The Effects of a Criminal Record on Employment, Welfare Participation, and Health:

A Model of Long-run Behaviors and Outcomes when Lagged Variables are Missing Non-Randomly*

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Abstract

We study the collateral consequences of women's criminal records on their future employment, welfare participation, and health outcomes. We jointly estimate dynamic structural equations for life-cycle behaviors (employment, school enrollment, and welfare receipt), criminal offenses, and general and mental health outcomes using a cohort of disadvantaged women surveyed at five non-uniform intervals over thirteen years. The detailed survey questions allow us to construct annual behavioral histories so that we can explain contemporaneous behaviors by time-varying policy variables as well as uniformly-lagged past behaviors. However, because the wording of survey questions may differ by responses to preceding questions, individual behaviors may be missing non-randomly in some years. We address the endogeneity of important lagged determinants by modeling observed behaviors over time, conditional on being observed/known, as well as the probability of their missingness. Both the behaviors and the missingness, which is defined partially by the variation in wording at each wave and partially by a woman's chosen behaviors, are functions of her endogenous histories of behaviors and outcomes, exogenous characteristics, permanent and time-varying correlated unobserved heterogeneity, and random shocks. The econometric approach allows us to differentiate between possible direct causal impacts of criminal record on health and indirect effects on health through employment, education, and welfare receipt. We use the estimated dynamic model to simulate behaviors and health trajectories based on different criminal record histories and policy scenarios.

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1 Introduction

During the first decade of the 21st century, U.S. courts processed around 20 million criminal cases per year, resulting in felony or misdemeanor records for many individuals participating in criminal activity. Although almost 75 percent of state defendants and 90 percent of federal defendants plead guilty or are found guilty, a record of an individual's criminal interactions, including arrest and charge information and, in some states, subsequent disposition, is created. In 2012, the Department of Justice reported that local, state, and federal law enforcement agencies maintained criminal history records on approximately 100 million individuals (Sabol, 2014; Shannon et al., forthcoming).

Statistics document that women are less likely than men to commit crimes generally and, hence, are less likely to have a criminal history. Additionally, female offenders are more likely to be apprehended for misdemeanor charges than felony charges relative to their male counterparts.[1] When charged with these lower-level criminal acts, an innocence plea requires bail and a second hearing, or jail time (regardless of the severity of the offense) if the individual cannot secure bail. To avoid or minimize these pecuniary and time costs, and often under the advice of legal counsel in the form of an appointed public defender, over 95 percent of women plead guilty at their first court appearance.

Documented criminal behavior carries with it a set of "collateral consequences". The consequences are considered "collateral" because they are not imposed by the justice system as part of the punishment for the crime (i.e., prison, fines, or probation). Rather, these legally-imposed consequences include loss or restriction of a professional license, ineligibility for public funds such as welfare and financial aid for higher education, loss of voting rights, ineligibility for jury duty, and deportation for immigrants. In all jurisdictions throughout the U.S., judges are not obligated to warn of these collateral consequences (except deportation) prior to an admission of guilt by plea agreement or upon a finding of guilt by trial.

[1] Recent statistics, however, suggest that criminal behaviors — violent crimes, misdemeanors, and delinquency — are increasing at faster rates among women than among men (DOJ 2014).

The potential impact of criminal activity and its consequences on health has received little attention in the literature. To date, most of the studies of the criminal justice system and health have focused on disease transmission and health care services during incarceration, even though incarcerated individuals account for less than one percent of adults in the U.S. in 2015 (Kaeble and Glaze, 2016). With one in three Americans having a record of past criminal behavior, researchers have turned their attention recently to the collateral consequences triggered by criminal behavior that may negatively impact health.

In this paper, we examine how the collateral consequences of a criminal past impact women. Our data allow us to pay particular attention to disadvantaged women (i.e., those who are racial/ethnic minorities, and/or poor, and/or lower-educated). These women are likely to rely on a patchwork of public benefits and low-wage, service-sector jobs to support themselves and their children. They often have poor mental and physical health and engage in risky health behaviors (Kneipp, 2000; Kneipp et al., 2012). Among this group of women, the most common criminal behaviors are low-level misdemeanor crimes (e.g., non-payment for bad checks, traffic violations, drug possession), rather than felonies, and may not generate a prison sentence. Yet, the associated fines, punishments, and general uncertainty following interaction with the criminal court system, may *directly* explain the observed poor health among these women.

Additionally, employment and education are positively correlated with health. The primary welfare program in the U.S. (Temporary Assistance for Needy Families, or TANF) provides eligible women with income support, education and job training, job-placement assistance, and transportation, among other things, but recipients also face work requirements (fulfilled by employment, on-the-job training, community service, and educational training). The collateral consequences of a criminal record, which may affect employment options, welfare eligibility, and educational opportunities, may *indirectly* contribute to the poor health status of this group through employment, welfare, and schooling channels (Graetz, 1993; Roelfs et al., 2011). Despite several published findings describing bivariate associations among these variables of interest, the relationships do not shed light on the more complex causal mechanisms that may underlie how a criminal record, employment, welfare assistance, and education intersect to influence the health of disadvantaged women. Our study addresses this gap using 4,898 women from the Fragile Families and Child Wellbeing Study (FF) — a nationally-representative, longitudinal survey of predominantly disadvantaged women from cities with populations larger than 200,000 — to estimate a dynamic model of the interrelated relationships over time.

In public health circles, employment and welfare income, education, and social support services are referred to as social determinants of health. Decades of scientific findings document associations between the health of an individual and the types of social determinants that the collateral consequences of criminal behavior are most likely to impact. Only recently have conversations across public health, social service, and criminal justice sectors ignited to explore the potential negative, but indirect, effects on health of the collateral consequences of criminal activity. Moreover, to date, these conversations have been at the theoretical level, with no scientific evidence demonstrating an empirical link. In part, this is because data have not been available to study these links. Yet, if we are to better understand the health disparities that exist — where groups with higher socioeconomic status have the best health, and those with lower socioeconomic status have the worst — then we need to understand how criminal charge- and conviction-related collateral consequences might be contributing to these disparities.

In order to understand the relationships of interest in this research, we jointly model the dynamic behaviors (i.e., employment, welfare receipt, and schooling) and outcomes (i.e., criminal record and health) over time, rather than simply examine their static correlations (where behavior and outcomes across time are treated as independent).[2] Examining the longitudinal relationships across individuals allows us 1.) to establish direction of causality of relevant explanatory variables; 2.) to determine histories of behaviors and outcomes endogenously and to use these as time-varying explanatory variables for subsequent behaviors and outcomes; 3.) to incorporate exogenous time-varying local- and state-level policy variables related to the employment, welfare, education, criminal justice, and health systems as

[2]We are unable to model participation in criminal activity because we only observe outcomes (i.e., charges, convictions, and incarcerations) of individuals who were caught committing a crime.

possible determinants of behaviors and outcomes; 4.) to allow for both permanent and time-varying individual-level unobserved heterogeneity that may additionally explain observed correlations in these behaviors and outcomes; and 5.) to test the importance of behaviors on both short-term and long-term health. To do so, we jointly estimate the dynamic equations explaining observed behaviors and outcomes and quantify the effects of previous behaviors, outcomes, and state and local policies on current behaviors. These behaviors, in turn, impact health outcomes each period, where health may subsequently play a role in the behaviors of individuals. Using the estimated dynamic model, we simulate short-run and long-run responses to changes in behavior and outcome histories as well as policy variables.

One challenge has been finding a data set that follows individuals over time and contains detailed information on criminal behaviors. We determined that the Fragile Families and Child Wellbeing Study (FF) provides the best information for examining the effects of lower-level crimes rather than incarceration and contains information on behaviors and health outcomes. It follows a sample of at-risk women who gave birth in large U.S. cities between 1998 and 2000. Figure 1 depicts the timing of the baseline and four follow-up surveys over a 14-year period. Importantly, the figure details the number of women surveyed in a particular calendar year. Another challenge has been to construct a research sample from the available data that will capture the dynamic relationships described above. While the FF survey is often used as a sample with (up to) 5 observations per participant, we show that the responses of the individuals to different questions in the survey allow us to determine behaviors in each year of the study period. Hence, we are able to construct behavioral histories that allow us to model contemporaneous behaviors dynamically. The knowledge of behaviors each year also allows us to merge relevant policy variables by calendar year, making use of all of the variation in these variables across location (at the state- or local-level) and time.

Our dynamic model, derived from a theory of economic decisionmaking, suggests that previous behaviors and outcomes impact current behaviors and outcomes. Thus, estimation requires that we have consistent (in time) measures of an individual's past behaviors. For example, when explaining employment of a woman today, we want to know whether she was employed or not at a given time in the past, and we need the length of the lags in behavior

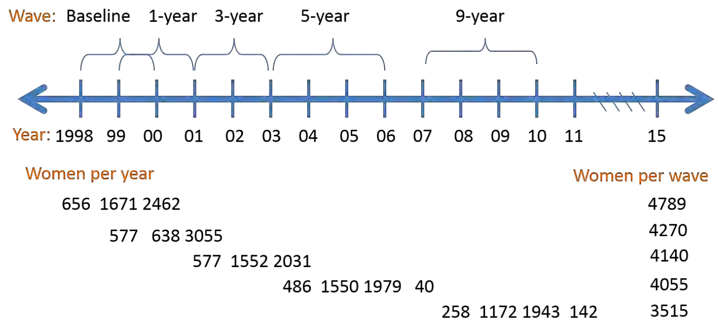

Figure 1: Timeline of Fragile Family Interviews

to be the same each period. Although the FF data are collected in five waves that are not equidistant apart (i.e., one-, two-, and four-year gaps), the survey includes questions about past behaviors or the last time an individual engaged in a behavior. We are able to construct one-year lagged behavioral variables for about 65 percent of the participants each year. We discovered, however, that knowledge of an individual's histories is not exogenous. That is, an individual's responses regarding behaviors in period t determine which questions about previous behaviors she is subsequently asked. This endogeneity of "data availability" requires that we modify our empirical model to account for correlation (through both observables and unobservables) between one's behaviors and the availability of behavioral information each period. We have devised a way to model this correlation econometrically, and still uncover the desired unbiased causal effects of explanatory variables of interest.[3] Other authors using this dataset, and similar datasets, have not been able to make use of its richness given their reliance on static methods, analysis of behaviors only at the wave level, or limited controls for pre-determined variables.

In the next section we review the literature relevant to this study and provide a little background on employment and social services policies related to criminal records. In Section 3, we present a simple theoretical framework to motivate the empirical model that we estimate, and we detail the set of correlated equations, derived from this framework, that form the estimated likelihood function. The data are discussed in detail in Section 4. Section 5 provides

[3]It is also the case that changes in question wording across survey waves provides some exogenous variation in observability of behaviors each year.

some preliminary results from estimation of a set of correlated structural equations (i.e., demand and production functions) via full information maximum likelihood and simulations from that estimated data-generating process.

2 Review of Related Literature

2.1 Deterrence and Crime

There are several reviews of the economics and criminology literatures that discuss the influence of policing, punishment, and (pre-crime) employment and educational opportunities as deterrents to crime (Lochner and Moretti, 2004; Levitt and Miles, 2006; Tonry, 2008; Durlauf and Nagin, 2011; Nagin , 2013; and Chalfin and McCrary, 2017). We will add more here about this literature.

We focus on the collateral consequences of criminal behavior, namely having a criminal record history, which may affect (post-crime) employment and education opportunities as well as welfare eligibility in order to understand the effects of employment, welfare receipt, and schooling/training on health transitions over time. These collateral consequences should serve as additional deterrents in an individual's decision to commit a crime. However, individuals may be unaware of these consequences. Similarly, they may be unsure of the magnitude, and even direction, of the effects. Such risk-perception, both with regard to direct penalties for crimes as well as the collateral consequences, can greatly affect observed behaviors. Indeed, policy effectiveness depends upon the extent to which individuals correctly perceive risks (Apel and Nagin, 2011).

Although we began this project with an interest in post-crime health outcomes, we recognize the potential correlation in criminal behavior (and, hence, the existence of a criminal record) and other behaviors that influence health through both observed and unobserved characteristics. And, of course, this individual unobserved heterogeneity may be correlated with health outcomes. As such, we, as researchers, have to explain any observed criminal behavior in our longitudinal sample. The relevant literature suggests avenues through which employment and education may affect decisions regarding illegal behaviors. Higher wage rates increase the opportunity cost of spending time in any activities outside of work, including criminal activities. Hence, work experience, years of schooling, and being employed should be negatively correlated with crime. Employment also magnifies the costs of adjudication and subsequent punishments involving prison/jail time or community service since these interfere with gainful activities. Education may increase patience (i.e., rate of time preference) or risk aversion, thereby reducing the utility one receives from committing a crime. In addition to affecting one's utility of illicit behavior, employment and education may influence rates of criminal detection and apprehension as well as degree of punishment. Researchers have used self-reported data from individual surveys as well as aggregate data from Uniform Crime Reports (UCR) to demonstrate these relationships (e.g., Lochner and Moretti, 2004; Lochner, 2004). Lastly, schooling limits the amount of time for criminal behavior (assuming the activities are mutually exclusive). Alternatively, schooling, especially among adolescents, may contribute to criminal activity through congregation/proximity effects (i.e., concentration of the young and impressionable), social network effects (i.e., gangs), and market facilitation effects (i.e., drug-dealing).

Supplemental income through federal and state resources (such as welfare or TANF) could ameliorate financial pressures to resort to criminal activity to finance consumption. TANF also requires and supports employment or educational training, improving the chances of being able to support oneself through legal employment activities. The additional oversight that accompanies participation in the welfare system may create an additional deterrence effect by increasing the risk of losing housing, benefits, or one's children if criminal activity is suspected or proven.

Participation in criminal activity also depends on the probability of being caught and of being punished if caught. The literature exploring the role of this uncertainty as a deterrence considers both actual and perceived probabilities measured by official statistics (e.g., number of police, police expenditures, arrest measures) or self-reported perceptions. (See Lochner, 2007 for a deeper discussion of this subject.) In our work, we do not observe participation in criminal activity. Rather, we observe the outcome, if caught. That is, we know

— based on self-reports by the respondent (mother) and, in some cases, by the father — whether an individual has been charged, convicted, and/or incarcerated. Additionally, the economics literature on criminal behaviors emphasizes the importance of state dependence and unobserved determinants of crime in the decisionmaking process (Merlo and Wolpin, 2015; Mancino et al., forthcoming).

2.2 Employment and Criminal Offense Record

In this subsection we consider how a criminal offense record may impact employment. Federal law does not prohibit employers from asking about or obtaining a potential employee's criminal record. However, federal Equal Employment Opportunity (EEO) laws and Title VII of the Civil Rights Act of 1964 (Title VII) make it illegal to discriminate when using criminal record information. Employers should not screen individuals based on their record if it disadvantages a protected class of people (e.g., based on race, national origin, sex, and religion) or if the information is not relevant to responsibilities of the job. Arrest information is available on criminal records, but may not be proof of participation in criminal activity. In some states, an individual's arrest record, by itself, may not be used by an employer to justify a negative employment action (e.g., firing or suspending an employee or not hiring an applicant). However, an arrest may trigger an inquiry into whether the conduct underlying the arrest justifies such action (EEOC, 2012). Some states allow employers to look back only five years or to consider felonies but not misdemeanors. Juvenile records are generally sealed.

Many occupations require certification or licensure. Licensure boards in most states can deny licenses to people convicted of particular crimes. Examples of occupations that may refuse to hire an individual with a criminal conviction include those in health care (e.g., dental assistance), those that help children (e.g., child care and teaching) and those that serve the elderly (e.g., caregivers in nursing homes or home health care). Similarly, individuals with offenses involving alcohol may not be hired in occupations that include selling or serving alcohol. Individuals with offenses related to money may not be hired by banks or other financial institutions.

Researchers have found that employers, independent of legally-imposed requirements and restrictions surrounding criminal record uses, are less likely to hire individuals with a conviction history, possibly due to a stigma of untrustworthiness. In fact, research has shown that employers would be more likely to hire recipients of public assistance or individuals with little work experience than those considered ex-convicts (Holzer, 1996; Decker et al., 2014). Given the large number of African-American males with a conviction or incarceration record, scholars have debated whether policies that require reporting of criminal records disproportionately harm African Americans. However, recent research finds that jurisdictions that have "banned the box" (where a box is used to indicate a criminal record history on employment applications) experienced lower employment rates of young, low-skilled, black and Hispanic men when criminal record status was not observable (Doleac and Hansen, 2016). That is, without information, employers are more likely to statistically discriminate.

