	-0.03	0.05	0.06	0.05	0.17	0.06	0.14	0.07	0.01	0.03	-0.01	0.04	0.22	0.03	-0.10	0.02
Age^2/100	0.08	0.07	-0.04	0.07	-0.14	0.09	-0.09	0.08	1.6e-3	0.05	0.04	0.05	0.02	0.04	0.23	0.04
Not employed	-0.57	0.35	-1.45	0.35	-1.05	0.51	-3.07	0.68	-0.97	0.21	-9.25	0.68	0.77	0.53	-0.69	0.20
$\tilde{p}$	-7.30	3.22	-7.57	3.03	-8.03	3.58	-19.11	3.89	-5.07	2.46	-7.98	3.20	4.65	2.29	-32.14	1.43
$\tilde{p}\times$ age	0.82	0.10	0.73	0.10	0.85	0.12	1.11	0.14	0.82	0.07	0.62	0.08	0.50	0.08	1.74	0.05
$\tilde{p}^2$	5.41	3.43	6.54	3.08	9.03	3.70	19.94	4.22	4.62	2.69	0.57	2.96	0.67	2.33	34.83	1.59
$\tilde{p}^2\times$ age	-0.86	0.11	-0.81	0.10	-0.96	0.12	-1.23	0.14	-0.89	0.08	-0.70	0.08	-0.79	0.07	-1.91	0.06
Criminal record	-0.09	0.12	-0.31	0.17	0.64	0.28	0.48	18.96	-0.34	0.14	-0.34	0.97	0.46	1.31	0.46	NA
Type = 2	0.20	0.11	0.01	0.08	0.14	0.09	-0.35	0.19	-0.18	0.06	0.14	0.06	-0.15	0.07	-0.22	0.04
Probability that Individual Is Interviewed																
Constant	1.77	0.99	4.08	0.98	4.99	1.31	8.51	2.15	4.73	0.63	4.57	0.65	7.14	0.92	6.17	0.86
Age	-0.13	0.05	-0.14	0.05	-0.27	0.07	-0.38	0.12	-0.16	0.04	-0.15	0.04	-0.26	0.05	-0.23	0.05
Age^2/100	0.13	0.07	0.12	0.07	0.29	0.09	0.43	0.15	0.13	0.05	0.10	0.05	0.24	0.06	0.22	0.06
Not employed	0.25	0.26	1.39	0.47	-0.73	0.37	1.82	1.14	0.64	0.20	0.40	0.18	-1.30	0.21	-0.14	0.19
Criminal record	-0.50	0.14	0.39	0.21	-0.15	0.36	-0.33	10.39	0.52	0.11	0.11	0.58	0.61	5.46	0.61	NA
Observed prior wave	2.68	0.10	3.09	0.09	2.55	0.12	3.34	0.20	2.90	0.06	3.54	0.06	3.06	0.09	3.68	0.07
Type = 2	2.12	0.11	-1.70	0.11	2.47	0.17	-2.73	0.22	-2.00	0.10	-2.48	0.08	-2.95	0.11	-2.59	0.10

table continues on next page

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	0.82	1.27	0.72	1.11	-5.69	2.39	-4.34	2.43	3.77	1.17	1.73	1.56	28.17	7.71	28.30	18.28
Age	-0.12	0.07	-0.11	0.06	0.18	0.12	0.19	0.19	-0.25	0.07	-0.03	0.07	-0.89	0.26	-0.82	0.45
$\text{Age}^2/100$	0.29	0.09	0.34	0.09	0.28	0.16	3.8e-3	0.36	0.42	0.10	0.22	0.09	0.74	0.23	0.75	0.23
$\tilde{p}$	16.86	4.95	34.98	5.12	50.00	10.41	37.99	14.93	26.52	4.87	35.13	6.32	-46.64	19.13	-17.85	49.60
$\tilde{p}\times$ age	-0.39	0.14	-0.89	0.16	-1.64	0.36	-0.87	0.41	-0.55	0.14	-0.89	0.18	1.15	0.46	0.27	1.10
$\tilde{p}^2$	-8.51	5.44	-27.74	5.49	-40.71	10.37	-26.50	14.29	-21.17	5.34	-30.00	5.83	36.64	15.13	9.86	33.91
$\tilde{p}^2\times$ age	0.24	0.15	0.80	0.16	1.39	0.34	0.58	0.34	0.50	0.16	0.76	0.16	-0.91	0.38	-0.15	0.76
Criminal record	-0.80	0.14	-0.28	0.23	-0.87	0.54	-1.89	33.15	-0.56	0.13	-0.69	1.60	-0.67	6.03	-0.67	NA
Type = 2	0.50	0.19	-1.73	0.16	0.79	0.22	-0.86	0.41	-0.17	0.14	-1.48	0.16	-1.39	0.28	-1.67	0.29
Distribution of Observed Earnings, Dispersion Parameter sigma																
Constant	3.94	15.81	-11.57	12.74	14.79	16.28	6.87	26.27	15.43	6.97	18.74	4.79	-36.61	2.92	23.28	3.37
Age	2.81	0.51	2.13	0.41	1.66	0.56	2.38	0.92	1.18	0.25	1.11	0.17	2.69	0.14	-0.11	0.17
$\text{Age}^2/100$	-3.20	0.36	-0.91	0.25	-1.04	0.44	-2.72	0.77	0.58	0.24	1.31	0.14	-1.60	0.18	-1.95	0.23
$\tilde{p}$	-50.00	57.63	-6.55	48.86	-50.00	62.33	-50.00	95.26	-50.00	32.45	-39.39	23.14	-12.79	22.53	-7.91	19.81
$\tilde{p}\times$ age	-5.66	1.62	-4.91	1.49	-4.31	1.88	-3.77	2.74	-8.98	1.04	-11.31	0.72	-9.59	0.77	7.38	0.51
$\tilde{p}^2$	8.12	55.35	50.00	46.67	41.33	61.59	-33.64	92.30	50.00	33.82	50.00	22.92	50.00	28.98	-50.00	21.02
$\tilde{p}^2\times$ age	7.10	1.60	3.86	1.41	4.72	1.85	6.72	2.74	9.95	1.08	11.19	0.72	11.14	0.97	-6.72	0.54
Criminal record	-4.27	0.97	-5.05	0.96	-22.81	1.81	-3.03	2.1e2	2.63	0.95	-8.29	7.91	-22.96	7.41	-22.96	NA
Initial Distribution																
Working	2.05	0.29	3.85	0.55	3.11	0.56	20.02	2.6e6	2.80	0.22	4.00	0.44	3.35	0.32	2.69	0.12
In jail	-0.75	0.39	-0.62	0.70	-0.90	0.79	15.43	2.6e6	-1.06	0.32	-3.85	3.37	-2.51	7.02	-3.47	NA
Kumaraswamy alpha	0.04	0.12	0.13	0.10	0.23	0.14	-0.08	0.45	0.28	0.07	0.29	0.06	-0.28	0.13	-0.58	0.09
Kumaraswamy beta	0.05	0.16	0.33	0.11	0.51	0.14	1.07	0.37	0.38	0.08	0.23	0.07	0.01	0.11	0.53	0.08
Probability of a Criminal Record, Initial Distribution																
Constant	-2.07	0.91	-2.32	1.29	-3.48	15.66	-3.74	73.83	-2.11	0.55	-17.71	5.5e5	-14.11	103.33	-15.08	NA
Not employed	-28.03	NaN	-0.08	2.24	-32.88	NaN	-50.00	NaN	0.39	1.00	7.17	5.5e5	9.25	107.01	9.25	NA
In jail	1.24	0.64	2.01	1.62	31.60	NaN	3.74	2.1e2	2.61	0.77	-48.50	NaN	16.45	107.44	16.45	NA
$\tilde{p}$	-3.93	1.66	-7.01	6.53	-2.96	19.23	-8.32	5.6e2	-3.24	1.20	-47.49	1.1e7	9.85	120.94	9.85	NA
Type = 2	0.87	0.89	-0.21	1.13	0.79	12.42	-18.35	1.5e9	-0.37	0.68	8.07	2.1e4	1.99	13.39	1.99	NA
Probability of Belonging to Type 2																
Constant	3.94	0.65	-1.13	0.50	2.33	0.60	-2.47	1.53	-2.11	0.39	-2.90	0.60	-4.06	0.68	-8.45	1.29
$\widehat{\Pr}$(ever jailed)	2.00	0.49	-0.21	0.25	0.67	0.25	-0.35	0.40	-0.98	0.20	-0.51	0.15	-0.81	0.19	-1.15	0.20

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.