Time incarcerated may also erode job skills or acquired work experience, leaving individuals with fewer job opportunities when released. Alternatively, some prisoners may gain useful skills while in prison. This time may also impact mental and physical health negatively, leading to less health capital upon release. Reductions in human and health capital, however, may be legitimate reasons for an employer's lower productivity expectations as opposed to the stigma of untrustworthiness associated with ex-convicts.

Most of these studies mentioned above apply to previously-incarcerated men. Do these same findings appear for women? Galgano (2009) applied online to a variety of employers in Chicago to study employer responses to racial/ethnic differences. She finds no relationship between incarceration and the likelihood that a woman applicant would receive a callback from employers. Lalonde and Cho (2009) use administrative data for about 7,000 women who served time in prison in Illinois. They find that incarceration actually produces a short-term employment boost for women that dissipates over time. It is possible that these women were under community supervision after release, in which employment is a requirement in some states.

In another online application study in Phoenix, Arizona, Decker et al. (2014) find that white women were significantly more likely to receive a callback than African American women, but not Hispanic women. However, a criminal record did not add to the disadvantage faced by African American women. They also find evidence that employers are less likely to hire women who have been incarcerated than men. Nearly 60 percent of male job applicants with a prison record would have been called for a job interview, while only 30 percent of women with the same prison record would have been called for an interview.

2.3 Social Services and Criminal Offense Record

Criminal offense-triggered collateral consequences may also result in restrictions on eligibility and receipt of many social services. For example, the 1996 federal welfare law (The Personal Responsibility and Work Opportunity Reconciliation Act) imposes a lifetime ban on anyone convicted of a drug-related felony from receiving federally-funded food assistance (Supplemental Nutrition Assistance Program, or SNAP) and cash assistance (Temporary Assistance to Needy Families, or TANF). Unless a state passes legislation opting out of the federal law, individuals with these convictions are permanently barred from receiving benefits even if the otherwise-eligible individual has a successful job history or has participated in drug and alcohol treatment. State modifications include providing benefits to individuals who have completed treatment programs or to those with convictions for simple possession rather than felony convictions, or limiting the duration of the ban. A 1988 amendment to the Higher Education Act of 1965 delays or denies students with a history of drug offense of federal financial aid. Individuals with a prior history of criminal activity can be screened out of public housing applications and some public housing authorities may deny eligibility for federally-assisted housing based on an arrest that never led to a conviction. These bans, which preclude access to the social services that disadvantaged women heavily rely on for income support and assistance to overcome employment barriers, likely compound their risk for a life trajectory of unemployment, poverty, and poor health.

2.4 Social Determinants of Health

Social determinants of health (SDOH), or the factors that shape the conditions in which people live, explain the vast majority of health disparities in the U.S. (Braveman, 2000; Braveman et al., 2011; Marmot, 2000; Marmot and Wilkinson, 2000; Woolf and Braveman, 2011). Living at or near poverty, having a low level of education, and/or belonging to a racial/ethnic minority group (henceforth collectively referred to as disadvantaged) have long been known to be more robust risk factors of poor health than lack of access to healthcare or genetic predisposition to disease. This relationship is starkly depicted among women, where over 40 percent of single-mother families live in poverty; 68 percent have no education beyond high school; and greater than 70 percent are Black or Hispanic (US Census Bureau, 2011.) Poor health mirrors this distribution, with disadvantaged women having greater than three times the rate of cardiovascular disease, diabetes mellitus, and mental health disorders than more advantaged women (NCHS, 2012). Studies have also shown that disadvantaged women are exposed to greater, more persistent, and more deleterious forms of chronically stressful environments than women who are more advantaged (Kalil, 2001; Grzywacz et al., 2004) The frequent unemployment, material hardship, food insecurity, lack of social support, and discrimination that characterize these environments lead to high levels of psychological distress and subsequent physiological changes that are associated with the development of depression, functional decline, and other disease states (e.g., Karlamangla et al., 2002; Steptoe et al., 2002; McEwen, 2003; Williams et al., 2012). Despite improved access to care for disadvantaged women, large disparities in psychological distress and morbidity across most disease states remain (IOM, 2012). This information suggests that interventions to reduce health disparities may not address all the factors that precipitate psychological distress or other root causes of poor health in this group. Although studies have depicted the biological mechanisms underlying the psychological distress-poor health association, our understanding of whether and how system-level factors precipitate the psychological distress experienced by disadvantaged groups has lagged behind. Among disadvantaged women in the U.S., system- and policy-level obstacles make it difficult to secure and maintain employment and the economic safety net programs perceived as important for their self-sufficiency (Brown and Barbosa, 2001).

Associations found in longitudinal studies, systematic reviews, and meta-analyses suggest that returning to work after a period of unemployment improves health, even for disadvantaged women (e.g., Kneipp et al., 2011). Disadvantaged women, however, remain highly vulnerable to recurrent unemployment and its associated health risks. Given that a steady accumulation of work experience is an important predictor of future employment for these women, employment today, while addressing immediate financial needs, has long-term implications for reducing unemployment-related health risks over their lifetime. While there is much economic evidence on the causal relationship between employment and health (Currie and Madrian, 1999), there is less work establishing the roles of employment at the intensive margin (e.g., occupation, hours of work, promotion, job stressors). Identification of causal effects is hampered by two considerations: 1.) initial endowments, education, and health impact occupation/employment decisions (i.e., non-random selection) and 2.) healthy (or deleterious) investment behaviors are chosen jointly with individual decisions regarding employment (i.e., confounding). Thus, there is little consensus on the size and direction of the many different employment effects on health.

Discuss the economic evidence regarding the effects of welfare on health.

Discuss the economic evidence regarding the effects of education on health.

2.5 Missing Data

The theoretical econometric literature addresses problems with missing endogenous variables. Specifically, underreporting and imputations introduce measurement error (Bound and Krueger 1991; Bound, Brown, Duncan, and Rodgers 1994). Applied empirical work is often hampered by underreporting and missing data. In fact, it has been shown that attempts to deal with underreported or imputed endogenous variables using instrumental variable techniques may overstate the causal effect of policy-related programs and interventions (Stephens and Unayama, 2015).

If the non-reporting is random, then a researcher may conduct analysis using only the non-imputed subsample. Alternatively, when values are missing randomly, methods that account for selection using observable characteristics (e.g., inverse propensity score weighting) may be employed (Bollinger and Hirsch, 2006). Another approach is to construct a new set of imputations using the instruments as part of the imputation process, and then using the full sample to estimate the outcome of interest (Hirsch and Schumacher, 2004; Heckman and Lafontaine, 2006).

Stephens and Unayama (2015) discuss the inconsistency of the Instrumental Variables (IV) estimator when the endogenous regressor is underreproted or imputed even if the instrument is perfectly measured. Mogstad and Wiswall (2012) examine the consistency of the IV estimator when the instrument is only observed for a subset of observations. Often, however, the observability of data depends on unobservables (i.e., selection). Semykina and Wooldridge (2013) address consistent estimation, in this case, using backward substitution for the lagged dependent variable. We consider an alternative approach (described in detail in Section 4).

3 Description of Data

Because the data we have obtained for this empirical investigation dictates the empirical model we estimate, we describe the data before detailing the theoretical motivation and resulting empirical framework. We searched for relevant data sets through the Interuniversity Consortium for Political and Social Research (ICPSR) and the University of Michigan Survey Research Center using the key terms arrest, convict, conviction, jail, or prison combined with health, TANF, and employment. We examined data from FF, as well as the National Longitudinal Survey of Youth (NLSY), the National Longitudinal Study of Adolescent Health (Add Health), Welfare, Children, and Families: a Three-City Study, the Panel Study of Income Dynamics (PSID), and the Survey of Income and Program Participation (SIPP). Only FF, however, had (1) sufficient detail in the variables of interest, (2) a long observation period and frequent measurement occasions, and (3) a predominantly lower SES sample —

all of which are needed to explore the relationships of interest. The FF study was designed to understand how social context, policies, and environmental conditions affect families at high risk for ongoing poverty and poor outcomes on several dimensions.[4] Approximately 75 percent of the sample includes at-risk, or fragile, families headed by unmarried mothers.

This cohort study follows 4,898 women in 20 large U.S. cities (defined as populations of 200,000 or more) who have just given birth. Sixteen of the 20 cities were selected to comprise the nationally-representative sample. The five waves of interviews with both the mothers and fathers, if present, are conducted when the children are born, and when they are ages one, three, five and nine. Notice, in Figure 1, that the interviews span each year from 1998 to 2010.[5] Although 3,515 (72 percent) of women are interviewed in wave five (i.e., nine years after baseline interview), 2,986 (61 percent) participated in all waves. Because we wish to construct the histories of annual behaviors and outcomes, we use data from all women with three or more waves (4,482) of continuous participation (4,130). Due to missing information on important exogenous variables, the research sample contains 2,898 women with a total of 13,475 *person-wave* observations. Table 1 describes our research sample by the survey participation patterns.

Table 1: Empirical Distribution of Research Sample by Wave Participation Patterns

Wave: 1	2	3	4	5	Number
Yes	Yes	Yes	Yes	Yes	2,185
Yes	Yes	Yes	Yes	No	411
Yes	Yes	Yes	No	Yes	103
Yes	Yes	Yes	No	No	119
Yes	No	Yes	Yes	Yes	80

The interviews collect information on demographic characteristics, relationships, employment status, welfare receipt, schooling status, criminal records, and the general and mental health of the child's mother. Survey questions inquire about current statuses at the time of

[4]Center for Research on Child Well-Being. Fragile Families and Child Wellbeing Study: About the Fragile Families and Child Wellbeing Study. 2012; http://www.fragilefamilies.princeton.edu/about.asp. Accessed December 5, 2012.

[5]A few women were dropped initially due to insufficient data at baseline.

the interview, as well as experiences before the baseline wave and between waves. In order to model women's dynamic life-cycle behaviors and outcomes, we use the retrospective survey questions to construct an annual-based longitudinal data set. Table 2 shows the research sample size in each year and attrition by year, with a total of 28,666 *person-year* observations. The next subsection explains how we create the annual-based variables describing behaviors and outcomes.

Table 2: Empirical Distribution of Annualized Research Sample by Year

Year	Sample Size	Attriters	Attrition Rate
1998	1,092	-	-
1999	2,818	-	-
2000	2,826	-	-
2001	2,847	20	0.70
2002	2,878	46	1.60
2003	2,832	202	7.13
2004	2,630	117	4.45
2005	2,513	245	9.75
2006	2,268	3	0.13
2007	2,265	-	-
2008	2,125	-	-
2009	1,500	-	-
2010	72	-	-

Number of person-year observations: 28,666

3.1 Description of Behaviors and Outcomes

Employment

The initial (baseline) survey takes place in a hospital following the birth of a child (wave 1), and asks these mothers when they last worked at a regular job. Then, in waves 2 through 5, the survey asks whether the mother did regular work in the last week. If the answer is yes, the mother is asked in wave 2 the age of the child when the mother went back to work for the first time after the child was born. In waves 3 to 5, however, no further questions are asked about work experience between waves. If the answer is no to regular work in the last week, women are asked when they last worked at a regular job. Based on women's answers to these questions, we recover their employment status each year. We also keep track of person-years for which the individual's employment status can not be inferred. For example, if a woman worked in the preceding weeks of both the wave 4 and wave 5 interviews, no information is asked about her employment status in the years between these two waves (up to four years), and we create a variable indicating that we "do not know employment status" for each year in between. Given that the questions asked to each individual depend on her (endogenous) answers to the preceding questions, the "do not know employment status" indicator is also endogenous and varies by person/year. In other words, the missingness associated with employment status is not missing randomly.

Welfare receipt

In each wave, a question is asked about whether the respondent received welfare in the past 12 months. In waves 2 through 5, if the respondent did receive welfare in the past 12 months, a follow-up question is asked about whether the respondent is currently receiving welfare and for how long she has received welfare. If the respondent did not receive welfare in the past 12 months, or is not currently receiving welfare, the follow-up question inquires about when she last received welfare. Based on answers to these questions, we construct an indicator for whether the respondent receives welfare in each year. Again, for years in which welfare receipt status can not be inferred, we define a "do not know welfare status" indicator, which is an endogenous variable similar to the missing employment variable defined above.

School Enrollment and Education Level

To construct school enrollment status we use responses from waves 2 through 5 to questions about whether the respondent is currently attending any school/trainings/program/classes, and whether she has completed any training programs or years of schooling since the last interview. In addition, in waves 3 through 5, respondents are asked whether they have taken classes to improve job skills since the last interview. If the respondent has completed programs/schooling or taken classes since the last interview, we assume she has been enrolled in school in the years between interviews.[6]

The school enrollment variable defines per-period behavior. We also construct a variable summarizing the accumulated education of a respondent each period. The wave 1 survey asks each woman about her highest grade completed, and in waves 2 through 5 it asks what programs or schooling she has completed if she has completed any since the last interview. Based on the answers to these questions, we create nine education categories for each person-year: less than eight years of schooling, some high school, high school diploma, G.E.D., some college, technical school, bachelor's degree, graduate or professional school, and training program. We allow each individual to have more than one education category, except in cases where one category is strictly superior to the other. For example, a woman can have both a high school degree and a technical school degree, but if she obtains a bachelor's degree, the high school degree indicator is set to zero.[7]

Charges, convictions and incarcerations

We do not have any information on participation in crime. However, we do observe information on charges, convictions, and incarceration for those women who are caught committing a crime. With regard to these offenses, the wave 3 survey asks whether the respondent has ever been charged or convicted. If a respondent has been convicted, the survey queries about the number of times she has been convicted, as well as the years of her first and most recent convictions. Then, in waves 4 and 5, respondents are asked if they have been charged or convicted since the last interview. However, no question is asked about the timing of the new charges or conviction, if any, and we randomly assign the charge year and the conviction year among the years between the current and the previous interviews. In waves 3 and 5, the respondent is asked whether she has ever been incarcerated. If she has, follow-up questions

[6]Specifically, we fill in school enrollment status up to two years prior to the interview year for wave 2-4 positive responses, and up to four years from the interview year of wave 5 if the response is positive.

[7]Specifically, technical school and training program can be combined with any of the other categories. G.E.D. and some college may also occur simultaneously.

are asked about the timings of her first and most recent incarcerations. Based on these questions, we create a variable for each individual's charge, conviction and incarceration status by year, as well as their criminal history up to each year (i.e., ever charged, ever convicted, ever incarcerated, years since the last conviction, and years since the last incarceration). We also created a variable indicating whether the last conviction involved a drug-related crime. In addition to the mother's responses to criminal record questions, the father of her child, if present, is also asked about the mother's criminal record. To take into account that the female respondents might misreport their criminal records, we use the report from the child's father to double-check and update the female criminal records.[8]

General and mental health outcomes

In wave 2 through 5, respondents are asked to report their general health (as either excellent, very good, good, fair or poor). We use the answers from the interview years as the measure of general health when treated as a dependent variable.[9] When health is used as an explanatory variable, we fill in the values of health for the years between interviews by evenly dividing the reported general health in the nearest preceding and following interviews (i.e., interpolating/extrapolating by individual).

The wave 2 through 5 surveys provide two measures of mental health reflecting whether the mother meets the depression criteria — a conservative measure and a liberal measure. We use the liberal measure from the interview years as the dependent variable for a women's mental health. When mental health is used as an explanatory variable, we fill in the values for the years between interviews by using the liberal measure from the nearest subsequent interview.[10]

[8] In concurrent work, we are exploring imputations to correct for underreporting of criminal activity. Our work to date suggests that criminal records are likely among 20 percent of the sample, rather than the eight percent that we observe (for being ever charged by wave 5). Subsequent work may incorporate these imputations. However, our imputations are for having ever been charged, convicted, or incarcerated by each interview wave, and yearly information on charges, convictions, and incarcerations are impossible to impute.

[9] In the results we present later, we treat these outcomes as a continuous variable rather than a polychotomous variable to minimize the number of estimated parameters.

[10] We corrected mistakes in the Fragile Families' construction of the liberal measure of the depression indicator. Details are available from the authors.

Table 3 provides descriptive statistics for the dependent variables that form our jointly estimated set of correlated equations (to be described in Section 4). Most of the variables are defined over all person-years, and are explained using dynamic specifications (i.e., variation in their values may be explained by variation in pre-determined, or lagged, endogenous variables). The initial condition variables represent information observed at baseline that cannot be explained by a dynamic equation.