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 State Next Period																
Constant	-4.80	1.57	-0.81	1.03	-0.12	1.54	0.99	1.03	-3.21	0.92	-1.67	0.49	1.48	0.66	5.36	0.63
Age	0.36	0.08	0.12	0.05	0.06	0.11	0.01	0.06	0.23	0.05	0.15	0.03	0.02	0.04	-0.23	0.04
$Age^2/100$	-0.47	0.11	-0.17	0.07	-0.09	0.14	1.4e-3	0.08	-0.30	0.06	-0.18	0.04	-0.04	0.05	0.35	0.05
Not employed	0.51	1.12	-1.14	0.65	-0.62	0.37	0.33	0.43	0.65	0.49	-0.37	0.27	-2.23	0.38	0.06	0.34
Not employed × age	-0.12	0.03	-0.05	0.02	-0.03	0.01	-0.07	0.01	-0.09	0.01	-0.07	0.01	-0.02	0.01	-0.10	0.01
p_til	7.81	2.18	8.80	1.42	11.17	1.29	10.43	1.47	7.68	1.01	9.80	0.66	8.49	0.86	8.50	0.77
$\tilde{p}^2$	-6.29	2.11	-5.81	1.49	-8.08	1.41	-6.91	1.99	-4.60	0.98	-7.13	0.69	-6.03	0.92	-7.29	0.78
In jail	8.00	7.0e3	-1.57	NA	-1.57	3.0e4	-1.57	NA	7.60	3.3e3	7.60	NA	7.60	NA	7.60	NA
Criminal record	-0.43	1.31	0.39	NA	0.39	4.2e3	0.39	NA	-0.75	4.49	-0.75	NA	-0.75	NA	-0.75	NA
Type = 2	-0.68	0.23	-0.05	0.14	-0.60	0.17	0.00	0.39	0.00	NaN	-0.29	0.06	-0.44	0.08	-0.28	0.08
Probability of Incarceration Next Period																
Constant	-10.75	30.10	-13.20	NA	-12.27	3.6e2	-12.29	NA	-10.45	39.67	-13.81	NA	-14.07	NA	-15.73	NA
Age	0.38	1.32	0.46	NA	0.46	17.73	0.46	NA	0.47	2.27	0.47	NA	0.47	NA	0.47	NA
$Age^2/100$	-0.59	2.07	-0.63	NA	-0.63	23.58	-0.63	NA	-0.68	3.09	-0.68	NA	-0.68	NA	-0.68	NA
Not employed	-2.45	4.16	-1.74	NA	-1.74	1.2e2	-1.74	NA	-14.96	7.1e5	-14.96	NA	-14.96	NA	-14.96	NA
p_til	1.72	10.97	-3.61	NA	-3.61	6.8e2	-3.61	NA	-1.99	27.70	-1.99	NA	-1.99	NA	-1.99	NA
In jail	11.66	7.0e3	0.37	NA	0.37	3.5e4	0.37	NA	5.51	3.3e3	5.51	NA	5.51	NA	5.51	NA
Criminal record	2.17	2.03	3.85	NA	3.85	1.1e4	3.85	NA	2.92	4.86	2.92	NA	2.92	NA	2.92	NA
Type = 2	1.57	8.32	-0.87	NA	-0.87	25.33	-0.87	NA	-11.88	1.9e5	-11.88	NA	-11.88	NA	-11.88	NA
Latent Earnings Decile, Kumaraswamy Parameter alpha																
Constant	-0.04	0.56	-1.56	0.29	-2.18	0.30	-2.57	0.22	0.46	0.33	-1.20	0.18	-1.30	0.18	-3.95	0.12
Age	0.03	0.02	0.05	0.01	0.07	0.01	0.10	0.01	-0.04	0.01	0.02	0.01	0.05	0.01	0.15	4.8e-3
$Age^2/100$	-0.08	0.03	-0.02	0.02	-0.05	0.01	-0.08	0.01	-0.01	0.02	-3.6e-3	0.01	-0.04	0.01	-0.14	0.01
Not employed	-3.38	2.74	-0.75	0.35	-1.55	0.53	-0.90	0.37	0.04	0.17	0.43	0.30	-0.91	0.48	-3.26	1.04
p_til	-6.06	1.77	8.12	0.90	6.72	1.04	5.28	0.81	-3.70	1.02	7.87	0.56	5.05	0.62	6.08	0.42
$\tilde{p}\times$ age	0.26	0.04	-0.02	0.02	0.02	0.02	0.03	0.02	0.23	0.03	-0.05	0.01	0.01	0.02	0.04	0.01
$\tilde{p}^2$	7.81	1.85	-4.73	0.98	-3.93	1.02	-2.31	0.93	4.73	0.98	-5.70	0.54	-2.49	0.62	-3.31	0.46
$\tilde{p}^2\times$ age	-0.24	0.05	0.01	0.02	-0.02	0.02	-0.04	0.02	-0.19	0.02	0.06	0.01	-0.01	0.02	-0.04	0.01
Criminal record	-0.34	1.56	-0.66	NA	-0.66	1.7e5	-0.66	NA	0.61	9.65	0.61	NA	0.61	NA	0.61	NA
Type = 2	0.29	6.6e-2	-0.03	0.04	-0.02	2.2e-2	8.9e-4	0.04	0.89	0.05	-0.56	0.02	-0.53	0.03	5.0e-4	0.01
Latent Earnings Decile, Kumaraswamy Parameter beta																
Constant	2.69	1.27	0.30	0.86	-0.15	0.73	-1.78	0.80	4.45	0.84	1.75	0.40	0.17	0.39	-0.88	0.33
Age	-0.01	0.06	-0.02	0.05	0.01	0.04	0.10	0.05	-0.17	0.04	-0.05	0.02	0.07	0.02	0.02	0.02
$Age^2/100$	-0.06	0.09	0.08	0.07	0.02	0.06	-0.01	0.08	0.10	0.05	0.08	0.03	-0.08	0.03	0.05	0.03
Not employed	-2.63	0.81	-0.19	0.27	-0.19	0.30	-0.50	0.29	0.51	0.30	1.98	0.58	-0.23	0.34	-0.79	0.26
p_til	-21.58	3.65	6.87	4.59	-8.98	2.95	-9.08	2.39	-16.61	2.27	4.28	1.27	0.34	1.44	-26.11	1.26
$\tilde{p}\times$ age	0.76	0.09	0.54	0.12	0.94	0.09	0.74	0.08	0.73	0.06	0.19	0.04	0.24	0.04	1.50	0.05
$\tilde{p}^2$	20.45	3.61	-6.24	5.05	9.61	3.22	12.05	2.69	13.39	2.19	-5.41	1.25	0.15	1.43	28.45	1.35
$\tilde{p}^2\times$ age	-0.79	0.10	-0.64	0.13	-1.03	0.10	-0.92	0.08	-0.70	0.06	-0.20	0.04	-0.29	0.04	-1.64	0.05
Criminal record	-0.98	3.55	4.85	NA	4.85	5.3e4	4.85	NA	1.58	21.66	1.58	NA	1.58	NA	1.58	NA
Type = 2	1.05	0.15	-0.11	0.13	-0.15	9.7e-2	-0.20	0.12	1.62	0.06	-1.46	0.04	-1.56	0.05	-0.05	0.04
Probability that Individual Is Interviewed																
Constant	4.17	1.41	8.89	1.48	4.90	1.15	6.20	1.46	3.51	1.00	4.03	0.63	3.57	0.92	5.39	0.74
Age	-0.24	0.07	-0.36	0.08	-0.16	0.06	-0.26	0.08	-0.18	0.05	-0.16	0.03	-0.15	0.05	-0.16	0.04
$Age^2/100$	0.27	0.09	0.39	0.10	0.15	0.08	0.28	0.10	0.15	0.06	0.14	0.04	0.13	0.06	0.11	0.05
Not employed	-1.06	0.27	0.01	0.29	1.08	0.36	-0.42	0.30	0.04	0.17	-0.56	0.11	-0.24	0.16	-0.45	0.16
Criminal record	0.01	1.97	1.85	NA	1.85	2.5e3	1.85	NA	2.36	7.11	2.36	NA	2.36	NA	2.36	NA
Observed prior wave	3.51	0.15	3.02	0.12	3.15	0.09	3.36	0.13	3.50	0.06	4.09	0.05	4.27	0.06	3.53	0.07
Type = 2	1.94	0.21	-2.84	0.14	-2.56	0.15	-2.13	0.13	1.53	0.10	-1.67	0.08	-1.56	0.09	-2.95	0.10

table continues on next page

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	-4.64	1.60	-2.63	1.24	6.71	2.95	28.65	10.32	-0.74	1.33	2.51	1.05	3.30	1.40	3.19	1.16
Age	0.05	0.07	0.08	0.07	-0.16	0.11	-0.82	0.28	-0.09	0.06	-0.14	0.06	-0.30	0.11	-2.3e-3	0.06
$Age^2/100$	0.06	0.10	0.00	0.11	0.26	0.12	0.70	0.21	0.22	0.08	0.33	0.08	0.71	0.20	-0.06	0.07
p_til	21.74	7.07	26.63	6.00	3.06	10.75	-29.97	33.92	11.53	5.32	25.62	4.51	48.76	9.44	9.12	5.62
$\tilde{p}\times$ age	-0.32	0.18	-0.51	0.16	-0.24	0.29	0.38	0.78	-0.18	0.14	-0.57	0.13	-1.13	0.27	-1.5e-3	0.14
$\tilde{p}^2$	-11.82	8.32	-19.32	6.34	1.84	10.21	20.08	29.40	-0.30	5.96	-17.99	4.41	-38.77	9.13	-6.33	5.72
$\tilde{p}^2\times$ age	0.19	0.21	0.38	0.16	0.12	0.27	-0.15	0.69	0.02	0.15	0.42	0.12	0.91	0.25	-0.03	0.14
Criminal record	-0.45	1.44	10.75	NA	10.75	6.1e9	10.75	NA	2.6e-3	2.76	2.6e-3	NA	2.6e-3	NA	2.6e-3	NA
Type = 2	0.42	0.25	-0.14	0.26	-1.95	0.17	-3.33	0.25	1.03	0.13	-0.43	0.13	-0.32	0.20	-1.30	0.15
Distribution of Observed Earnings, Dispersion Parameter sigma																
Constant	29.66	34.47	19.00	11.96	5.74	5.57	50.00	30.26	1.23	13.68	-7.58	4.09	-10.21	4.80	50.00	4.57
Age	1.06	1.14	1.31	0.42	0.82	0.23	0.01	1.02	2.61	0.48	-0.49	0.17	-0.50	0.19	-1.14	0.21
$Age^2/100$	-0.48	0.81	0.99	0.32	0.23	0.23	-0.24	0.79	-3.29	0.31	-0.18	0.18	-0.19	0.22	-1.04	0.26
p_til	-9.66	1.3e2	-45.20	60.74	-44.58	39.47	-50.00	107.01	-50.00	54.98	50.00	29.11	50.00	36.14	-29.85	16.15
$\tilde{p}\times$ age	-8.01	3.40	-11.69	1.88	-8.61	1.26	2.32	3.09	-5.40	1.64	4.81	0.90	5.69	1.04	7.25	0.43
$\tilde{p}^2$	19.17	1.5e2	50.00	66.73	50.00	49.89	-50.00	107.80	18.11	59.33	33.53	48.08	50.00	66.62	-50.00	16.58
$\tilde{p}^2\times$ age	8.93	3.85	13.04	2.07	10.88	1.58	-4.30	3.16	7.67	1.77	-4.41	1.44	-5.72	1.78	-5.89	0.43
Criminal record	5.34	24.03	-32.17	NA	-32.17	1.9e4	-32.17	NA	3.88	58.82	3.88	NA	3.88	NA	3.88	NA
Initial Distribution																
Working	1.39	0.47	1.23	0.20	1.37	0.21	1.32	0.16	1.13	0.23	1.95	0.10	2.97	0.24	2.58	0.17
In jail	-25.02	NaN	-25.01	NA	-24.08	NaN	-24.10	NA	-21.37	1.7e8	-24.73	NA	-24.99	NA	-26.65	NA
Kumaraswamy alpha	-0.15	0.23	-0.05	0.15	-0.40	0.16	-0.05	0.12	-0.42	0.19	0.24	0.06	0.10	0.07	-0.80	0.09
Kumaraswamy beta	0.26	0.25	0.37	0.15	0.27	0.12	1.21	0.19	-0.45	0.16	0.94	0.06	1.10	0.07	0.35	0.07
Probability of a Criminal Record, Initial Distribution																
Constant	-36.93	NaN	-30.83	NA	-29.91	NaN	-29.92	NA	-2.78	9.63	-6.14	NA	-6.40	NA	-8.06	NA
Not employed	-1.84	NaN	0.08	NA	0.08	NaN	0.08	NA	-16.23	1.8e7	-16.23	NA	-16.23	NA	-16.23	NA
In jail	-8.79	NaN	-31.70	NA	-31.70	NaN	-31.70	NA	-1.62	NaN	-1.62	NA	-1.62	NA	-1.62	NA
p_til	-11.52	NaN	0.79	NA	0.79	NaN	0.79	NA	-6.75	72.69	-6.75	NA	-6.75	NA	-6.75	NA
Type = 2	-8.07	NaN	2.83	NA	2.83	NaN	2.83	NA	-0.42	29.11	-0.42	NA	-0.42	NA	-0.42	NA
Probability of Belonging to Type 2																
Constant	7.74	1.89	-3.34	1.32	-0.17	0.98	-1.99	1.43	-0.89	0.58	2.61	0.59	3.06	0.78	3.86	0.81
$\widehat{\Pr}$(ever jailed)	1.91	0.54	-0.46	0.34	0.15	0.19	-0.07	0.24	-0.31	0.12	0.60	0.12	0.68	0.15	0.84	0.13

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), earnings (Figure G.2), and nonemployment (Figure G.3), as well as the bias induced by conditioning on observed outcomes (Figure G.4).