Table 3: Descriptive Statistics for Dependent Variables

	Variable name	Mean	Std Dev	Min	Max
Behaviors	Nonemployment at t (conditional on knowing info)	0.387	0.487	0	1
	Welfare receipt at t (conditional on knowing info)	0.171	0.377	0	1
	School enrollment at t	0.258	0.438	0	1
Caught	Charged at t	0.022	0.148	0	1
	Convicted at t (conditional on being charged)	0.618	0.486	0	1
Health	General health at t	3.746	0.957	1	5
	Depression at t	0.168	0.374	0	1
Selection	Do not know employment status at t	0.349	0.477	0	1
	Do not know welfare status at t	0.055	0.228	0	1
	Attrition at the end of t	0.117	0.321	0	1
Initial	Ever charged, convicted, or incarcerated at $t = 1$	0.034	0.182	0	1
	General health at $t = 1$	3.928	0.924	1	5
	Depression at $t = 1$	0.145	0.352	0	1

Probabilities/densities of these correlated variables form the likelihood function, which is estimated via FIML using DFRE to model the correlation.

The observed variables that explain variation in these dependent variables include endogenous explanatory variables and exogenous explanatory variables (as well as individual unobservables that will be described later). Summary statistics for the endogenous variables are included in Table 4. Table 5 summarizes the individual-level exogenous variables. Interactions and polynomials of variables may also enter the specifications.

In addition to the FF data, we obtain aggregated, geographically-identified data from a number of other public use files to represent the exogenous policy variation that might explain individual behaviors and outcomes. These variables are constructed from data from the Department of Labor; the Department of Health and Human Services Administration; Urban Institute's Welfare Rule Database; the Department of Justice, Bureau of Justice Statistics; the Centers for Medicaid and Medicare; the Cost of Living Index; National Centers

Table 4: Descriptive Statistics for Endogenous Individual Explanatory Variables

Variable name	Mean	Std Dev	Min	Max
Employment history				
Employed in $t-1$	0.581	0.493	0	1
Employment in $t-1$ missing	0.423	0.494	0	1
Welfare receipt history				
Received welfare in $t-1$	0.171	0.376	0	1
Welfare receipt in $t-1$ missing	0.074	0.262	0	1
Schooling history				
Enrolled in school in $t-1$	0.245	0.430	0	1
School enrollment in $t-1$ missing	0.015	0.121	0	1
Less than eight years of education entering t	0.040	0.197	0	1
Some high school entering t	0.257	0.437	0	1
High school degree entering t	0.246	0.431	0	1
GED degree entering t	0.067	0.250	0	1
Some college entering t	0.223	0.416	0	1
Technical school entering t	0.078	0.269	0	1
Bachelor's degree entering t	0.092	0.289	0	1
Graduate degree entering t	0.062	0.241	0	1
Training program entering t	0.070	0.256	0	1
Criminal history				
Charged in $t-1$	0.020	0.140	0	1
Charge status in $t-1$ missing	0.058	0.234	0	1
Convicted in $t-1$	0.014	0.115	0	1
Conviction status in $t-1$ missing	0.063	0.243	0	1
Incarcerated in $t-1$	0.009	0.094	0	1
Incarceration status in $t-1$ missing	0.024	0.154	0	1
Conviction in $t-1$ is drug-related	0.227	0.420	0	1
Conviction in $t-1$ is drug-related missing	0.336	0.473	0	1
Ever charged entering t	0.106	0.308	0	1
Ever charged status entering t missing	0.095	0.293	0	1
Ever convicted entering t	0.072	0.259	0	1
Ever convicted status entering t missing	0.076	0.265	0	1
Ever incarcerated entering t	0.050	0.217	0	1
Ever incarcerated status entering t missing	0.060	0.237	0	1
Years since last conviction entering t	4.484	4.143	1	31
Years since last conviction entering t missing	0.064	0.245	0	1
Years since last incarceration entering t	3.840	2.591	1	14
Years since last incarceration entering t missing	0.084	0.278	0	1
General health and depression history				
General health entering t	3.778	0.946	1	5
Depression entering t	0.165	0.371	0	1

Table 5: Descriptive Statistics for Exogenous Individual Explanatory Variables

Variable name	Mean	Std Dev	Min	Max
Time-invariant individual variables in year 1998				
Black race	0.611	0.488	0	1
Non-white non-black race	0.118	0.322	0	1
Hispanic ethnicity	0.164	0.371	0	1
Demographic characteristics missing	0.003	0.052	0	1
Respondent's mother highest grade completed	11.862	2.775	0	18
Respondent's mother highest grade completed missing	0.082	0.274	0	1
Respondent's father highest grade completed	11.973	2.665	0	18
Respondent's father highest grade completed missing	0.398	0.490	0	1
Respondent's mother deceased	0.079	0.270	0	1
Respondent's mother deceased missing	0.249	0.433	0	1
Respondent's father deceased	0.133	0.339	0	1
Respondent's father deceased missing	0.137	0.344	0	1
Time-variant individual variables over all person-years				
Married	0.306	0.461	0	1
$\times$ Black race	0.084	0.277	0	1
$\times$ Other race	0.064	0.245	0	1
$\times$ Hispanic ethnicity	0.086	0.280	0	1
Marriage status missing	0.094	0.291	0	1
Number of children	2.131	1.375	0	11
Number of children missing	0.532	0.499	0	1
Age	10.946	6.821	14	52
Time trend	6.344	3.173	1	13

for Environmental Information; and the Department of Education. Variables of interest include average unemployment rates (by county); average state TANF benefit levels, by family size; and the number of criminal arrests by state, per year, among others. State- and local-level exogenous variables for each year are collected from these external sources and matched to FF respondents. Table 6 details the state/local policy environment variables (summarized over all years and all individuals in the 20 large cities represented in the FF data).[11]

4 Theoretical Motivation and Empirical Framework

4.1 Theory of Behavior

To motivate the empirical analysis, we begin be describing an individual's life-cycle decisions regarding employment (e_t), welfare receipt (r_t), schooling (s_t), and criminal activity (c_t). We use a Bellman equation approach to depict the lifetime value of each available alternative in period t, but we have no intention of parameterizing the utility function, solving the model, and estimating the structural parameters of the optimization problem. Data limitation prevent such an approach from being feasible. Yet, the theoretical set up lends guidance to specification and identification of our multiple structural equation approach (i.e., jointly estimated demand and production functions and stochastic realizations). For simplicity, we model employment at the extensive margin and let the discrete employment alternatives include non-employment ($e = 0$) and employment ($e = 1$). An individual who is eligible for social services (e.g., income, housing, food and medical care assistance programs) may select to receive it ($r = 1$) or not ($r = 0$). The schooling alternatives are participation in a schooling activity ($s = 1$) or not ($s = 0$).[12] Finally, we model alternatives regarding criminal activity as simply participation in illegal activity ($c = 1$) or not ($c = 0$).[13] Let d_t^{ersc}

[11]Appendix Table A1 provides the level of variation and the sources for these data. In estimation, we subtract a rounded value of the mean of each variable (indicated in the table) from the observed value.

[12]Schooling can involve formal educational pursuits or training opportunities, such as those required for some cash assistance programs.

[13]Each of the alternatives could be expanded to be more realistic and to better capture the roles of a history of documented criminal activity. For example, we could exam hours of work or occupational choices. We could specify the particular type of crime committed. This level of specificity is not necessary

Table 6: Descriptive Statistics for State-level Exogenous Price and Supply-Side Variables

Variable name	Mean	Std Dev	Min	Max
Employment variables				
Quarterly employment: female with low SES **	12.684	23.630	3.13	249.40
Quarterly employment: female with low education **	28.234	1.598	23.10	35.76
New hire rate: female with low SES *	0.438	0.259	0.09	1.38
New hire rate: female with low education *	0.485	0.092	0.23	0.77
New hire rate missing	0.061	0.239	0.00	1.00
Hiring rate as % of quarterly employment: female with low SES	15.447	2.395	8.14	22.69
Hiring rate as % of quarterly employment: female with education	14.164	1.869	8.27	20.00
End of quarter hiring rate missing	0.040	0.196	0.00	1.00
Average monthly earnings: female with low SES (in 000s)	1.801	0.454	1.00	2.83
Average monthly earnings: female with low education (in 000s)	1.810	0.181	1.26	2.30
Average monthly earnings of new hires missing	0.061	0.239	0.00	1.00
Unemployment rate: white female	4.332	1.256	1.70	11.20
Unemployment rate: white female missing	0.038	0.191	0.00	1.00
Unemployment rate: black female	8.578	2.502	3.30	23.10
Unemployment rate: black female missing	0.044	0.205	0.00	1.00
Unemployment rate: Hispanic female	7.269	2.291	2.20	20.40
Unemployment rate: Hispanic female missing	0.227	0.419	0.00	1.00
Welfare variables				
TANF monthly benefit: three person family	355.683	140.169	136.06	788.26
Sanction severity	0.435	0.496	0.00	1.00
Drug felony eligibility	0.340	0.474	0.00	2.00
Schooling variables				
Average public 4-year college tuition (in 000s)	4.732	1.477	2.01	9.69
Average private 4-year college tuition (in 000s)	17.062	3.157	4.25	28.16
Average public 2-year college tuition (in 000s)	1.800	0.723	0.30	5.49
Crime-related variables				
Violent offenses ***	7.953	2.401	1.67	23.81
Number of female prisoners **	1.046	0.530	0.15	2.69
State and local expenditure — police protection ****	206.399	55.588	104.823	935.822
State and local expenditure — judicial and legal ****	94.262	35.443	44.670	276.277
State and local expenditure — corrections ****	182.985	38.454	86.170	555.131
Health-related variables				
Annual average temperature	56.487	6.897	25.10	75.30
Annual lowest temperature	67.508	7.669	32.70	82.80
Annual highest temperature	45.465	6.210	17.50	67.70
Annual precipitation (in inches)	39.195	10.809	6.24	137.54
Number of non-elderly, non-disabled adults with Medicaid *	3.941	3.061	1.32	14.80
Medicaid information missing	0.713	0.452	0.00	1.00
Percent of counties HPSA designated: primary care	17.369	16.045	0	94.118
Percent of counties HPSA designated: mental health care	11.772	13.256	0	61.538
Average cigarette price ($/pack)	3.448	0.682	1.941	7.921
State and federal cigarette taxes as % of average retail price	28.039	8.797	10.500	57.789
Average wine price ($/bottle)	5.666	0.758	3.942	7.923
Average beer price ($/6-pack)	6.521	0.827	3.974	8.408
Alcohol prices missing	0.002	0.041	0	1

Note: * per female population age 20-64; ** per thousand female population age 20-64; *** per thousand population age 20-64; **** per capita. Dollar amounts are in year 2000 dollars.

indicate the mutually-exclusive joint combinations of the employment (e), welfare receipt (r), schooling (s), and crime (c) alternatives in period t.

Each combination of the alternatives is not available in every period. Rather, employment depends on a job being offered at the beginning of period t (O_t) and welfare participation depends on eligibility for services in period t (R_t). More specifically, the probabilistic offer of employment depends on one's accumulated past behaviors: work experience (E_t^1), education level (E_t^2), and criminal record history (CR_t).[14] Eligibility for social services is also a stochastic function of accumulated past behaviors: previous earned income (Y_{t-1}^1), welfare experience (E_t^3), and criminal record history (CR_t).[15] For the purposes of this study, we allow a criminal record history to impact job offer probabilities as well as eligibility for social services. In order to focus on the primary behaviors of interest, we do not model other important decisions of women (e.g., marital status and fertility) that also interact with and influence the decisions we do model.

Next we define the per-period utility associated with each combination of alternatives. As usual, utility depends on a composite consumption good (X_t), leisure (L_t), and the modeled behaviors, which are constrained by one's budget and available time. That is, alternative-specific utility is

$$U_t = u(X_t, L_t, d_t^{ersc}, \epsilon_t^u; D_t, H_t, C_t) \; \forall t$$

where demographic characteristics (D_t) and health (H_t) shift preferences for consumption, leisure, and modeled behaviors. We also allow the individual's utility to depend on her "caught" state in t (C_t), which depends on whether or not she was "caught" committing a crime during the previous period. This caught state could include jail time or incarceration; it may also involve pecuniary fines or community service.[16]

to demonstrate the channels through which a criminal record may impact behaviors and subsequent health outcomes.

[14]Given the data we have from FF, the criminal record history consists of separate indicators of whether the individual has ever been charged, convicted, or incarcerated for criminal activity entering period t and variables indicating years since the last conviction and years since last incarceration. By construction, incarcerated individuals were also convicted and charged, and convicted individuals were also charged.

[15]In theory, TANF eligibility is determined by income and asset thresholds set by each U.S. state and depends on both cumulative years of experience and years of continuous participation in the program, which we denote by E_t^3.

[16]Note that if $C_t = 1$ then by default the individual (who committed criminal activity last period and is in the caught state in the current period) has a criminal record entering period t. The purpose of both the

Consumption and leisure are defined by the budget and time constraints, respectively. Individuals receive income (Y_t) from legal employment, illegal activity, and social programs if eligible, and spend their income on private or public housing accommodations (A_t, assumed a necessity), family food consumption (F_t, assumed a necessity) which depends on the number of children (K_t) and marital status (M_t), health care inputs (HC_t), schooling/training after high school (s_t), crime costs if caught, and other consumption (X_t). That is,

$$\begin{aligned} Y_t^1 \cdot e_t + Y_t^2 \cdot c_t + Y_t^3 \cdot r_t &= P_t^A(r_t) \cdot A_t(K_t, M_t) + P_t^F(r_t) \cdot F_t(K_t, M_t) + P_t^H(r_t) \cdot HC_t \\ &\quad + P_t^S(CR_t) \cdot s_t + P_t^C \cdot C_t + P_t^X \cdot X_t \end{aligned}$$

where Y_t^1 is per-period employment income, Y_t^2 is income from criminal activity, and Y_t^3 is cash assistance from the welfare program. These income values depend on experience in each of the activities, among other things. Pecuniary prices are denoted by the vector $P_t = [P_t^A, P_t^F, P_t^H, P_t^S, P_t^C, P_t^X]$. Out-of-pocket prices of housing, food, and health care depend on the receipt of social services, in-kind assistance (e.g., SNAP) and Medicaid (subsequently referred to as welfare), which depend on eligibility. Prices of schooling depend on an individual's record of criminal activity (CR_t) via ineligibility for student loans. Crime costs includes fines, legal fees, and court costs.

An individual's leisure time (L_t) is constrained by her total time in a period (TT_t) and time spent in legal employment, illegal criminal activity, health care activities (e.g., time to visit a physician's office, exercise, etc.), schooling, and child care. Specifically,

$$TT_t = Q_t^E \cdot e_t + Q_t^C \cdot c_t + Q_t^C \cdot C_t + Q_t^H \cdot HC_t + Q_t^S \cdot s_t + f(Q_t^K, K_t, M_t) + L_t$$

where time prices, denoted by the vector $Q_t = [Q_t^E, Q_t^C, Q_t^H, Q_t^S, Q_t^K]$ represent the amount of time each behavior requires, with child care time being a function of the time prices, the number of children, and marital status.[17] With regard to criminal activity, participation in crime in period t takes time; similarly, being in a caught state in period t may result in lost time (e.g., court appearance, community service).

vectors in the information set is meant to distinguish between indicators of recent caught criminal activity and a history of past caught criminal activity. While we have years since last conviction and incarceration, which by definition defines whether the criminal record is recent, we do not know years since last charge.

[17] Individuals could also pay someone to care for children.

We assume that individuals are forward looking, and make decisions about behaviors (i.e., employment, welfare receipt, schooling, and criminal activity) to maximize the sum of discounted expected utility over one's lifetime. Job offers (O_t) determine whether or not legal employment is an available alternative. Eligibility for welfare (R_t) determines whether or not it is an available alternative. A criminal record depends on whether or not an individual who commits illegal activity in t is caught in $t+1$ (C_{t+1}). We model these stochastic outcomes by the following probabilities:

$$\begin{aligned} p(O_t = 1) &= f^O(e_{t-1}, E_t^1, E_t^2, CR_t, D_t, Z_t^E) \\ p(R_t = 1) &= f^R(Y_t^1, E_t^3, CR_t, D_t, Z_t^R) \\ p(C_{t+1} = 1) &= f^C(e_t, c_t, CR_t, D_t, Z_t^C) \end{aligned}$$

where the vector $Z_t = [Z_t^E, Z_t^R, Z_t^C, Z_t^H]$ represents exogenous characteristics of the employment, welfare, criminal justice/law enforcement, and health systems (and includes pecuniary and time prices, P_t and Q_t).