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

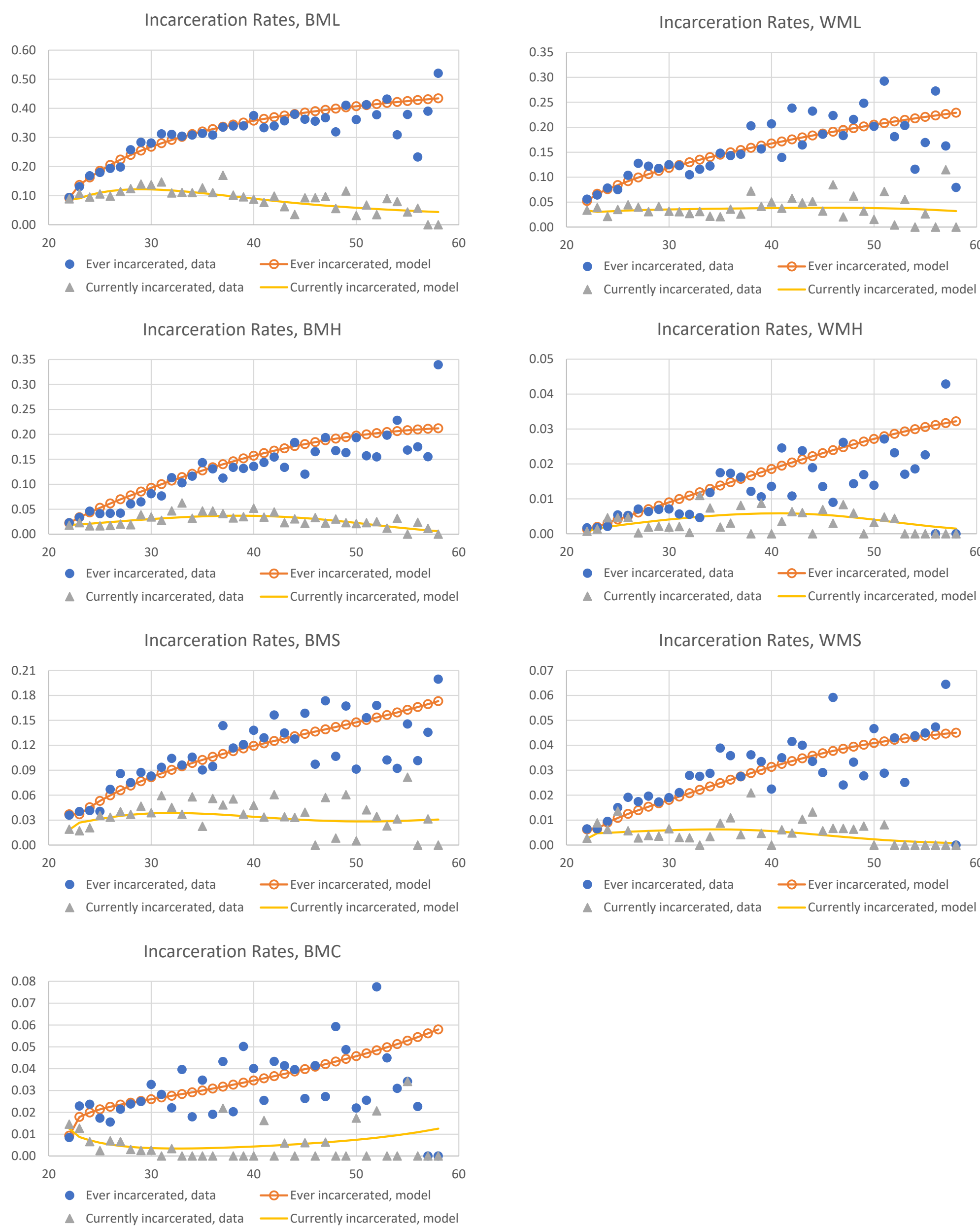


Figure G.2: Earnings, Model and Data, Men

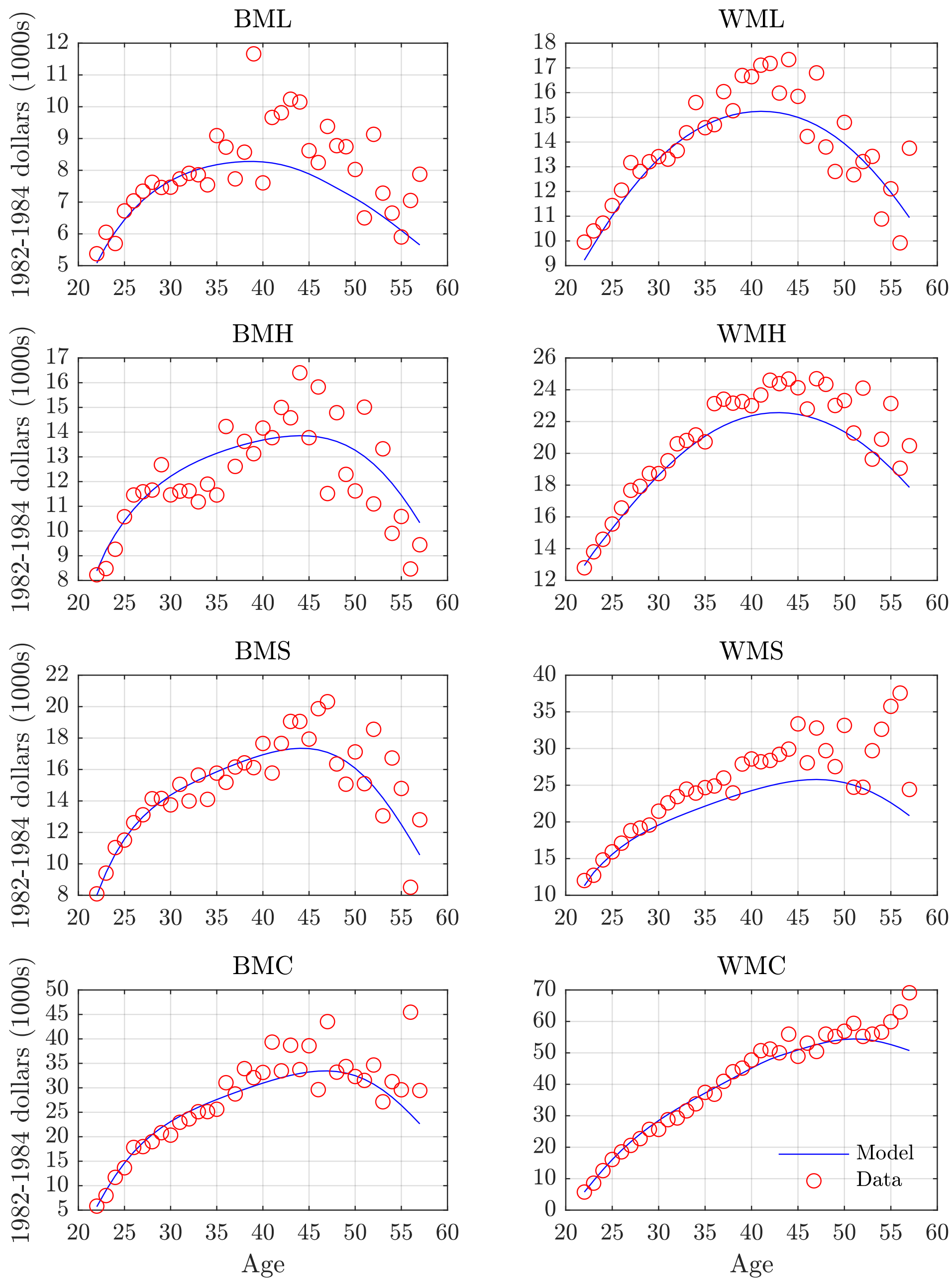