Similarly, health in future periods is stochastic and uncertain and depends on current health and health inputs in period t. Health evolution, or the health production function, is modeled as

$$\begin{aligned} H_{t+1} &= f^H(H_t, HC_t, D_t, Z_t^H) \\ &= g^H(H_t, CR_t, e_t, r_t, s_t, c_t, D_t, Z_t^H) \end{aligned}$$

Note that, because we do not model health care consumption and time allocation decisions (about both medical and non-medical health inputs) explicitly, we substitute the determinants of this input demand into the health production function. We assume that health inputs are chosen after the employment, welfare receipt, schooling, and criminal activity behaviors are chosen for the period. This assumption implies that some exogenous own- and cross-price variables (i.e., some elements of the vectors P_t and Z_t) do not independently impact health transitions conditional on the observed behaviors.

The specification of the health production function allows us to test three possible channels through which a criminal record (which reflects one's history of being caught — charged, convicted, or incarcerated — for criminal behavior) may impact health. First, a criminal record may directly affect health (which we call the *direct* effect). Criminal record also indirectly affects health through its impact on observed behaviors during the period (which we call the *indirect contemporaneous* effect). Additionally, a criminal record may indirectly affect future health through changes in current period health (which we term the *indirect dynamic* effect). More specifically,

$$\frac{dH_{t+1}}{dCR_t} = \frac{\partial H_{t+1}}{\partial CR_t}\frac{\partial CR_t}{\partial CR_t} + \frac{\partial H_{t+1}}{\partial B_t}\frac{\partial B_t}{\partial CR_t} + \frac{\partial H_{t+1}}{\partial H_t}\frac{\partial H_t}{\partial CR_{t-1}}$$

where $B_t = [e_t, r_t, s_t]$ denotes the vector of contemporaneous behaviors. Note that our model distinguishes between being caught at the end of t, or prior to period $t+1$, for criminal behavior during period t and a previous history of being caught. Thus, the first two terms above measure the effect of recent and historical arrests, while the third term captures the effect of historical arrests on health entering period t (and not the effect of being caught during t). The latter term is only observed when we calculate long-term impacts, and not relevant for short-term impacts conditional on health entering the period.

Using a recursive Bellman equation representation, we express one's lifetime utility of choosing alternatives $e_t = e, r_t = r, s_t = s,$ and $c_t = c$ in period t in health state $H_t = h$ and caught state $C_t = j$ as

$$\begin{aligned}
V^{hj}_{ersc}(\Omega_t, \epsilon^u_t | O_t = o, R_t = \ell) \;\; = \\
& u(X_t, L_t, d^{ersc}_t, \epsilon^u_t; D_t, H_t = h, C_t = j) + \beta\Bigg[\sum_{j'=0}^{1} p(C_{t+1} = j') \sum_{h'=0}^{H} p(H_{t+1} = h') \\
& E_t\Big[\sum_{o'=0}^{1} p(O_{t+1} = o') \sum_{\ell'=0}^{1} p(R_{t+1} = \ell') \max_{e'r's'c'} V^{h'j'}_{e'r's'c'}(\Omega_{t+1}, \epsilon^u_{t+1} | O_{t+1} = o', R_{t+1} = \ell') | d^{ersc}_t = 1\Big]\Bigg] \\
& \forall\, t, t = 1, \ldots, T \text{ and } \forall\, e, r, s, c\,.
\end{aligned}$$

Given functional forms for the utility function and stochastic probabilities, a researcher could form a likelihood of observing the behaviors and outcomes in the data using probabilities of each of the alternative combinations and probabilities or densities of the stochastic outcomes. Alternatively, one could derive (linearized) demand functions for the behaviors being modeled and recover reduced-form parameters, rather than estimate the primitive parameters of the decisionmaking process. Variation in the observed behaviors would depend on information available to the individual at the point of decisionmaking, namely $\Omega_t = [CR_t, H_t, E_t^1, E_t^2, E_t^3, D_t, Z_t]$. The information known by the individual includes her endogenous record of criminal activity, health, and experience in each of the behavior areas entering period t as well as exogenous demographics (including number of kids and marital status), prices and supply-side determinants, and system characteristics. The theoretical framework makes explicit the avenues through which a record of criminal activity may influence health.

4.2 Empirical Model

There are a number of aspects of the theoretical model that are unobserved in our data, and most data for that matter. These include criminal activity (i.e., the action (c_t) not the criminal record (CR_{t+1}) if caught) and hence the probability of being caught ($p(C_{t+1} = 1)$); the employment offer probability ($p(O_t = 1)$); and all the determinants of eligibility for public assistance ($p(R_t = 1)$). Hence, it is difficult to estimate the decisionmaking problem described above. To measure the direct and indirect effects of a record of criminal activity on health, we jointly estimate the derived structural demand equations (behaviors) and health production functions (outcomes) using the theoretical model to guide the empirical specification. Theory also provides meaningful variables for identification and we discuss those in detail below.

While an individual solving this decisionmaking problem chooses (all 4) behaviors simultaneously, we focus specifically on the employment behavior in order to explain its determinants. Since the other behaviors are chosen jointly, they depend on the same set of determinants. The latent variable describing the demand for each employment outcome, V_e^*, is

$$V_e^* = V_e(e_{t-1}, r_{t-1}, s_{t-1}, C_t, CR_t, H_t, D_t, Z_t) + u_t^{E_e} \ , e = 0, 1$$

where $u_t^{E_e}$ represents unobserved determinants of each employment alternative e. Employment behavior in period t depends on the observable histories of employment, welfare receipt, and schooling; having recently been caught and having a criminal record (which includes the histories of charge, conviction, and incarceration); health; demographics; and the vector of price and supply-side, or system-level, variables (Z_t).

While the entire history of one's behavior is a potential state variable (e.g., years of work experience), we include only the lagged behavior (i.e., employment in period $t-1$) due to data constraints. (Specifically, our data suffer from missing information on some behaviors in some periods and we do not know historical values of some behaviors at baseline.) The dependence of employment behavior in period t on one's employment behavior in period $t-1$ suggests that the unobserved determinants of employment in period t could be correlated with unobserved determinants of employment in period $t-1$. To allow for this correlation, we decompose the error terms, u_t^j, which capture the unobserved determinants of each equation j (with other equations described below), into a permanent individual component (μ), a time-varying serially-independent individual component (ν_t), and an idiosyncratic component (ϵ_t); specifically, $u_t^j = \mu^j + \nu_t^j + \epsilon_t^j$. The idiosyncratic error (ϵ_t^j) is assumed to be serially-uncorrelated and its distribution dictates the probability or density of the outcome variable of interest, conditional on the other delineated unobserved heterogeneity terms. Correlation in behaviors over time and attributable to unobservables is captured by the permanent individual unobserved heterogeneity vector (μ). The serially-independent unobserved heterogeneity vector (ν_t) plays a different role by capturing correlation among behaviors within a time period (which we explain below). Replacing $u_t^{E_e}$ with its decomposition, the probabilities of being non-employed ($e_t = 0$), relative to being employed ($e_t = 1$), in period t are

$$\ln\left[\frac{p(e_t = 0)}{p(e_t = 1)}\right] = f^E(e_{t-1}, r_{t-1}, s_{t-1}, C_t, CR_t, H_t, D_t, Z_t) + \mu^E + \nu_t^E \ . \quad (1)$$

with the assumption that ϵ_t^E is Extreme value-distributed (with its difference being logistically distributed).

The theoretical framework suggests that welfare participation and schooling are chosen jointly with employment each period. These are also jointly chosen with criminal activity, but this latter behavior is unobserved in our data set and cannot be modeled empirically. Because they are jointly chosen, and may exhibit cross price effects if they are substitutes or complements, the derived demands for these behaviors are a function of the same set of determinants including the full vector of price and supply-side variables. The jointly-determined welfare participation and schooling probabilities, in log odds, are

$$\ln\left[\frac{p(r_t=1)}{p(r_t=0)}\right] = f^R(e_{t-1}, r_{t-1}, s_{t-1}, C_t, CR_t, H_t, D_t, Z_t) + \mu^R + \nu_t^R \quad (2)$$

$$\ln\left[\frac{p(s_t=1)}{p(s_t=0)}\right] = f^S(e_{t-1}, r_{t-1}, s_{t-1}, C_t, CR_t, H_t, D_t, Z_t) + \mu^S + \nu_t^S \; . \quad (3)$$

Theory suggests that the behaviors are dynamic (i.e., depend on previous histories of behaviors). Theory also suggests that each of these behaviors (i.e., employment, welfare participation, and schooling) — along with criminal activity, which is unobserved — are chosen simultaneously. The observed outcomes may be correlated through observed variation in the explanatory variables or through common individual-level unobserved variation. That is, for example, $cov[u_t^E, u_t^R] \neq 0$. The specification of the error correlation allows the behaviors to be correlated through a permanent unobserved characteristic of individuals (μ) as well as an unobserved characteristic that varies over time and creates correlation across behaviors within the time-period (ν_t).

To recap, the permanent unobservable allows for correlation across equations as well as over time, such that the unobserved determinants of lagged behaviors are correlated with the unobserved determinants of current behaviors. The time-varying unobserved heterogeneity allows for correlation contemporaneously across the behaviors. We specify the distributions of these unobservables when we formally discuss estimation of the full set of probabilities and densities entering the likelihood function.

A vector $Z_t = [Z_t^E, Z_t^R, Z_t^S, Z_t^C, Z_t^H]$ describes the exogenous policy environment that influences behaviors and outcomes. It is assumed that individuals know these policy variables entering each decisionmaking period.[18] Note that the entire vector impacts the behavioral decisions at the beginning of the period. Subsequent outcomes may not depend on the full

[18]To avoid modeling beliefs about how these policy variables evolve, we assume they are known at the beginning of each period, and a woman believes they will stay the same over time. The values are updated each period when a woman observes the current environment. Remember, however, that we do not intend to solve the individual's optimization problem and estimate a parameterized version of the model, so an assumption about beliefs is only necessary to the extent that it impacts our identification strategy.

vector of prices/supply side variables conditional on the observed behaviors. These variables provide the theoretical justification for identification of the empirical model.

What is uncertain to an individual when she is making her period t decisions about the behaviors (inclluding criminal activity) is whether she will get caught for her criminal actions this period. That is, she does not know if she will be in a "caught" state in period $t+1$. We define probabilities of being caught, defined by the criminal outcomes we observe in the FF data. Using information on timing of new offense records, we model the probability of a new charge, conviction, and incarceration entering period $t+1$ ($C^1_{t+1}, C^2_{t+1}, C^3_{t+1}$, respectively) as

$$\begin{aligned} \ln\left[\frac{p(C^1_{t+1}=1)}{p(C^1_{t+1}=0)}\right] &= f^{C^1}(e_t, r_t, s_t, C_t, CR_t, H_t, D_t, Z^C_t) + \mu^{C^1} + \nu^{C^1}_t \\ \ln\left[\frac{p(C^2_{t+1}=1|C^1_{t+1}=1)}{p(C^2_{t+1}=0|C^1_{t+1}=1)}\right] &= f^{C^2}(e_t, r_t, s_t, C_t, CR_t, H_t, D_t, Z^C_t) + \mu^{C^2} + \nu^{C^2}_t \\ \ln\left[\frac{p(C^3_{t+1}=1|C^2_{t+1}=1)}{p(C^3_{t+1}=0|C^2_{t+1}=1)}\right] &= f^{C^3}(e_t, r_t, s_t, C_t, CR_t, H_t, D_t, Z^C_t) + \mu^{C^3} + \nu^{C^3}_t \ . \end{aligned} \tag{4}$$

where the unobserved determinants are replaced with the decomposition stated above. Hence, the behaviors (i.e., employment, welfare receipt, and schooling) and these probabilities of a charge, conviction, and/or incarceration are allowed to be correlated through individual permanent and time-varying unobservables, μ and ν_t. Being charged, convicted, or incarcerated activates a criminal record, denoted by the vector $CR_t = [CR^1_t, CR^2_t, CR^3_t]$ (i.e., each indicator equal to one if ever charged, convicted or incarcerated entering period t; zero otherwise).[19] This vector of variables also includes the number of years since the last conviction or incarceration. Because so few women in our sample are incarcerated during the survey period, we do not model the incarceration probability; however, we do control for having recently been incarcerated, having ever been incarcerated, and years since last incarceration.

Having observed the period t behaviors and the criminal record outcomes associated with unobserved criminal activity behavior, we model the health production functions for both general health (H^1_t) and mental health (H^2_t). The variables that determine health evolution,

[19]Note that individuals who are convicted are also charged, and those incarcerated have been charged and convicted.

or the health outcome entering period $t+1$, are

$$\begin{aligned} H_{t+1}^{h} &= f^{H^h}(H_t, HC_t, D_t, Z_t^H) + \mu^{H^h} + \nu_t^{H^h} + \epsilon_t^{H^h} \\ &= f^{H^h}(H_t, CR_t, e_t, r_t, s_t, c_t, D_t, Z_t^H) + \mu^{H^h} + \nu_t^{H^h} + \epsilon_t^{H^h} \\ &= f^{H^h}(H_t, CR_t, e_t, r_t, s_t, C_{t+1}, D_t, Z_t^H) + \mu^{H^h} + \nu_t^{H^h} + \epsilon_t^{H^h} \ , \quad h = 1, 2 \end{aligned} \tag{5}$$

where the production function depends on current period health and behaviors as well as criminal record histories. Importantly, health production depends on health care consumption, which we do not observe. If we assume that health care consumption decisions are made after the employment, welfare receipt, schooling, and criminal activity behaviors, then we can substitute its determinants into the first equation above. (The added variables would include the pecuniary and time prices of, for example, medical care, cigarettes, exercise, etc., which we include in Z_t^H.) Because criminal activity is not observed, we include the observed outcome C_{t+1}, to reflect the effect of being caught (for behavior in period t) on subsequent health. Note that a history of criminal behavior, captured by CR_t may also impact health evolution.

4.3 Missing Endogenous Variables

Often a researcher encounters an empirical specification with an endogenous variable that is underreported or imputed, but the instrumental variable is not underreported or imputed. Consider our equation 1 where lagged employment is a determinant of current employment or equation 5 where current employment impacts future health. As explained in Section 4, employment (and welfare receipt) are not observed for all individuals in every time period. For each period t, we construct a variable indicating whether information is not known, nk_t, about the endogenous time t variable of concern (in our case, employment in t, which becomes an endogenous explanatory variable for outcomes in the next period). Here, $nk_t = 1$ indicates that the value is not observed by the econometrician and $nk_t = 0$ indicates that the value is observed. Because we are modeling outcomes over time, the variable of interest, employment, is both a dependent variable in period t and an explanatory variable for the health outcome in period $t+1$. Additionally, its lagged value partially explains the current value of employment. Within any period t, then, we only have observations on the behavior conditional on it being known (i.e., $nk_t = 0$). In the typical case where the endogenous regressor is reported or unreported and imputed, the OLS estimate of the marginal effect of the endogenous regressor is the weighted average of the estimators for each sub-group based on nk_t. For ease of explanation, we simplify the employment equation determinants and consider a linear probability model. The simplified dynamic specification is

$$e_t|nk_t = 0 = f(e_{t-1}, nk_{t-1}, x_t, z_t) + \epsilon_t$$

where the values of lagged employment,

$$e_{t-1} = \begin{cases} e_{t-1} & \text{if } nk_{t-1} = 0 \\ 0 & \text{if } nk_{t-1} = 1 \end{cases}$$

are either observed, or replaced with a zero for those observations where employment is not observed and we include in the regression a missing value indicator, nk_{t-1}. The variables x_t represent exogenous individual-specific variables that may explain employment, such as gender, race, and age, and that may be time invariant or time-varying. The variables z_t represent exogenous labor-demand side shifters (such as local unemployment rates or local sector-specific average wages) and are time-varying. We ignore the other endogenous explanatory variables (as in Equation 1) in order to focus on the endogeneity and missingness of lagged employment. There are two sources of identification of the marginal effect of lagged employment on current employment. First, the histories of exogenous time-varying individual variables creates variation across individuals over time. Second, it is common to include additional identifying instruments through the lagged demand-side variables, such that last period unemployment rates impact last period employment status of the individual, but have no independent effect on the individual's current period employment, conditional on the observed lagged employment.

Now we consider two scenarios. The underreporting (or missingness due to not knowing the value) could be random or non-random. In the case that it is randomly missing, the true marginal effect can be computed based on the observed probability of missing. However, when it is missing non-randomly, we need to consider both the case of selection on observables and selection on unobservables that might be correlated with the outcome of interest. A variety of methods exist to address the first case, and are relatively straightforward (Bollinger and Hirsch 2006; Hirsch and Schumacher 2004; Heckman and Lafontaine 2006; and Hirsch 2006). In the latter case, it has been suggested to estimate a "selection into having the information" equation jointly with the observed outcomes conditional on knowing the information. In our notation above, this amounts to jointly estimating the the selection equation, $p(nk_t = 1)$, and the outcome of interest, $e_t|nk_t = 0$. As the literature suggests, one needs an exclusion restriction, or a variable that explains whether the information is known but that does not impact the outcome of interest. However, such an instrument is not necessary if we consider the availability of information to be jointly determined with the outcome. In our data, we observe employment in time t based on responses to questions in time $t+1$ as well as the wording of the questions. That is, in some waves, but not others, if someone was employed at the time of the survey, then we know nothing about their employment between the previous survey wave and the current survey wave. However, if they were non-employed, we have some information about employment behavior between the survey waves. The availability of information depends both on observed and unobserved individual characteristics (that determine employment behavior at t) as well as differences in wording of the questions across survey waves (i.e., exogenous, random variation).

In this case, we propose to jointly model the selection equation and the behavior equation as functions of the same variables, while allowing them to depend on common permanent unobservables and common time-varying unobservables. This modeling approach addresses potential correlation in unobservables that lead to selection bias as well as potential correlation resulting from the endogenity of the lagged behavior in explaining the current period behavior. We modify the employment, welfare participation, and charge probabilities (Equations 1 and 2 and 4) to reflect that they are conditional on us observing the behavior or charge, and include (in the jointly estimated likelihood function) probabilities to describe the observability of these behaviors. Specifically,

$$\begin{aligned}
\ln\left[\frac{p(e_t=0|nk_t^E=0)}{p(e_t=1|nk_t^E=0)}\right] &= f^E(e_{t-1},r_{t-1},s_{t-1},C_t,CR_t,H_t,D_t,Z_t)+\mu^E+\nu_t^E \\
\ln\left[\frac{p(r_t=1|nk_t^R=0)}{p(r_t=0|nk_t^R=0)}\right] &= f^R(e_{t-1},r_{t-1},s_{t-1},C_t,CR_t,H_t,D_t,Z_t)+\mu^R+\nu_t^R \\
\ln\left[\frac{p(C_{t+1}^1=1|nk_{t+1}^C=0)}{p(C_{t+1}^1=0|nk_{t+1}^C=0)}\right] &= f^{C^1}(e_t,r_t,s_t,C_t,CR_t,H_t,D_t,Z_t^C)+\mu^{C^1}+\nu_t^{C^1}
\end{aligned} \tag{6}$$

where the probabilities of not knowing the employment, welfare receipt, and charge information are

$$\begin{aligned}
\ln\left[\frac{p(nk_t^j=1)}{p(nk_t^j=0)}\right] &= f^{NK_j}(e_{t-1},r_{t-1},s_{t-1},C_t,CR_t,H_t,D_t,Z_t)+\mu^{NK_j}+\nu_t^{NK_j}\;\; j=E,R \\
\ln\left[\frac{p(nk_{t+1}^C=1)}{p(nk_{t+1}^C=0)}\right] &= f^{NK_C}(e_t,r_t,s_t,C_t,CR_t,H_t,D_t,Z_t^C)+\mu^{NK_C}+\nu_t^{NK_C}
\end{aligned} \tag{7}$$

Equations 3-7 describe the probabilities or densities that form an individual's contribution to the likelihood function and capture the behaviors and outcomes we observe in the data. We estimate the likelihood function using full information maximum likelihood (FIML) and a discrete factor random effects approach (DFRE) to account for the correlation contemporaneously and over time. Rather than make distributional assumptions to integrate out the correlated unobserved heterogeneity, the DFRE estimation method, initially suggested by Heckman and Singer (1983) in single equations and extended to jointly-estimated equations by Mroz and Guilkey (1992) and Mroz (1999), assumes that the correlated error terms have discrete distributions with several mass points of support, μ_m, and accompanying probability weights, θ_m , $m=1,\ldots,M$, where M is determined empirically. The mass points and weights are estimated jointly with the other parameters of the model, with just a few normalization assumptions for identification (i.e., we normalize one set of mass points to be zero). Analogously, the points of support of the time-varying heterogeneity, $\nu_{\ell t}$, and the probability weights, ψ_ℓ , $\ell=1,\ldots,L$, are estimated. We estimate the model by maximum likelihood for a fixed M and L. We then vary the size of M and L independently, re-estimate, and compare log-likelihood values (i.e., likelihood ratio test) to obtain the best fit. We also examine the resulting estimated distributions and changes in the coefficients of endogenous variables to determine which UH distributions provide the most improvement.

5 Estimation Results

Here we present and discuss findings from estimation of a dynamic, empirical model of behaviors (e.g., employment, welfare receipt, schooling/training), criminal record, and health outcomes (e.g., general health and depression) that are flexibly correlated through permanent and time-varying individual observed and unobserved heterogeneity. This model makes use of the *annual* observations from women surveyed five times over nine years (and over a thirteen year span), and jointly models the endogenous probability of us, as the researchers, not observing employment, welfare receipt, and charges. The structural equations are dynamic, such that past behaviors and outcomes may effect current behaviors and outcomes, creating avenues for direct and indirect effects of criminal record on health.

Fit of the model to observed data

Our preferred model involves 14 equations (i.e., 11 dynamic equations and 3 initial condition equations) estimated using FIML and DFRE to allow for the correlated unobserved heterogeneity. Estimates of the many parameters are provided in Appendix Tables A2-A15. Because the dynamic specification has many feed-forward effects, includes interactions, and may be non-linear, it is difficult to quantify the effects of interest simply by examining the parameter estimates themselves. Thus, we simulate the model using the estimated parameters and calculate marginal effects. We demonstrate in Figures 2 and 3 that the estimated model provides a data generating process that fits the observed data very well. In fact, we fit the data well when we use the observed explanatory variables directly (labeled "Simulated: het, no upd") as well as when we simulate dynamically (i.e., as the women age from the year 1997) and update the endogenous behaviors and outcomes that serve as lagged variables in subsequent simulations of behaviors and outcomes (labeled "Simulated: het, upd").[20] The results from estimation of each probability or density equation by itself and, hence, without the correlated unobserved heterogeneity (labeled "Simulation: no het, no upd") are also included in the figures.

[20]Here, "het" indicates the jointly estimated model allowing for correlated unobserved heterogeneity and "upd" indicates that the simulations are updated dynamically.

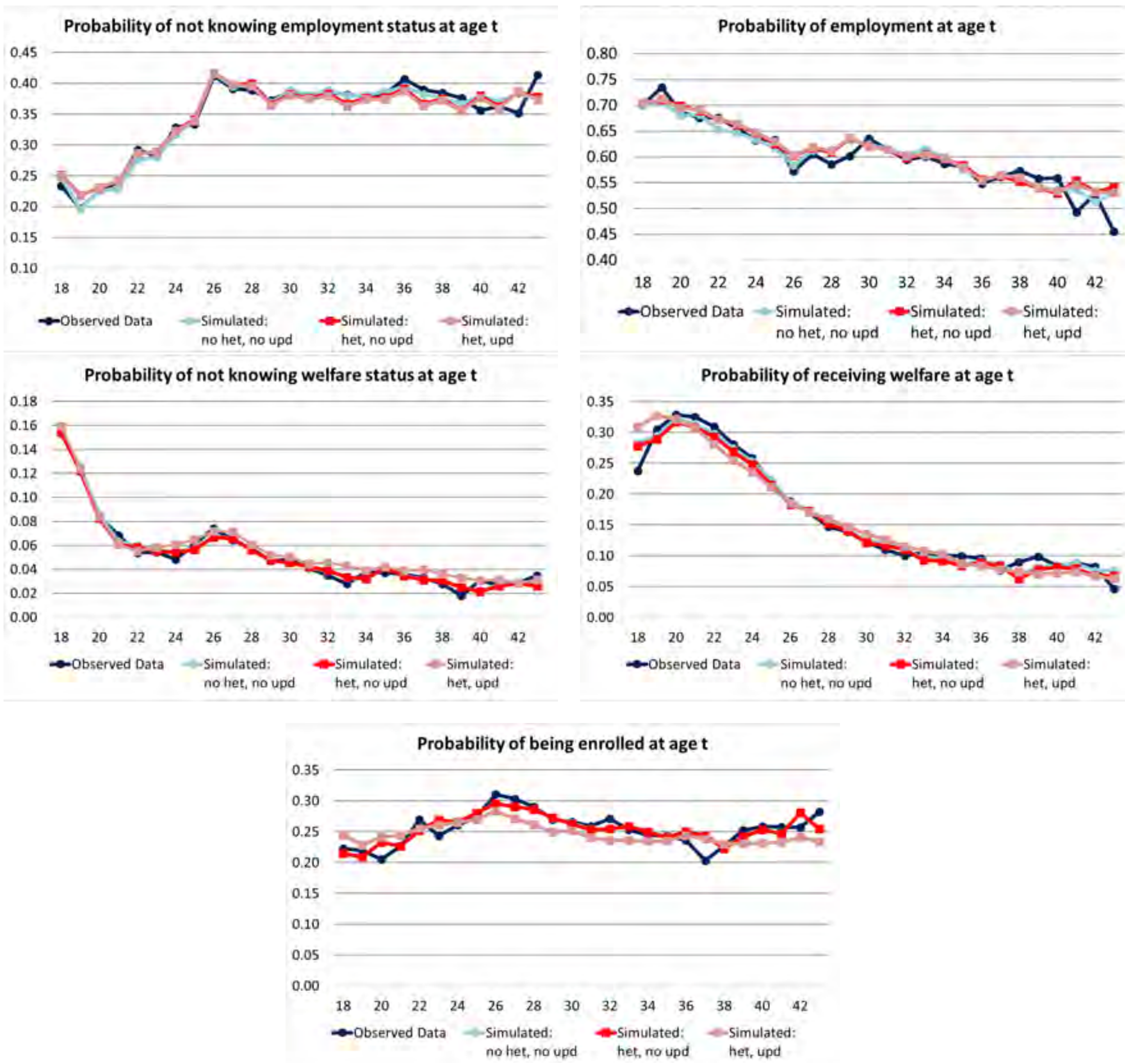

Figure 2: Graphical Comparison: Observed Data vs. Estimated Data Generating Process for Behaviors

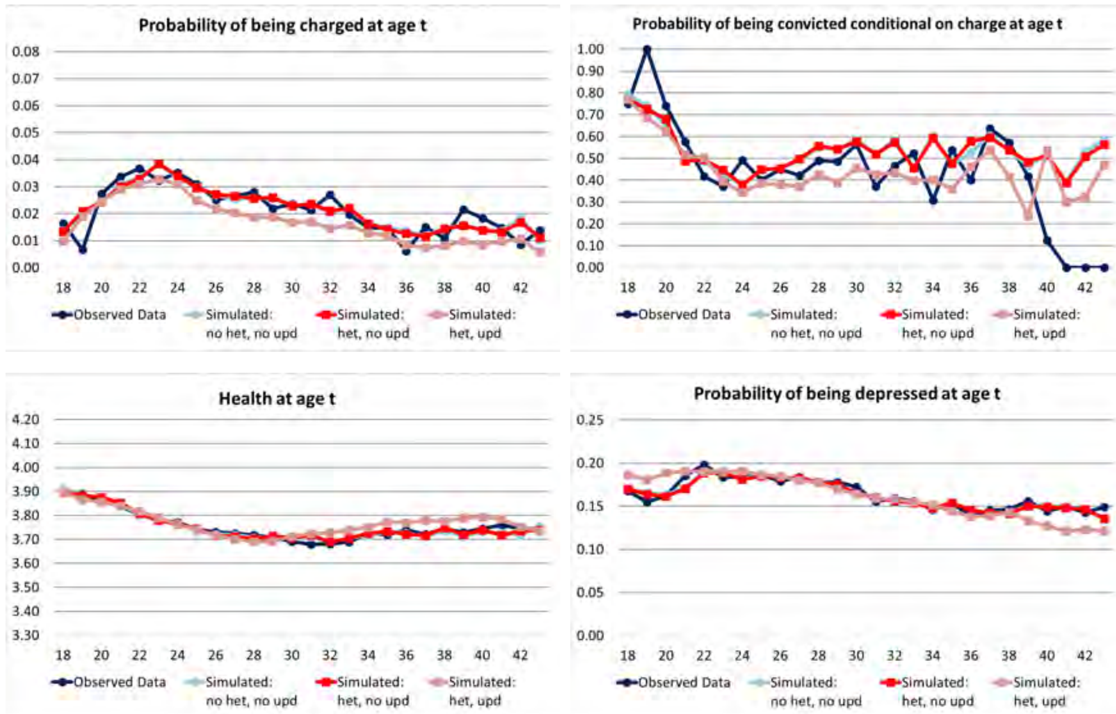

Figure 3: Graphical Comparison: Observed Data vs. Estimated Data Generating Process for Charge, Conviction, and Health Outcomes

In Figure 4 we depict the model's prediction of employment and welfare receipt conditional on those behaviors being observed in the data. We also depict what our data generating process predicts for employment and welfare receipt for all women, unconditional on observing their reported behavior. That is, when we simulate the behavior and outcomes of women, we do so for all women in the sample; the estimation procedure corrects estimates for potential selection bias by jointly modeling the probability of observing employment and welfare receipt. Note that the unconditional employment probabilities are larger than those for whom we know their employment information. This finding suggests that those missing employment information in any period t (a relatively smaller proportion) have a significantly greater probability of being employed than is observed in our *annualized* data. Similarly, the unconditional probability of welfare receipt is greater suggesting that those missing welfare information are significantly more likely to receive it than those for whom it is observed in any given period. Hence, we would likely come to incorrect conclusions if we estimated the model only on those for whom we have information.

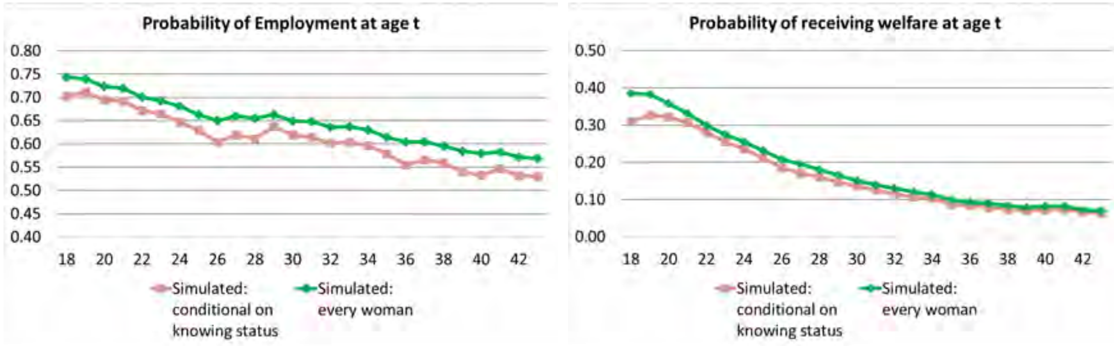

Figure 4: Employment and Welfare Receipt Comparisons: Simulations Conditional and Unconditional on Knowing Information

Direct and Indirect Effects of Criminal Record on Health

We now discuss our findings using the jointly-estimated model and the annualized data (with corrections for selection into observability of the annual behaviors of employment and welfare receipt) in order to recover causal impacts of a criminal record on health outcomes. To calculate these effects we simulate the model for R replications of each individual in the sample, where R=100. For each replication we randomly select the individual's permanent unobserved type using the estimated discrete distribution of the permanent unobserved heterogeneity, μ. Every time period, we randomly draw a time-varying unobservable for each replication from the estimated discrete distribution of the time-varying unobserved heterogeneity, ν_t.[21]

We begin by calculating the direct marginal effects of charges, convictions, and incarcerations last period on health next period, and the direct effects of a criminal offense history (via a criminal record). In Scenario 1 of Table 7, for example, we assume individuals have been charged in $t-1$ which implies that they have a criminal record. Because general health is estimated using ordinary least squares, we could examine the coefficients on these variables to find the marginal effect. However, as is shown in Appendix Table A9, the two variables in Scenario 1 enter directly and are interacted with the continuous physical health variable and the depression indicator. Given these interactions, we report the average marginal effect

[21]The estimated mass points for each equation and their estimated weights are provided in Table A15 of the Appendix. The best fit of our preferred model uses three permanent mass points and three time-varying mass points.

calculated through simulations (i.e., $\frac{\partial H_{t+1}}{\partial CR_t}$ of the total effect of criminal record on health defined in Section 4). We find that charge, conviction, or incarceration have no statistically significant direct causal impacts on health.