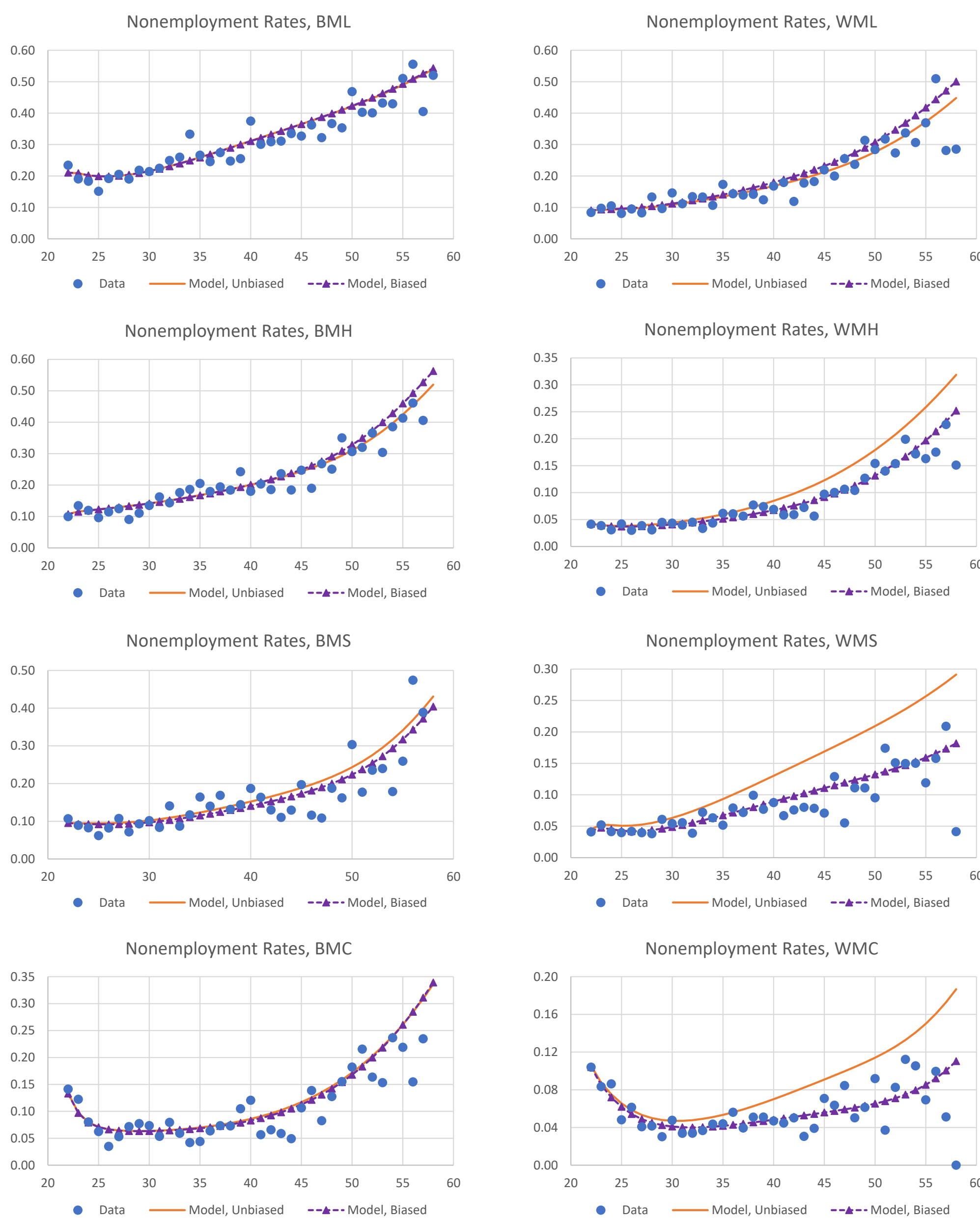
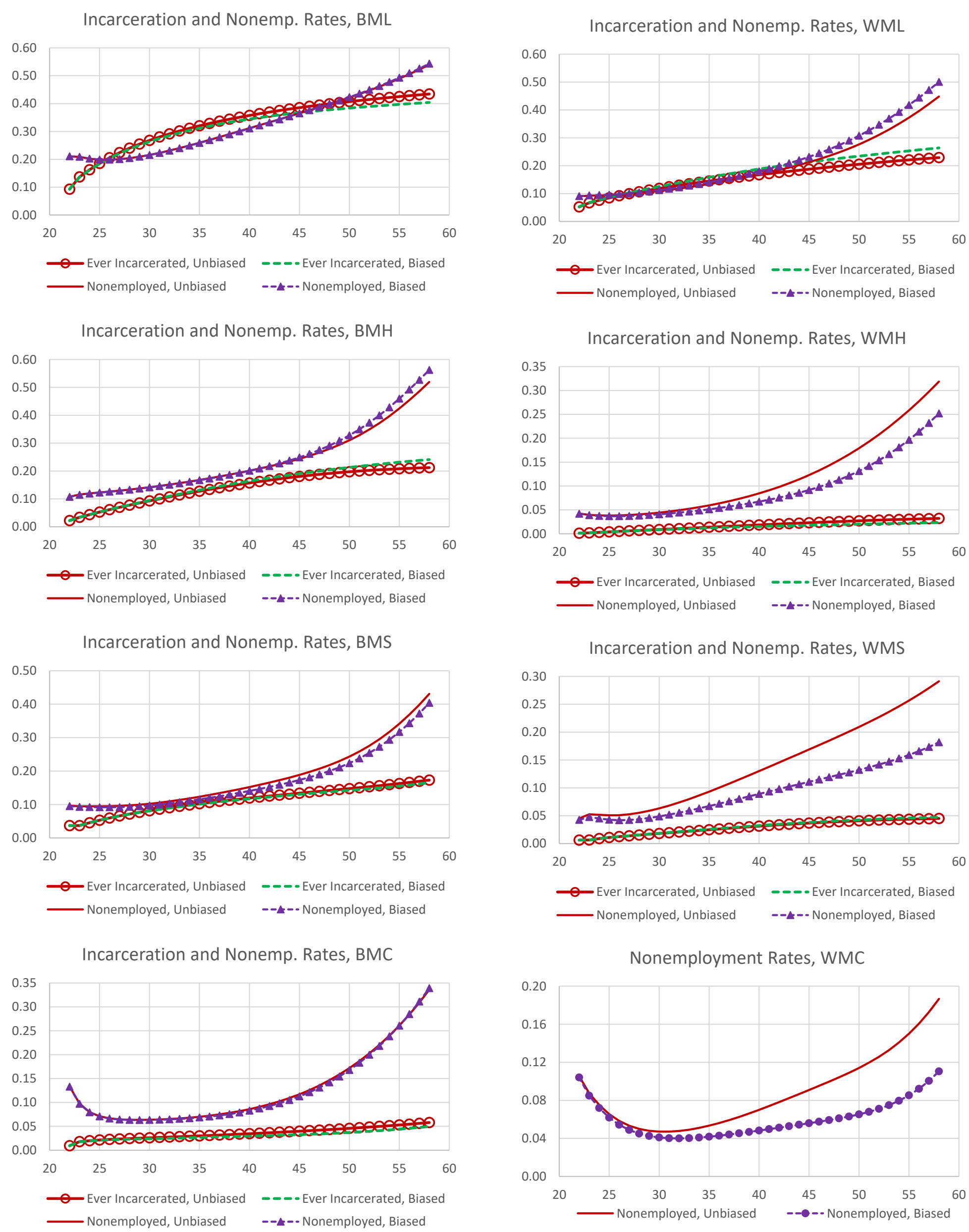


Figure G.3: Nonemployment Rates, Model and Data, Men



Note: "Biased" rates reflect non-reporting bias; "unbiased" rates do not.