Table 7: Contemporaneous Marginal Effects of Crime Record on Health and Depression

Comparison Scenarios Entering t						Average Outcomes in t		Contemporaneous ME (scenario - baseline)	
	charged	ever charged	convicted	ever convicted	ever incarcerated	health	depression	health	depression
Baseline	0	0	0	0	0	3.673	0.166		
						(0.464)	(0.268)		
Scenario 1	1	1	0	0	0	3.662	0.234	-0.010	0.067
						(0.477)	(0.285)	(0.043)	(0.047)
Scenario 2	1	1	1	1	0	3.687	0.188	0.014	0.021
						(0.471)	(0.278)	(0.041)	(0.030)
Scenario 3	1	1	1	1	1	3.695	0.192	0.023	0.026
						(0.472)	(0.276)	(0.043)	(0.031)
Scenario 4	0	1	0	0	0	3.689	0.172	0.017	0.006
						(0.459)	(0.265)	(0.021)	(0.013)
Scenario 5	0	1	0	1	0	3.666	0.166	-0.007	-0.001
						(0.461)	(0.267)	(0.021)	(0.013)
Scenario 6	0	1	0	1	1	3.674	0.170	0.002	0.003
						(0.462)	(0.265)	(0.022)	(0.018)

Note: Standard errors (in parentheses) are bootstrapped parametrically with 500 draws. *** p<0.01, ** p<0.05, * p<0.1.

We also examine the effects of criminal records on the behaviors that we model: employment, welfare receipt, and schooling/training (i.e., $\frac{\partial B_t}{\partial CR_t}$ of the total effect of criminal record on health defined in Section 4). Recall that the channels through which a criminal record may create collateral consequences may determine these behaviors (i.e., job offer probabilities, welfare eligibility, and student loan eligibility). Theory, and conventional belief, suggests that these collateral consequences are negative; that the criminal record, which reports contact with the criminal justice system, will impede participation in beneficial social determinants of health. The results in Table 8 suggest that those individuals ever charged and convicted are more likely to be employed and to receive welfare. Those ever charged are also more likely to be enrolled in schooling or training. These positive (and perhaps counter-intuitive) findings may reflect the required or promoted or provided resources for employment and social support services that contact with the criminal justice system affords. Sentencing for criminal convictions may involve probation, fines, restitution, and community service. However, one may receive a suspended sentence or deferred adjudication. These latter sentencing alternatives may be conditional on the defendant fulfilling particular conditions of the sentence such as participation in a substance abuse program, not committing any further crimes, or demonstrating a capacity to behave responsibly. As such, these may provide additional incentives to secure employment or enroll in a schooling or training program, especially among single mothers who may risk losing custody or supervision of children.

Table 8: Contemporaneous Marginal Effects of Crime Record on Behaviors

Comparison Scenarios Entering t						Average Probabilities of Behaviors in t			Contemporaneous ME (scenario - baseline)		
	charged	ever charged	convicted	ever convicted	ever incarcerated	employed	welfare	enrolled	employed	welfare	enrolled
Baseline	0	0	0	0	0	0.658	0.234	0.237			
						(0.266)	(0.149)	(0.237)			
Scenario 1	1	1	0	0	0	0.668	0.277	0.272	0.010	0.043	0.035
						(0.266)	(0.160)	(0.241)	(0.021)	(0.026)	(0.023)
Scenario 2	1	1	1	1	0	0.677	0.266	0.222	0.019	0.032	-0.015
						(0.266)	(0.158)	(0.237)	(0.022)	(0.025)	(0.020)
Scenario 3	1	1	1	1	1	0.670	0.261	0.209	0.012	0.027	-0.028
						(0.266)	(0.157)	(0.236)	(0.023)	(0.025)	(0.022)
Scenario 4	0	1	0	0	0	0.665	0.254	0.257	0.007	0.020	**0.019****
						(0.265)	(0.154)	(0.239)	(0.005)	(0.011)	(0.009)
Scenario 5	0	1	0	1	0	0.674	0.274	0.236	**0.016*****	**0.040*****	-0.001
						(0.265)	(0.159)	(0.237)	(0.006)	(0.015)	(0.007)
Scenario 6	0	1	0	1	1	0.666	0.269	0.223	0.008	**0.035****	-0.014
						(0.265)	(0.158)	(0.236)	(0.007)	(0.015)	(0.010)

Note: Standard errors (in parentheses) are bootstrapped parametrically with 500 draws. *** p<0.01, ** p<0.05, * p<0.1.

To complete the total impact derivation, we calculate the marginal effects of behaviors on health (i.e., $\frac{\partial H_{t+1}}{\partial B_t}$ of the total effect of criminal record on health defined in Section 4). Table 9 suggests that there are no statistically significant effects, on average, of employment, welfare receipt, and schooling on health or depression. However, we refer the reader to Appendix Tables A9 and A10, which show statistically significant coefficient estimates on these behaviors both by themselves and interacted with the associated health entering the period. Recall that general health is treated as a continuous variable that takes on the values 2 to -2, with the value of 0 reflecting good health. Thus, employment has positive effects on subsequent general health for those individuals who are in "better than" good health (i.e., excellent or very good health). Employment has a detrimental effect on health of individuals who are in fair or poor health. Similarly, employment appears to decrease the probability of depression among those not experiencing depression, but increases it among those who are depressed. Welfare receipt also has disparate effects on subsequent health among individuals with different levels of health entering the period. These findings suggest that policy effectiveness depends crucially on the prior health of disadvantaged women, and suggests that, perhaps, efforts to improve health might need to precede efforts to encourage employment or schooling.

Potential Policy Impacts

We now present a preliminary attempt to consider alternative policies related to criminal records. These preliminary findings have motivated additional estimation work, which we are currently pursing. We present the following as examples of the type of long-run simulations we can perform, but it is our intention to continue analyzing the results to get a better understanding of the heterogenous effects of criminal records and behaviors on subsequent health.

Having examined the contemporaneous effects of criminal record on behaviors and health, we turn to the long-run effects that reflect the dynamics of these correlated behaviors and outcomes. That is, a criminal record at some time in one's past impacts contemporaneous

Table 9: Contemporaneous Marginal Effects of Employment, Welfare Receipt, and Schooling on Health and Depression

Comparison Scenarios in t	Average Outcomes in t		Contemporaneous ME (scenario - baseline)	
	health	depression	health	depression
Baseline: Not employed	3.670	0.164		
	(0.466)	(0.273)		
Scenario: Employed	3.663	0.170	-0.007	0.005
	(0.462)	(0.259)	(0.005)	(0.025)
Baseline: Not Receiving Welfare	3.675	0.165		
	(0.464)	(0.267)		
Scenario: Receiving Welfare	3.671	0.174	-0.005	0.010
	(0.465)	(0.271)	(0.005)	(0.009)
Baseline: Not enrolled	3.672	0.167		
	(0.025)	(0.267)		
Scenario: Enrolled	3.677	0.170	0.005	0.003
	(0.466)	(0.272)	(0.003)	(0.011)

Note: Standard errors (in parentheses) are bootstrapped parametrically with 500 draws. *** p<0.01, ** p<0.05, * p<0.1.

behaviors and subsequent health. In turn, those behaviors and health outcomes impact future behaviors and outcomes. Our simulations of the estimated dynamic model allow us to capture those long-term impacts. We simulate four scenarios meant to capture the policy effect of "ignoring" the criminal record information in each of the social systems affecting the behaviors we model. For example, we first simulate the behavior of all replicated individuals in our sample assuming they are never charged, convicted or incarcerated (Baseline). We then simulate behavior assuming that each individual (replication) was charged and convicted in 1997 and never experienced a charge, conviction, or incarceration after that (Scenario 1). We compare the baseline and scenario 1 to a scenario where the same individual incurs the criminal record associate with the 1997 charge and conviction, but that its impact on employment is zero (Scenario 2). In the context where a criminal record may impede the probability of employment, this scenario is similar to a "ban the box" policy, where employers do not have access to criminal offense histories of potential employees. Scenarios 3 and 4 similarly "ban the box" on the probability of welfare receipt and schooling/training enrollment, respectively (i.e., set the coefficients on criminal record to zero).

Table 10: Long-term Marginal Effects of Criminal Record on Health and Depression in 2010 following a charge and conviction in 1997

Comparison Scenarios		Average Outcomes in 2010		Lifecycle ME (scenario - baseline)		Lifecycle ME (scenario 2/3/4 - scenario 1)	
		health	depression	health	depression	health	depression
baseline	never commit crime	3.265	0.205				
		(1.107)	(0.326)				
Scenario 1	charged and convicted in 1997, never again	3.152	0.196	-0.113	-0.009		
		(1.129)	(0.326)	(0.113)	(0.031)		
Scenario 2	charged and convicted in 1997, never again;	3.154	0.196	-0.111	-0.009	**0.002*** **	0.000
	for employment, act as if no crime ever	(1.129)	(0.326)	(0.113)	(0.030)	(0.001)	(0.001)
Scenario 3	charged and convicted in 1997, never again;	3.154	0.192	-0.111	-0.013	0.002	**-0.004*** **
	for welfare, act as if no crime ever	(1.129))	(0.326)	(0.113)	(0.031)	(0.002)	(0.001)
Scenario 4	charged and convicted in 1997, never again;	3.152	0.196	-0.113	-0.009	0.000	0.000
	for school, act as if no crime ever	(1.129)	(0.326)	(0.113)	(0.031)	(0.000)	(0.000)

Note: Standard errors (in parentheses) are bootstrapped parametrically with 500 draws. *** p<0.01, ** p<0.05, * p<0.1.

Based on the findings summarized in Table 10, a "ban the box" type policy leads to statistically significant, but very small, improvements in long term general health. A "ban the box" type policy regarding welfare receipt reduces the probability of depression by a very small amount.

Dynamic Mechanisms and Long-run Impacts

To understand the channels through which the criminal record has a long-term effect on health, we summarize the impact of each scenario on the behaviors of the replicated individuals over the 1998-2010 period. Looking at the last three columns of Table 11, we see that the probability of employment over the period decreases when criminal record histories are ignored. Recent economic evidence suggests that employers may be more likely to statistically discriminate when information on criminal record is not available (Doleac and Hansen, 2016). We also see that when a criminal history is ignored for welfare receipt, average welfare probabilities are smaller than in Scenario 1 and employment probabilities increase, possibly suggesting a pathway to employment through the services offered by the welfare system.

Table 11: Long-term Marginal Effects of Criminal Record on Behaviors (averaged over the 1998-2010 period)

Comparison Scenarios		Behaviors Level 1998-2010			Lifecycle ME (scenario - baseline)			Lifecycle ME (scenario 2/3/4 - scenario 1)		
		employed	enrolled	welfare	employed	welfare	enrolled	employed	welfare	enrolled
baseline	never commit crime	0.658	0.237	0.127						
		(0.265)	(0.267)	(0.212)						
Scenario 1	charged and convicted in 1997, never again	0.671	0.238	0.193	**0.012****	**0.066****	0.001			
		(0.264)	(0.266)	(0.229)	(0.006)	(0.032)	(0.010)			
Scenario 2	charged and convicted in 1997, never again; for employment, act as if no crime ever	0.655	0.238	0.193	**-0.003****	**0.066****	0.001	**-0.016****	**-0.000****	0.000
		(0.265)	(0.266)	(0.229)	(0.001)	(0.032)	(0.010)	(0.006)	(0.000)	(0.000)
Scenario 3	charged and convicted in 1997, never again; for welfare, act as if no crime ever	0.674	0.235	0.127	**0.015****	0.000	-0.002	**0.003*****	**-0.066****	**-0.003*****
		(0.264)	(0.266)	(0.212)	(0.006)	(0.001)	(0.010)	(0.001)	(0.032)	(0.001)
Scenario 4	charged and convicted in 1997, never again; for school, act as if no crime ever	0.671	0.239	0.193	**0.013****	**0.066****	**0.003****	0.000	0.000	0.002
		(0.264)	(0.267)	(0.229)	(0.006)	(0.032)	(0.001)	(0.000)	(0.000)	(0.009)

Note: Standard errors (in parentheses) are bootstrapped parametrically with 500 draws. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusion

To be determined after we have explored these results in greater depth.

We have considered new specifications, which include potentially important interactions that will allow us to test some of our conjectures based on the results presented in this paper to date. We did not have time to complete estimation, goodness of fit, and simulation for this presentation. We welcome suggestions from you that will improve our investigation and help us formulate conclusions.

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A Appendix: Estimation Results

Table A1: Additional Information for State-level Exogenous Price and Supply-Side Variables

Variable Description	Unit	Source
Employment variables		
Full quarter employment: female with low SES **		
Full quarter employment: female with low education **		
New hire rate: female with low SES *		
New hire rate: female with low education *		
End of quarter hiring rate as % of quarterly employment: female with low SES		
End of quarter hiring rate as % of quarterly employment: female with low education		
Average monthly earnings of new hires: female with low SES (in 000s)		
Average monthly earnings of new hires: female with low education (in 000s)		
Unemployment rate: white female		
Unemployment rate: black female		
Unemployment rate: Hispanic female		
Welfare variables		
TANF monthly benefit: three person family	state	Welfare Rule Database; Urban Institute
Sanction severity		
Drug felony eligibility		
Schooling variables		
Average public 4-year college tuition (in 000s)	state	National Center for Education Statistics
Average private 4-year college tuitions (in 000s)	state	National Center for Education Statistics
Average public 2-year college tuitions (in 000s)	state	National Center for Education Statistics
Crime-related variables		
Number of female prisoners **		
Violent offenses ***		
State and local expenditure: police protection ****		
State and local expenditure: judicial and legal ****		
State and local expenditure: corrections ****		
Health-related variables		
Annual average temperature	state	National Center for Environmental Information
Annual lowest temperature	state	National Center for Environmental Information
Annual highest temperature	state	National Center for Environmental Information
Annual precipitation (in inches)	state	National Center for Environmental Information
Number of non-elderly,non-disabled adults with Medicaid *	state	National Center for Environmental Information
Percent of counties HPSA designated: primary care		
Percent of counties HPSA designated: mental health care		
Average cigarette price ($/pack)		
State and federal cigarette taxes as % of average retail price		
Average wine price ($/bottle)		
Average beer price ($/6-pack)		

Note: * per female population age 20-64; ** per thousand female population age 20-64; *** per thousand population age 20-64; **** per capita. Low education: high school/GED or less. Dollar amounts are in year 2000 dollars.

Table A2: Estimation Results: Employment Status Not Known

Variable name	Coeff	Std Err	
Charged in $t-1$	0.392	0.207	*
Convicted in $t-1$	-0.035	0.370	
Ever charged entering t	0.132	0.186	
Ever convicted entering t	-0.264	0.284	
Ever incarcerated entering t	-0.001	0.243	
Health entering t	0.016	0.028	
Depressed entering t	0.112	0.067	*
Received welfare in $t-1$	-0.059	0.069	
Enrolled in school in $t-1$	0.149	0.061	**
Less than eight years of education entering t	-1.174	0.254	***
Some high school entering t	-0.974	0.195	***
High school degree entering t	-0.021	0.193	
GED degree entering t	-0.118	0.172	
Some college entering t	0.380	0.195	*
Technical school entering t	0.014	0.113	
Bachelor's degree entering t	0.143	0.217	
Graduate degree entering t	0.186	0.221	
Training program entering t	0.191	0.097	**
Age - 18	0.102	0.027	***
Age - 18 squared/100	-0.907	0.203	***
Age - 18 cubic/1000	0.181	0.048	***
Black race	0.201	0.080	**
Non-white non-black	0.019	0.111	
Hispanic	0.060	0.101	
Married	-0.279	0.308	
Black race×married	-0.330	0.632	
Number of children	-0.306	0.192	
Number of children squared	0.050	0.030	*
New hire rate: female with low SES *	2.188	0.544	***
New hire rate: female with low education *	-4.677	0.964	***
Hiring rate as % of quarterly employment: female with low SES	-0.194	0.058	***
Hiring rate as % of quarterly employment: female with education	0.345	0.072	***
Quarterly employment: female with low SES **	-0.003	0.002	
Quarterly employment: female with low education **	0.032	0.039	
Average monthly earnings: female with low SES (in 000s)	0.429	0.217	**
Average monthly earnings: female with low education (in 000s)	-0.802	0.378	**
Unemployment rate: white female	-0.192	0.057	***
Unemployment rate: black female	-0.116	0.017	***
Unemployment rate: Hispanic female	0.012	0.020	
Average public 4-year college tuition (in 000s)	-0.061	0.043	
Average private 4-year college tuition (in 000s)	0.029	0.023	
Average public 2-year college tuition (in 000s)	-0.472	0.112	***
TANF monthly benefit: three person family	-0.001	0.001	
Sanction severity	-0.385	0.085	***
Violent offenses ***	0.046	0.020	**
Number of female prisoners **	0.230	0.166	
Drug felony eligibility	0.141	0.077	*
Annual average temperature	-1.138	0.800	
Annual lowest temperature	0.514	0.405	
Annual highest temperature	0.599	0.403	
Annual precipitation (in inches)	0.050	0.774	
Number of non-elderly, non-disabled adults with Medicaid *	-0.326	0.172	*
Time trend (1=2001)	0.473	0.074	***
Time trend squared	-0.092	0.022	***
Time trend cubic	0.009	0.002	***
Constant	-8.650	0.700	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A3: Estimation Results: Non-employment Status

Variable name	Coeff	Std Err	
Charged in $t-1$	-0.018	0.265	
Convicted in $t-1$	-0.008	0.311	
Ever charged entering t	-0.050	0.169	
Ever convicted entering t	-0.055	0.249	
Ever incarcerated entering t	0.050	0.197	
Health entering t	-0.034	0.023	
Depressed entering t	-0.107	0.055	**
Received welfare in $t-1$	0.330	0.056	***
Enrolled in school in $t-1$	-0.364	0.052	***
Less than eight years of education entering t	1.137	0.191	***
Some high school entering t	0.858	0.153	***
High school degree entering t	0.176	0.152	
GED degree entering t	0.014	0.143	
Some college entering t	-0.168	0.154	
Technical school entering t	0.035	0.102	
Bachelor's degree entering t	0.066	0.172	
Graduate degree entering t	0.063	0.178	
Training program entering t	-0.132	0.089	
Age - 18	-0.022	0.021	
Age - 18 squared/100	0.481	0.164	***
Age - 18 cubic/1000	-0.114	0.039	***
Black race	-0.472	0.068	***
Non-white non-black	0.055	0.086	
Hispanic	-0.081	0.079	
Married	0.244	0.064	***
Black race×married	-0.226	0.114	**
Number of children	0.100	0.048	**
Number of children squared	-0.009	0.008	
New hire rate: female with low SES *	-1.639	0.445	***
New hire rate: female with low education *	1.510	0.893	*
Hiring rate as % of quarterly employment: female with low SES	0.184	0.040	***
Hiring rate as % of quarterly employment: female with education	-0.194	0.061	***
Quarterly employment: female with low SES **	0.004	0.002	**
Quarterly employment: female with low education **	0.008	0.033	
Average monthly earnings: female with low SES (in 000s)	-0.020	0.192	
Average monthly earnings: female with low education (in 000s)	-0.267	0.319	
Unemployment rate: white female	-0.138	0.045	***
Unemployment rate: black female	0.061	0.014	***
Unemployment rate: Hispanic female	0.050	0.016	***
Average public 4-year college tuition (in 000s)	-0.031	0.034	
Average private 4-year college tuition (in 000s)	-0.057	0.019	***
Average public 2-year college tuition (in 000s)	0.224	0.093	**
TANF monthly benefit: three person family	0.001	0.001	***
Sanction severity	-0.080	0.068	
Drug felony eligibility	0.174	0.058	***
Violent offenses ***	0.015	0.016	
Number of female prisoners **	0.021	0.135	
Annual average temperature	-0.837	0.803	
Annual lowest temperature	0.468	0.404	
Annual highest temperature	0.373	0.404	
Annual precipitation (in inches)	-0.667	0.596	
Number of non-elderly, non-disabled adults with Medicaid *	0.049	0.162	
Time trend (1=2001)	0.319	0.058	***
Time trend squared	-0.004	0.017	
Time trend cubic	-0.003	0.001	**
Constant	0.222	0.413	

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A4: Estimation Results: Welfare Receipt Status Not Known

Variable name	Coeff	Std Err	
Charged in $t-1$	0.959	0.319	***
Convicted in $t-1$	-0.316	0.724	
Ever charged entering t	0.074	0.247	
Ever convicted entering t	0.127	0.380	
Ever incarcerated entering t	-0.416	0.296	
Health entering t	-0.088	0.035	**
Depressed entering t	0.093	0.085	
Received welfare in $t-1$	0.146	0.103	
Enrolled in school in $t-1$	-0.083	0.085	
Less than eight years of education entering t	0.215	0.342	
Some high school entering t	0.219	0.277	
High school degree entering t	0.143	0.283	
GED degree entering t	0.111	0.239	
Some college entering t	-0.068	0.287	
Technical school entering t	0.187	0.143	
Bachelor's degree entering t	-0.480	0.355	
Graduate degree entering t	-0.069	0.338	
Training program entering t	0.006	0.119	
Age - 18	-0.027	0.031	
Age - 18 squared/100	-0.094	0.269	
Age - 18 cubic/1000	0.038	0.068	
Black race	0.310	0.092	***
Non-white non-black	0.050	0.120	
Hispanic	-0.063	0.117	
Married	-0.775	0.540	
Black race×married	0.279	0.851	
Number of children	-0.186	0.148	
Number of children squared	0.018	0.025	
New hire rate: female with low SES *	-0.102	0.808	
New hire rate: female with low education *	-0.770	0.957	
Hiring rate as % of quarterly employment: female with low SES	0.081	0.095	
Hiring rate as % of quarterly employment: female with education	-0.053	0.110	
Quarterly employment: female with low SES **	0.002	0.003	
Quarterly employment: female with low education **	-0.026	0.057	
Average monthly earnings: female with low SES (in 000s)	0.486	0.391	
Average monthly earnings: female with low education (in 000s)	-1.797	0.720	**
Unemployment rate: white female	-0.005	0.091	
Unemployment rate: black female	-0.065	0.025	***
Unemployment rate: Hispanic female	-0.041	0.029	
Average public 4-year college tuition (in 000s)	0.130	0.061	**
Average private 4-year college tuition (in 000s)	0.008	0.033	
Average public 2-year college tuition (in 000s)	0.098	0.161	
TANF monthly benefit: three person family	0.000	0.001	
Sanction severity	-0.121	0.116	
Drug felony eligibility	0.119	0.098	
Violent offenses ***	-0.008	0.027	
Number of female prisoners **	0.553	0.236	**
Annual average temperature	-0.164	0.819	
Annual lowest temperature	0.139	0.411	
Annual highest temperature	0.029	0.418	
Annual precipitation (in inches)	-0.276	0.963	
Number of non-elderly, non-disabled adults with Medicaid *	1.501	0.276	***
Time trend (1=2001)	-0.319	0.104	***
Time trend squared	0.211	0.034	***
Time trend cubic	-0.018	0.003	***
Constant	-7.465	0.897	***

Note: Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A5: Estimation Results: Welfare Receipt Status

Variable name	Coeff	Std Err	
Charged in $t-1$	0.262	0.226	
Convicted in $t-1$	-0.353	0.291	
Ever charged entering t	0.237	0.178	
Ever convicted entering t	0.227	0.258	
Ever incarcerated entering t	-0.058	0.210	
Health entering t	-0.087	0.027	***
Depressed entering t	0.071	0.062	
Received welfare in $t-1$	3.032	0.052	***
Enrolled in school in $t-1$	0.157	0.058	***
Less than eight years of education entering t	0.474	0.188	**
Some high school entering t	0.583	0.151	***
High school degree entering t	0.227	0.154	
GED degree entering t	0.175	0.139	
Some college entering t	-0.067	0.157	
Technical school entering t	0.095	0.102	
Bachelor's degree entering t	-1.144	0.238	***
Graduate degree entering t	-0.350	0.206	*
Training program entering t	0.053	0.093	
Age - 18	0.006	0.025	
Age - 18 squared/100	-0.321	0.217	
Age - 18 cubic/1000	0.086	0.054	
Black race	0.554	0.069	***
Non-white non-black	0.179	0.088	**
Hispanic	-0.015	0.087	
Married	-0.946	0.122	***
Black race×married	0.043	0.184	
Number of children	0.221	0.070	***
Number of children squared	-0.021	0.011	*
New hire rate: female with low SES *	0.161	0.567	
New hire rate: female with low education *	0.171	0.915	
Hiring rate as % of quarterly employment: female with low SES	-0.058	0.050	
Hiring rate as % of quarterly employment: female with education	0.025	0.070	
Quarterly employment: female with low SES **	0.000	0.002	
Quarterly employment: female with low education **	-0.063	0.041	
Average monthly earnings: female with low SES (in 000s)	-0.188	0.241	
Average monthly earnings: female with low education (in 000s)	0.222	0.372	
Unemployment rate: white female	0.000	0.058	
Unemployment rate: black female	0.026	0.018	
Unemployment rate: Hispanic female	0.025	0.020	
Average public 4-year college tuition (in 000s)	0.020	0.044	
Average private 4-year college tuition (in 000s)	-0.012	0.026	
Average public 2-year college tuition (in 000s)	0.199	0.108	*
TANF monthly benefit: three person family	0.000	0.001	
Sanction severity	-0.248	0.083	***
Drug felony eligibility	0.098	0.073	
Violent offenses ***	-0.001	0.021	
Number of female prisoners **	-0.066	0.182	
Annual average temperature	0.658	0.811	
Annual lowest temperature	-0.217	0.408	
Annual highest temperature	-0.479	0.409	
Annual precipitation (in inches)	1.247	0.729	*
Number of non-elderly, non-disabled adults with Medicaid *	-0.060	0.199	
Time trend (1=2001)	0.236	0.075	***
Time trend squared	-0.149	0.022	***
Time trend cubic	0.011	0.002	***
Constant	-2.375	0.611	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A6: Estimation Results: School Enrollment Status

Variable name	Coeff	Std Err	
Charged in $t-1$	0.110	0.164	
Convicted in $t-1$	-0.229	0.236	
Ever charged entering t	0.144	0.110	
Ever convicted entering t	-0.149	0.172	
Ever incarcerated entering t	-0.106	0.152	
Health entering t	0.026	0.019	
Depressed entering t	0.058	0.045	
Received welfare in $t-1$	0.210	0.048	***
Enrolled in school in $t-1$	2.217	0.037	***
Less than eight years of education entering t	-0.633	0.148	***
Some high school entering t	-0.024	0.092	
High school degree entering t	0.195	0.093	**
GED degree entering t	0.395	0.088	***
Some college entering t	0.679	0.093	***
Technical school entering t	0.419	0.063	***
Bachelor's degree entering t	0.690	0.105	***
Graduate degree entering t	0.758	0.109	***
Training program entering t	0.448	0.057	***
Age - 18	-0.158	0.018	***
Age - 18 squared/100	0.836	0.142	***
Age - 18 cubic/1000	-0.160	0.034	***
Black race	0.312	0.045	***
Non-white non-black	0.063	0.059	
Hispanic	-0.078	0.055	
Married	-0.326	0.072	***
Black race×married	0.149	0.109	
Number of children	-0.071	0.053	
Number of children squared	0.009	0.009	
New hire rate: female with low SES *	-0.843	0.406	**
New hire rate: female with low education *	0.513	0.919	
Hiring rate as % of quarterly employment: female with low SES	0.028	0.038	
Hiring rate as % of quarterly employment: female with education	-0.009	0.057	
Quarterly employment: female with low SES **	0.001	0.002	
Quarterly employment: female with low education **	-0.047	0.027	*
Average monthly earnings: female with low SES (in 000s)	-0.307	0.158	*
Average monthly earnings: female with low education (in 000s)	-0.272	0.246	
Unemployment rate: white female	-0.041	0.038	
Unemployment rate: black female	0.019	0.011	*
Unemployment rate: Hispanic female	-0.018	0.013	
Average public 4-year college tuition (in 000s)	-0.002	0.027	
Average private 4-year college tuition (in 000s)	-0.012	0.013	
Average public 2-year college tuition (in 000s)	0.122	0.068	*
TANF monthly benefit: three person family	0.001	0.000	**
Sanction severity	0.051	0.054	
Drug felony eligibility	-0.003	0.049	
Violent offenses ***	-0.017	0.013	
Number of female prisoners **	-0.190	0.104	*
Annual average temperature	-0.720	0.715	
Annual lowest temperature	0.382	0.360	
Annual highest temperature	0.359	0.357	
Annual precipitation (in inches)	-0.882	0.371	**
Number of non-elderly, non-disabled adults with Medicaid *	0.209	0.119	*
Time trend (1=2001)	0.293	0.048	***
Time trend squared	-0.045	0.014	***
Time trend cubic	0.001	0.001	
Constant	-2.075	0.299	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A7: Estimation Results: Criminal Charge Status

Variable name	Coeff	Std Err	
Ever charged entering t	0.934	0.242	***
Ever convicted entering t	0.534	0.290	*
Ever incarcerated entering t	0.892	0.210	***
Health entering t	-0.170	0.046	***
Depressed entering t	0.525	0.099	***
Employed in t	0.146	0.116	
Received welfare in t	0.225	0.105	**
Enrolled in t	-0.066	0.106	
Less than eight years of education entering t	0.182	0.403	
Some high school entering t	0.347	0.318	
High school degree entering t	-0.047	0.330	
GED degree entering t	0.202	0.269	
Some college entering t	0.011	0.332	
Technical school entering t	0.219	0.209	
Bachelor's degree entering t	-0.371	0.419	
Graduate degree entering t	-0.224	0.447	
Training program entering t	-0.098	0.177	
Age - 18	0.024	0.063	
Age - 18 squared/100	-0.409	0.514	
Age - 18 cubic/1000	0.085	0.121	
Black race	-0.136	0.115	
Non-white non-black	-0.095	0.151	
Hispanic	-0.404	0.140	***
Married	-0.550	0.157	***
Black race×married	-0.099	0.276	
Number of children	0.048	0.102	
Number of children squared	-0.003	0.015	
Violent offenses ***	0.026	0.018	
Number of female prisoners **	0.301	0.094	***
Time trend (1=2001)	1.135	0.105	***
Time trend squared	-0.336	0.030	***
Time trend cubic	0.023	0.002	***
Constant	-3.997	0.444	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A8: Estimation Results: Criminal Conviction Status

Variable name	Coeff	Std Err	
Ever charged entering t	0.490	0.740	
Ever convicted entering t	-3.132	0.833	***
Ever incarcerated entering t	3.417	0.760	***
Health entering t	-0.141	0.139	
Depressed entering t	-0.326	0.302	
Employed in t	0.228	0.327	
Received welfare in t	0.070	0.306	
Enrolled in t	-0.327	0.390	
Less than eight years of education entering t	-0.547	0.892	
Some high school entering t	-0.505	0.491	
High school degree entering t	-0.151	0.534	
GED degree entering t	-0.176	0.542	
Some college entering t	-0.261	0.559	
Technical school entering t	-0.355	0.787	
Bachelor's degree entering t	-1.126	0.918	
Graduate degree entering t	-1.646	1.162	
Training program entering t	0.129	0.648	
Age - 18	-0.091	0.132	
Age - 18 squared/100	0.992	1.062	
Age - 18 cubic/1000	-0.273	0.263	
Black race	-0.163	0.351	
Non-white non-black	-0.119	0.639	
Hispanic	0.479	0.561	
Married	-0.099	0.516	
Black race×married	-1.279	0.993	
Number of children	-0.601	0.285	**
Number of children squared	0.097	0.044	**
Violent offenses ***	-0.077	0.053	
Number of female prisoners **	-0.957	0.355	***
Time trend (1=2001)	-3.937	0.695	***
Time trend squared	0.734	0.170	***
Time trend cubic	-0.039	0.012	***
Constant	5.547	0.973	***

Note: Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A9: Estimation Results: General Health