Figure G.4: Model-predicted Incarceration and Nonemployment Rates, with and without Observation Bias, Men

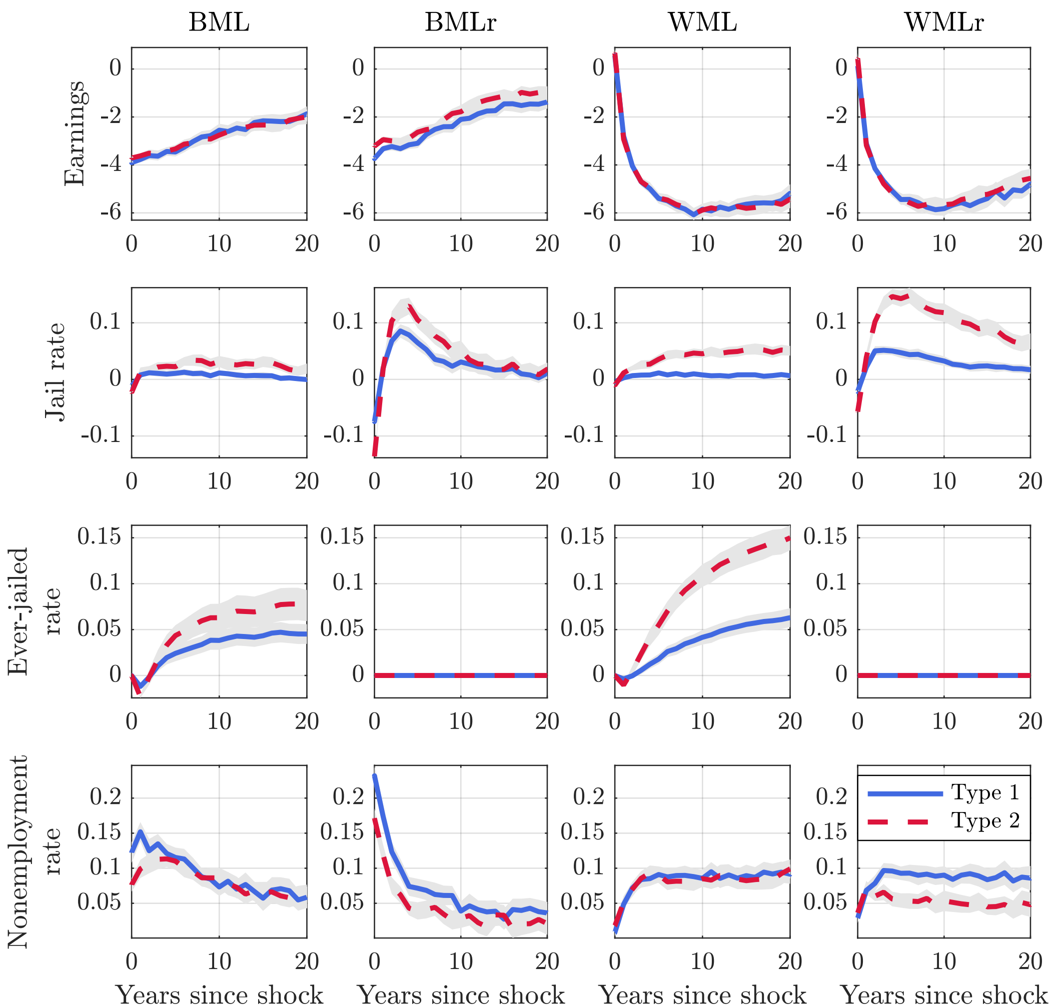


Note: “Biased” rates reflect non-reporting bias; “unbiased” rates do not.

H Q5 to Q3 Shocks and Q5 to Q7 Shocks

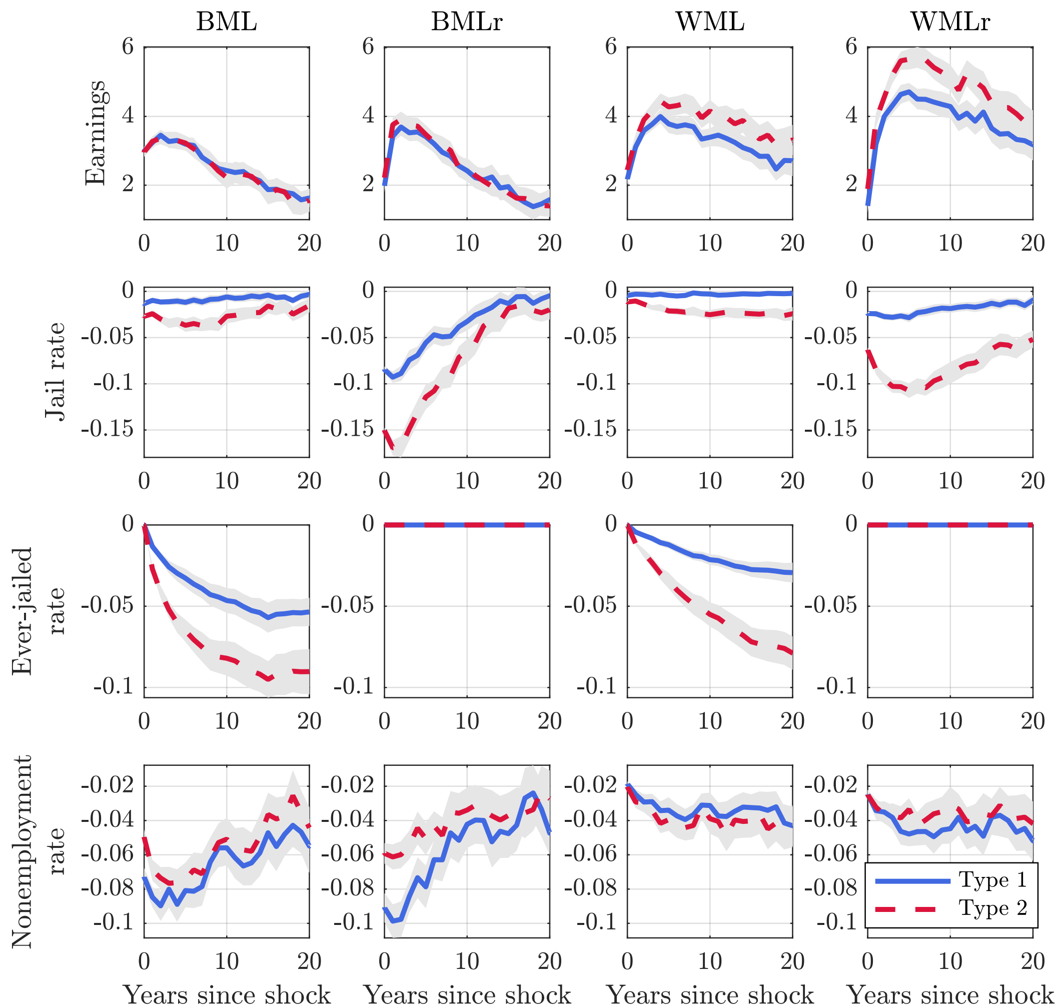
Table 2 also shows that men with low latent earnings potential are more likely to transition to incarceration or nonemployment. We examine these dynamics more carefully in Figures H.1 and H.2, which plot the effects of moving down (from decile 5 to decile 3) or up (from decile 5 to decile 7) the distribution of earnings potential.

Figure H.1: 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 incarceration record/incarceration record. Earnings are measured in thousands of 1982-1984 dollars.

Figure H.2: 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 incarceration record/incarceration record. Earnings are measured in thousands of 1982-1984 dollars.

Figure H.1 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 Black men, the shock has a large initial impact that shrinks monotonically. For White men, the initial effect of the shock is small—in fact it is slightly positive—but the earnings loss expands rapidly in subsequent years. This reflects heterogeneity in the mapping from latent states to observed outcomes, an issue we examine more closely in Appendix I below.

Table H.1 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 incarceration record who is hit by a nonemployment shock will on average suffer a lifetime earnings loss of $141,300; the latent earnings potential shock generates an average loss of $124,400.

Figure H.1 and Table H.1 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 an incarceration record, a negative earnings shock implies an additional 0.9 years in jail, while a nonemployment shock also implies an additional 1.2 years. A negative earnings shock also implies higher future nonemployment, although the increases are smaller than those following the nonemployment shock itself.

Table H.1: GIRF statistics by shock, group type, and response variable

GIRF for a bad latent earnings transition: Q5 to Q3								
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-3.7	0.6	-3.3	0.3	-4.4	-1.4	-4.1	-4.2
Lifetime earnings	-63.8	-124.4	-42.8	-116.0	-95.9	-169.6	-97.4	-183.7
Future years E	-3.1	-3.8	-2.3	-4.0	-2.7	-2.4	-2.4	-2.7
Future years N	2.6	3.1	1.3	2.5	2.4	2.3	1.7	1.8
Future years J	0.6	0.7	0.9	1.5	0.4	0.1	0.7	1.0
GIRF for a good latent earnings transition: Q5 to Q7								
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	3.0	2.3	2.2	1.6	3.5	3.9	2.6	3.8
Lifetime earnings	55.3	79.1	53.1	96.0	72.5	106.0	74.6	141.4
Future years E	2.4	1.7	2.8	2.6	1.6	0.6	1.6	0.3
Future years N	-1.8	-1.3	-1.3	-1.5	-1.3	-0.6	-1.1	-0.4
Future years J	-0.6	-0.4	-1.6	-1.2	-0.2	-0.0	-0.5	0.1

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

Figure H.2 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 H.1, 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.

I Restricting the Observation Matrix

Figure H.1 and Table H.1 show that for White men without a high school diploma, a fall in latent earnings potential from the fifth to the third decile leads earnings to initially rise. Given that the distribution of observed earnings is centered around the rank of the earnings potential bin, as shown in equation (16), this may seem surprising. However, the dispersion of observed earnings, controlled by the parameter $\sigma_{\mathbf{z}_1}$, also varies across the earnings potential bins. In the case at hand, the distribution of observed earnings becomes much more dispersed when earnings potential falls, raising mean earnings.

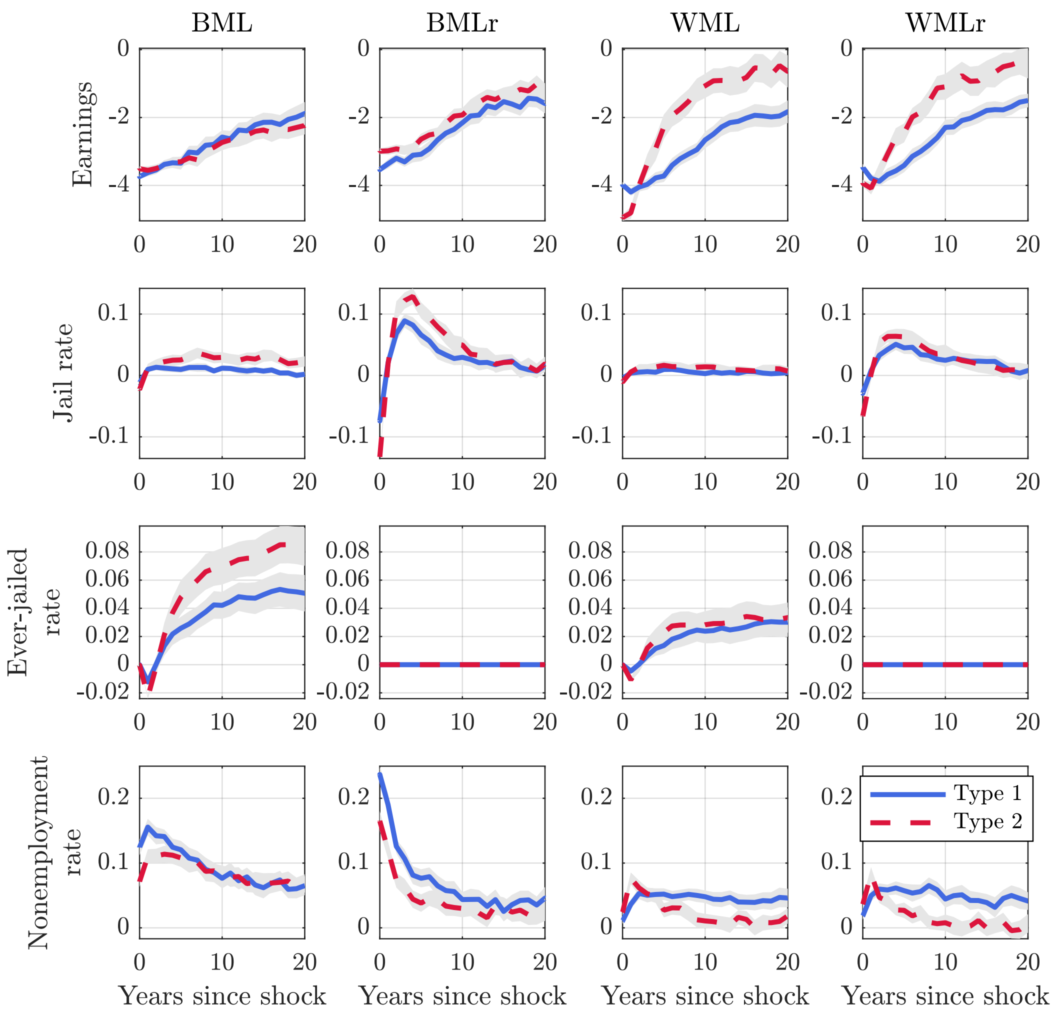
Recall from equation (17) that $\sigma_{\mathbf{z}_1} = \left|\mathbf{z}_1(a_t, \ell_t)\boldsymbol{\gamma}_E\right|$. It can also be shown that the conditional dispersion of observed earnings is most sensitive to changes in $\sigma_{\mathbf{z}_1}$ when $\sigma_{\mathbf{z}_1}$ is close to zero and approaches a uniform distribution as $\sigma_{\mathbf{z}_1}$ goes to zero. This means that the dispersion varies greatly when $\mathbf{z}_1(a_t, \ell_t)\boldsymbol{\gamma}_E$ moves above or below zero, which it does in some cases. To make $\sigma_{\mathbf{z}_1}$ behave more smoothly, we introduce an alternative specification where we replace equation (17) with

$$\sigma_{\mathbf{z}_1} = \exp\left(\mathbf{z}_1(a_t, \ell_t)\boldsymbol{\gamma}_E\right).$$

Figure I.1 and Table I.1 summarize the effects of earnings potential shocks in the reestimated model with this revised specification. In particular the figure shows that the alternate specification eliminates the counterintuitive effect of a Q5 to Q3 shock. The first row of the table shows that with this revision, a decline in latent earnings potential leads to an immediate decrease in earnings across all groups, in contrast to the increases that sometime appear in the first row of Table H.1. On the other hand, the restricted specification is associated with a much smaller change in lifetime earnings. The second row of Table I.1 shows that for White men without a high school diploma, a fall in latent earnings potential predicts a lifetime earnings loss of \$52,000; Table H.1 shows a loss of \$124,000.

We prefer the baseline, unrestricted specification for two reasons. The first is that in some groups, the estimates using the baseline specification have a significantly higher log-likelihood. The second is that in the revised and reestimated version, for several of the male groups, older men cycle between nonemployment and the bottom earnings decile on annual basis. Because the NLSY79 switches to a biennial frequency after

Figure I.1: GIRFs for a latent Q5 to Q3 shock, by race and incarceration history, men without a high school diploma when restricting the observation matrix



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

1994, such behavior is consistent with the data, as individuals have a high probability of returning to their initial state two years later. Although the bottom earnings decile has very low earnings, so that the financial effects of this cycling are smaller than they might first seem, we do not find it very plausible. Ruling out this behavior, however, would require us to restrict the parameter estimates even further.