Variable name	Coeff	Std Err	
Charged in $t-1$	0.033	0.037	
Convicted in $t-1$	0.055	0.050	
Ever charged entering t	-0.007	0.024	
Ever convicted entering t	-0.021	0.033	
Ever incarcerated entering t	0.005	0.029	
General health entering t×Charged in $t-1$	-0.116	0.026	***
General health entering t×Convicted in $t-1$	0.028	0.036	
General health entering t×Ever charged entering t	0.041	0.018	**
General health entering t×Ever convicted entering t	-0.005	0.025	
General health entering t×Ever incarcerated entering t	-0.004	0.022	
Depression entering t×Charged in $t-1$	0.062	0.056	
Depression entering t×Convicted in $t-1$	-0.115	0.075	
Depression entering t×Ever charged entering t	0.003	0.037	
Depression entering t×Ever convicted entering t	-0.017	0.049	
Depression entering t×Ever incarcerated entering t	0.043	0.046	
Health entering t	0.928	0.004	***
Depressed entering t	-0.037	0.012	***
Employed in t	-0.030	0.010	***
Received welfare in t	0.002	0.010	
Enrolled in t	0.027	0.009	***
General health entering t×Employed in t	0.037	0.006	***
General health entering t×Welfare receipt in t	-0.008	0.007	
General health entering t×Enrolled in school in t	-0.028	0.006	***
Depression entering t×Employed in t	-0.001	0.016	
Depression entering t×Received welfare in t	-0.013	0.019	
Depression entering t×Enrolled in school in t	-0.023	0.017	
Less than eight years of education entering t	-0.002	0.019	
Some high school entering t	0.001	0.014	
High school degree entering t	0.016	0.014	
GED degree entering t	0.001	0.015	
Some college entering t	0.014	0.015	
Technical school entering t	0.005	0.011	
Bachelor's degree entering t	0.044	0.016	***
Graduate degree entering t	0.032	0.017	*
Training program entering t	-0.001	0.010	
Age - 18	-0.006	0.003	**
Age - 18 squared/100	0.040	0.022	*
Age - 18 cubic/1000	-0.008	0.005	*
Black race	-0.013	0.007	*
Non-white non-black	0.011	0.009	
Hispanic	-0.018	0.009	**
Married	0.006	0.010	
Black race×married	0.002	0.017	
Number of children	-0.007	0.008	
Number of children squared	0.001	0.001	
Annual average temperature	0.022	0.052	
Annual lowest temperature	-0.008	0.026	
Annual highest temperature	-0.014	0.026	
Annual precipitation (in inches)	0.051	0.045	
Number of non-elderly, non-disabled adults with Medicaid *	0.018	0.016	
Time trend (1=2001)	0.004	0.004	
Time trend squared	-0.003	0.002	*
Time trend cubic	0.000	0.000	**
Constant	3.072	0.025	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A10: Estimation Results: Depression Status

Variable name	Coeff	Std Err	
Charged in $t-1$	1.876	0.340	***
Convicted in $t-1$	-0.893	0.525	*
Ever charged entering t	-0.129	0.377	
Ever convicted entering t	-0.150	0.477	
Ever incarcerated entering t	0.135	0.421	
General health entering t×Charged in $t-1$	-0.135	0.181	
General health entering t×Convicted in $t-1$	0.117	0.280	
General health entering t×Ever charged entering t	0.010	0.189	
General health entering t×Ever convicted entering t	0.188	0.234	
General health entering t×Ever incarcerated entering t	-0.305	0.207	
Depression entering t×Charged in $t-1$	-3.531	0.467	***
Depression entering t×Convicted in $t-1$	1.845	0.785	**
Depression entering t×Ever charged entering t	0.647	0.492	
Depression entering t×Ever convicted entering t	-0.293	0.646	
Depression entering t×Ever incarcerated entering t	0.330	0.625	
Health entering t	-0.178	0.046	***
Depressed entering t	4.780	0.090	***
Employed in t	-0.974	0.125	***
Received welfare in t	0.415	0.107	***
Enrolled in t	0.415	0.098	***
General health entering t×Employed in t	0.094	0.079	
General health entering t×Enrolled in school in t	0.005	0.063	
General health entering t×Welfare receipt in t	-0.076	0.068	
Depression entering t×Employed in t	2.575	0.156	***
Depression entering t×Enrolled in school in t	-0.900	0.128	***
Depression entering t×Received welfare in t	-0.456	0.144	***
Less than eight years of education entering t	0.283	0.221	
Some high school entering t	0.410	0.166	**
High school degree entering t	0.074	0.171	
GED degree entering t	0.401	0.154	***
Some college entering t	0.257	0.170	
Technical school entering t	0.213	0.114	*
Bachelor's degree entering t	-0.120	0.200	
Graduate degree entering t	0.061	0.209	
Training program entering t	0.024	0.106	
Age - 18	0.021	0.031	
Age - 18 squared/100	-0.267	0.249	
Age - 18 cubic/1000	0.061	0.059	
Black race	-0.132	0.075	*
Non-white non-black	-0.133	0.096	
Hispanic	-0.260	0.096	***
Married	-0.092	0.127	
Black race×married	0.041	0.222	
Number of children	-0.008	0.095	
Number of children squared	0.003	0.015	
Annual average temperature	0.259	0.812	
Annual lowest temperature	-0.071	0.410	
Annual highest temperature	-0.195	0.408	
Annual precipitation (in inches)	-0.264	0.878	
Number of non-elderly, non-disabled adults with Medicaid *	-0.071	0.186	
Time trend (1=2001)	0.200	0.056	***
Time trend squared	-0.090	0.020	***
Time trend cubic	0.007	0.002	***
Constant	-2.801	0.334	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A11: Estimation Results: Attrition at the end of t

Variable name	Coeff	Std Err	
Charged in t	-0.305	0.318	
Convicted in t	0.596	0.629	
Ever charged in t	0.481	0.275	*
Ever convicted in t	-0.960	0.655	
Ever incarcerated in t	0.653	0.612	
Health in t	0.041	0.050	
Depressed in t	-0.181	0.127	
Employed in t	0.013	0.136	
Received welfare in t	-0.497	0.138	***
Enrolled in t	0.004	0.117	
Less than eight years of education in t	0.699	0.387	*
Some high school in t	0.401	0.334	
High school degree in t	0.088	0.341	
GED degree in t	-0.217	0.284	
Some college in t	-0.048	0.343	
Technical school in t	-0.051	0.181	
Bachelor's degree in t	-0.062	0.377	
Graduate degree in t	0.208	0.380	
Training program in t	-0.223	0.164	
Age - 18	0.051	0.102	
Age - 18 squared/100	-0.502	0.779	
Age - 18 cubic/1000	0.134	0.175	
Black race	-0.276	0.134	**
Non-white non-black	0.110	0.131	
Hispanic	0.120	0.130	
Married	-0.173	0.124	
Black race×married	0.163	0.220	
Number of children	-0.143	0.099	
Number of children squared	0.013	0.015	
Time trend (1=2001)	-1.241	0.743	*
Time trend squared	0.622	0.250	**
Time trend cubic	-0.070	0.026	***
Constant	-2.000	0.750	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A12: Estimation Results: Initial Condition - General Health

Variable name	Coeff	Std Err	
Age - 18	-0.008	0.012	
Age - 18 squared/100	0.202	0.163	
Age - 18 cubic/1000	-0.069	0.055	
Black race	-0.142	0.042	***
Non-white non-black	-0.127	0.054	**
Hispanic	-0.117	0.052	**
Married	0.180	0.138	
Black race×married	-0.214	0.369	
Number of children	-0.111	0.117	
Number of children squared	0.027	0.031	
Respondent's mother highest grade completed	0.033	0.007	***
Respondent's father highest grade completed	0.012	0.007	*
Respondent's mother deceased	-0.054	0.079	
Respondent's father deceased	-0.140	0.059	**
Constant	3.862	0.161	***

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A13: Estimation Results: Initial Condition - Depression Status

Variable name	Coeff	Std Err	
Age - 18	-0.044	0.046	
Age - 18 squared/100	0.127	0.624	
Age - 18 cubic/1000	0.020	0.208	
Black race	0.144	0.137	
Non-white non-black	0.146	0.181	
Hispanic	-0.189	0.175	
Married	-0.185	0.733	
Black race×married	0.417	0.999	
Number of children	0.335	0.511	
Number of children squared	-0.065	0.133	
Respondent's mother highest grade completed	0.009	0.024	
Respondent's father highest grade completed	-0.056	0.024	**
Respondent's mother deceased	-0.365	0.277	
Respondent's father deceased	0.094	0.191	
Constant	-1.243	0.709	*

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A14: Estimation Results: Initial Condition - Ever Charged, Convicted, or Incarcerated

Variable name	Coeff	Std Err	
Age - 18	0.373	0.101	***
Age - 18 squared/100	-3.676	0.998	***
Age - 18 cubic/1000	1.006	0.292	***
Black race	0.124	0.345	
Non-white non-black	-0.060	0.499	
Hispanic	-0.531	0.488	
Respondent's mother highest grade completed	-0.044	0.059	
Respondent's father highest grade completed	-0.050	0.058	
Respondent's mother deceased	-0.714	0.989	
Respondent's father deceased	-0.167	0.609	
Constant	-3.812	0.438	***

Note: Standard errors in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Dollar amounts are in year 2000 dollars. Results for variables indicating missing values are not presented.

Table A15: Estimation Results: Correlated Unobserved Heterogeneity

	Permanent Mass Points						Time-varying Mass Points					
Dependent Variable	Coeff	Std Err		Coeff	Std Err		Coeff	Std Err		Coeff	Std Err	
Nonemployment at t	-3.064	0.073	***	-1.082	0.062	***	0.008	0.077		0.035	0.086	
Welfare receipt at t	-0.963	0.056	***	-0.411	0.097	***	0.247	0.093	***	-0.085	0.107	
School enrollment at t	0.292	0.040	***	0.175	0.066	***	0.096	0.082		0.101	0.094	
Charged at t	-0.350	0.119	***	-0.229	0.175		0.047	0.153		-0.190	0.184	
Convicted at t conditional on charged	-0.451	0.338		-0.123	0.504		-0.244	0.582		-0.239	0.648	
General health at t	0.010	0.008		0.033	0.013	**	-1.159	0.009	***	1.144	0.010	***
Depression at t	-0.303	0.066	***	-0.288	0.120	**	1.034	0.121	***	-1.108	0.172	***
Do not know employment status at t	4.104	0.077	***	1.944	0.082	***	-0.023	0.153		0.241	0.180	
Do not know welfare status at t	-0.345	0.078	***	0.091	0.115		0.220	0.220		-0.135	0.248	
Ever charged, convicted, or incarcerated at $t = 1$	-0.875	0.281	***	-18.139	1.025	***	0.000	1.000		0.000	1.000	
General health at $t = 1$	0.164	0.040	***	0.127	0.068	*	0.000	1.000		0.000	1.000	
Depression at $t = 1$	-0.623	0.127	***	-30.082	0.827	***	0.000	1.000		0.000	1.000	
Attrition at end of t	-0.243	0.147	*	-0.142	0.208		0.473	0.163	***	0.265	0.166	
Mass Point probability weights	0.479			0.238			0.063			0.047		

Note: Standard errors in parentheses.*** p<0.01, ** p<0.05, * p<0.1. Permanent and time-varying mass point 1 is set at 0.000, with estimated weights of 0.283 and 0.890, respectively.

B Associations between criminal record and health outcomes using wave data

Before estimating our preferred model, we begin by providing estimation results using the wave-by-wave data. That is, we use only the observations on an individual when she was interviewed and our empirical models are static. We use what the public health literature calls a social determinants of health model to examine the correlation between a criminal record and health. We also show how a criminal record is correlated with employment and welfare participation, and then consider whether employment mediates the effects of crime on health and whether welfare participation moderates those effects. Specifically, we estimate

$$H_{t+1} = \beta_0 + \beta_{c1} CR_t + \epsilon_t^H \ . \tag{8}$$

We then ask whether employment status in period t mediates the relationship between health and a criminal offense history, where

$$\begin{aligned} e_t &= \alpha_0 + \alpha_{c2} CR_t + \epsilon_t^E & (9) \\ H_{t+1} &= \beta_0 + \beta_{c3} CR_t + \beta_{e3} e_t + \epsilon_t^H \ . & (10) \end{aligned}$$

The paths relating CR_t, e_t, and h_{t+1} may be moderated by an individual's welfare participation status (r_t). We estimate

$$\begin{aligned} e_t &= \alpha_0 + \alpha_{c4} CR_t + \alpha_{r4} r_t + \alpha_{cr4} CR_t r_t + \epsilon_t^E & (11) \\ H_{t+1} &= \beta_0 + \beta_{c5} CR_t + \beta_{e5} e_t + \beta_{r5} r_t + \beta_{cr5} CR_t r_t + \epsilon_t^H \ . & (12) \end{aligned}$$

Figure B1 denotes the estimated coefficients that define the associations between variables of interest.

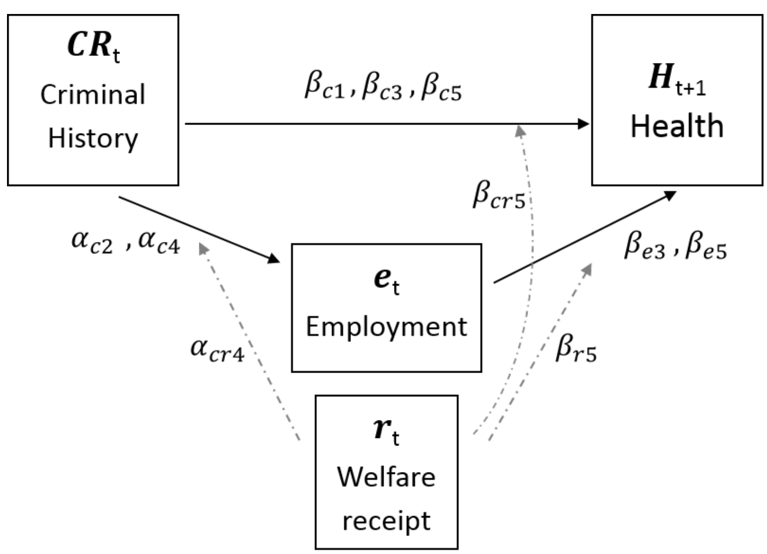

Figure B1: A Model of the Relationships

Table B1 provides estimates of the correlations under different model specifications. We examine the effects of a criminal record (e.g., ever charged, ever convicted, and ever incarcerated). Note that the effects should be summed, in that individuals who are ever convicted have also ever been charged and similarly, if ever incarcerated then an individual was also charged and convicted. The correlations suggest that a history of being charged negatively impacts general health and is positively correlated with the probability of being depressed. However, this association becomes insignificant for general health as controls for socioeconomic variables and individual unobserved random effects are added. In fact, conviction becomes significant at the 10% level for general health, and actually attenuates the negative effect on depression of being charged with a crime.

Table B1
Estimation Results: Criminal Record on Health Outcomes

Variable	Eqn 8, Spec 1			Eqn 8, Spec 2			Eqn 8, Spec 3			Eqn 10, Spec 3			Eqn 12, Spec 3			Eqn 12, Spec	
	Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev		Coeff	Std I
General Health																	
Ever charged	-0.184	0.078	***	-0.080	0.079		-0.046	0.077		-0.047	0.077		-0.043	0.078		0.030	0.077
Ever convicted	-0.055	0.109		-0.166	0.109	*	-0.145	0.108		-0.135	0.108		-0.134	0.107		-0.198	0.124
Ever incarcerated	-0.056	0.091		0.014	0.090		0.050	0.091		0.048	0.091		0.048	0.091		0.053	0.113
Employed										0.105	0.021	***	0.088	0.021	***	0.060	0.021
Receiving welfare													-0.121	0.026	***	-0.055	0.026
Ever charged x Receiving Welfare													0.018	0.087		0.047	0.076
R-squared		0.005			0.022			0.056			0.058			0.060			0.058
Depression																	
Ever charged	0.139	0.033	***	0.136	0.033	***	0.124	0.033	***	0.125	0.033	***	0.128	0.034	***	0.061	0.032
Ever convicted	-0.042	0.043		-0.040	0.044		-0.042	0.044		-0.046	0.044		-0.045	0.044		-0.009	0.047
Ever incarcerated	0.027	0.034		0.024	0.034		0.018	0.034		0.018	0.034		0.018	0.034		0.021	0.043
Employed										-0.034	0.008	***	-0.27	0.008	***	-0.016	0.008
Receiving welfare													0.054	0.010	***	0.032	0.011
Ever charged x Receiving Welfare													-0.027	0.034		-0.022	0.032
R-squared		0.007			0.010			0.020			0.021			0.024			0.022
Model specification																	
no controls		X															
demographics					X			X			X			X			X
social determinants								X			X			X			X
random effects																	X

Notes: *** indicates significance at the 1% level; **, at the 5% level; and *, at the 10% level. Errors are clustered at the individual level.
General health status takes on values from 1 to 5 and is estimated using Ordinary Least Squares; Depression is estimated as a linear probability model.
Demographics: age, race indicators, ethnicity indicator, cubic time trend.
Social determinants: married indicator, number of children, highest education level indicator and training indicators.
In results not shown, we find that having ever been convicted is negatively related to the probability of being employed (Eqn 9 and 11).
Having ever been charged is positively related to the probability of receiving welfare. Receiving welfare is negatively correlated with the probability of being employed (Eqn 11).