In any event, this specification choice has a fairly limited effect on the exercises involving incarceration and nonemployment. Table I.2 shows the GIRF analyses for these two shocks. Panel A of the table repeats for convenience the baseline results

Table I.1: GIRF statistics by shock, group type, and response variable, restricted observation matrix

GIRF for a bad latent earnings transition: Q5 to Q3								
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-3.5	-4.4	-3.1	-3.7	-4.4	-5.3	-4.5	-4.8
Lifetime earnings	-64.3	-51.7	-44.6	-45.0	-99.3	-119.6	-106.6	-96.6
Future years E	-3.3	-1.4	-2.3	-1.7	-2.8	-0.9	-2.5	-2.1
Future years N	2.7	1.2	1.4	1.1	2.5	0.8	1.7	1.0
Future years J	0.6	0.2	0.9	0.6	0.4	0.1	0.7	1.1
GIRF for a good latent earnings transition: Q5 to Q7								
Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	3.1	3.4	3.3	4.1	3.6	3.9	3.1	4.0
Lifetime earnings	61.9	42.1	57.4	49.9	77.1	89.6	79.0	88.1
Future years E	2.7	1.1	2.9	1.9	1.7	0.3	1.6	1.2
Future years N	-2.0	-0.9	-1.3	-1.1	-1.5	-0.3	-1.1	-0.6
Future years J	-0.7	-0.2	-1.6	-0.8	-0.3	-0.0	-0.5	-0.5

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

shown in Table 6 of the main text. Panel B shows the results for the alternative specifications. The two sets of results are similar qualitatively and in most cases fairly similar quantitatively as well. Table I.3 compares the predictions of the two specifications for the counterfactual experiments. Here too the results are similar qualitatively and in most cases similar quantitatively.

Table I.2: GIRF statistics by shock, group type, and response variable, baseline and restricted specifications

Panel A: Results using the baseline specification

GIRF for a transition to jail: Q5 to J

Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.3	-9.3	-6.3	-9.3	-9.2	-12.7	-10.2	-12.6
Lifetime earnings	-104.8	-170.7	-65.5	-155.4	-101.3	-257.5	-145.9	-252.4
Future years E	-9.8	-9.7	-5.3	-7.3	-5.6	-9.9	-5.6	-10.5
Future years N	2.1	3.9	1.1	2.7	1.3	3.8	2.1	2.6
Future years J	7.7	5.8	4.2	4.6	4.3	6.0	3.5	7.9

GIRF for a transition to nonemployment: Q5 to N

Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.3	-9.3	-5.6	-9.1	-9.2	-12.8	-10.0	-12.6
Lifetime earnings	-87.9	-141.3	-53.2	-116.2	-118.3	-134.1	-98.0	-86.8
Future years E	-7.1	-6.8	-4.3	-6.3	-7.2	-5.1	-5.6	-5.7
Future years N	6.5	6.2	3.1	5.3	7.2	4.8	5.6	3.2
Future years J	0.6	0.6	1.2	1.0	0.0	0.2	0.0	2.5

Panel B: Results using the restricted specification

GIRF for a transition to jail: Q5 to J

Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.2	-9.4	-6.2	-9.1	-9.2	-13.2	-9.7	-12.9
Lifetime earnings	-101.7	-178.9	-66.0	-86.7	-103.3	-313.4	-152.6	-199.2
Future years E	-9.5	-9.8	-5.3	-5.4	-5.6	-11.4	-5.7	-12.6
Future years N	1.9	3.6	1.1	1.4	1.3	2.9	2.2	1.9
Future years J	7.6	6.1	4.2	4.0	4.3	8.5	3.5	10.7

GIRF for a transition to nonemployment: Q5 to N

Response variable	BML	WML	BMLr	WMLr	BMH	WMH	BMHr	WMHr
Earnings	-6.2	-9.4	-5.5	-8.7	-9.2	-13.2	-9.5	-12.9
Lifetime earnings	-86.3	-123.6	-53.6	-93.4	-109.0	-120.2	-81.9	-148.2
Future years E	-7.1	-6.6	-4.3	-6.0	-6.9	-5.1	-5.1	-9.8
Future years N	6.5	6.3	3.2	5.4	7.0	4.4	5.2	3.4
Future years J	0.6	0.3	1.1	0.6	-0.0	0.7	-0.1	6.4

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

Table I.3: Means and medians by race and education, full model and counterfactual experiments, baseline and restricted specifications

	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Mean lifetime earnings, full model								
Baseline Specification	189	346	319	505	376	550	651	955
Restricted Specification	188	346	319	503	376	573	653	949
Differences in mean lifetime earnings: No incarceration								
Baseline Specification	32	19	14	5	23	5	13	3
Restricted Specification	32	28	14	4	24	6	13	5
Differences in mean lifetime earnings: No nonemployment								
Baseline Specification	81	78	81	51	86	112	86	160
Restricted Specification	80	84	80	63	85	90	126	156
Differences in mean lifetime earnings: No incarceration or nonemployment								
Baseline Specification	134	101	108	57	112	117	98	161
Restricted Specification	133	116	107	69	112	96	139	160
Median lifetime earnings, full model								
Baseline Specification	150	333	285	497	349	525	574	817
Restricted Specification	148	351	283	483	347	537	588	806
Differences in median lifetime earnings: No incarceration								
Baseline Specification	45	22	18	4	24	4	11	2
Restricted Specification	45	33	19	3	26	6	12	4
Differences in median lifetime earnings: No nonemployment								
Baseline Specification	102	84	95	41	92	89	53	142
Restricted Specification	103	94	97	50	92	71	83	111
Differences in median lifetime earnings: No incarceration or nonemployment								
Baseline Specification	146	102	115	45	113	92	62	144
Restricted Specification	148	118	119	54	114	76	94	116

Note: [B,W][M,F][L,H,S,C] denote Black/White, male/female, less than high school/high school/some college/college graduate; earnings are pre-tax thousands of 1982-1984 dollars.

J Decomposition Analysis, Details

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

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

Benchmark								
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	189	346	319	505	376	550	651	955
Lifetime earnings p10	29	98	91	203	124	207	291	381
Lifetime earnings p50	150	333	285	497	349	525	574	817
Lifetime earnings p90	423	630	620	824	672	984	1157	1929
Expected years E	21.3	27.8	26.9	31.9	28.5	30.9	31.4	32.9
Expected years J	3.1	1.3	1.0	0.2	1.2	0.2	0.2	0.0
Expected years N	11.5	6.9	8.2	4.0	6.4	4.9	4.4	3.1
Ever incarcerated by age 57	0.43	0.23	0.21	0.03	0.17	0.04	0.06	0.02
Earnings bin values switched across races								
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	236	278	419	385	463	447	900	686
Lifetime earnings p10	38	75	127	147	156	164	392	283
Lifetime earnings p50	188	271	376	377	431	426	781	596
Lifetime earnings p90	524	505	803	638	822	799	1639	1341
Expected years E	21.3	27.8	26.9	31.9	28.5	30.9	31.4	32.9
Expected years J	3.1	1.3	1.0	0.2	1.2	0.2	0.2	0.0
Expected years N	11.5	6.9	8.2	4.0	6.4	4.9	4.4	3.1
Ever incarcerated by age 57	0.43	0.23	0.21	0.03	0.17	0.04	0.06	0.02
Earnings shocks switched across races								
Variable	BML	WML	BMH	WMH	BMS	WMS	BMC	WMC
Lifetime earnings avg.	278	236	385	419	447	463	686	900
Lifetime earnings p10	75	38	148	127	164	155	283	392
Lifetime earnings p50	270	188	377	376	426	431	596	781
Lifetime earnings p90	505	523	638	803	799	822	1341	1639
Expected years E	27.8	21.3	31.9	26.9	30.9	28.5	32.9	31.4
Expected years J	1.3	3.1	0.1	1.0	0.2	1.2	0.0	0.2
Expected years N	6.9	11.6	4.0	8.2	4.9	6.4	3.1	4.4
Ever incarcerated by age 57	0.23	0.43	0.03	0.21	0.04	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.