The Dynamic Effects of a Criminal Record on Health:
A Model of Long-run Behaviors and Outcomes when Lagged Variables are Missing Non-Randomly*

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April 2022

Abstract

We study the collateral consequences of a criminal record on women's health outcomes through multiple social determinants. We jointly estimate dynamic structural equations for life-cycle behaviors (employment, school enrollment, and welfare receipt), criminal offenses (charge, conviction, and incarceration), and general and mental health outcomes using a cohort of disadvantaged women surveyed at five non-uniform intervals over fourteen years. The detailed survey questions allow us to construct annual behavioral and criminal 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. The econometric approach allows us to differentiate between 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.

*We appreciate the comments of Pamela Giustinelli, Juan Pantano, Chris Tabor, and seminar/conference participants at Johns Hopkins, Indiana, Iowa State, Western Ontario, the 2018 Health and Labour Market Workshop, the CSMGEP Session at the 2018 ASSA/AEA annual meetings, the 2017 Society of Labor Economists (SOLE) conference and the 2017 Annual Health Economics Workshop (AHEW). Financial support from the National Institutes on Minority Health and Health Disparities (grant #R21-MD009563) is gratefully acknowledged. Correspondence: donna_gilleskie@unc.edu.

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. While not all charges result in a guilty verdict (i.e., 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, is created. In some states but not all, subsequent disposition is recorded. In 2012, the U.S. Department of Justice reported that local, state, and federal law enforcement agencies maintained criminal history records on approximately 70-100 million individuals (Sabol, 2014; Shannon et al., 2017).

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 than their male counterparts to be apprehended for misdemeanor, rather than felony, charges.[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 (Bureau of Justice Assistance, 2011).

Documented criminal behavior carries with it a set of "collateral consequences". The consequences are considered "collateral" because they do not constitute 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 relative to men (DOJ 2014). Stevenson and Mayson (2018) estimate that misdemeanor crime, in general, is decreasing over the last two decades.

The relationship between criminal activity consequences and health of the offender has received little attention in the literature. To date, most of the studies of health related to the criminal justice system 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). The recent coronavirus (COVID-19) pandemic has exposed the increased health risks to people in prisons and jails with little agency to care for themselves (Nowotny et al., 2020). Other related work has examined the impact of criminal activity on the mental health and employment/leisure activities of victims and of the general public (e.g., Cornaglia et al., 2014; Janke et al., 2016; Bor et al., 2018; Bencsik, 2020). With one in three Americans having a record of past criminal behavior, the dynamic health effects of the collateral consequences triggered by one's own criminal behavior have the potential to impact many people over their lifespan.

In this paper, we examine how the collateral consequences of a criminal past impact the health of 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, that 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, the collateral consequences may impact health *indirectly* via its influence on employment, welfare receipt, and education. In general, employment and education are positively correlated with health, since income and education impact good (and bad) health input behaviors. For eligible individuals, the primary welfare program in the U.S. (Temporary Assistance for Needy Families, or TANF) is a source of income support, and also provides education and job training, job-placement assistance, and transportation, among other things. TANF recipients also face work requirements (fulfilled by employment, on-the-job training, community service, and educational training). The collateral consequences of a criminal record may indirectly contribute to the poor health status of disadvantaged women by influencing employment options, welfare eligibility, and educational opportunities (Graetz, 1993; Roelfs et al., 2011). Despite several published findings describing bivariate associations among these variables of interest (e.g., criminal record and employment; employment and health, etc.), 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 (Sheely and Kneipp, 2015). 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 inter-related 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 correlated relationships jointly. Moreover, to date, these conversations have been at the theoretical level, with no scientific evidence demonstrating an empirical link between health and the collateral consequences of criminal activity. In part, this lack of evidence 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 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 (i.e., dynamic demand and production functions) 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 play a role in the subsequent 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.

An important challenge was to find 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 (which are more common than incarceration among disadvantaged women) on longitudinal 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.[3] We Importantly, the figure details the number of women surveyed in a particular calendar year. Another challenge was to construct a research sample from the available data that captures 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

[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.

[3]The FF survey includes two additional waves conducted in 2015 and 2022. The 2015 data were not available when we began this study.

waves allow us to determine the behaviors of each individual in (almost) each year of the study period. Hence, we are able to construct behavioral histories that allow us to model contemporaneous behaviors dynamically (i.e., as dependent on past behaviors). Additionally, we are able to merge in relevant state- and local-level policy variables by calendar year, making use of all of the variation in these variables across location and time.

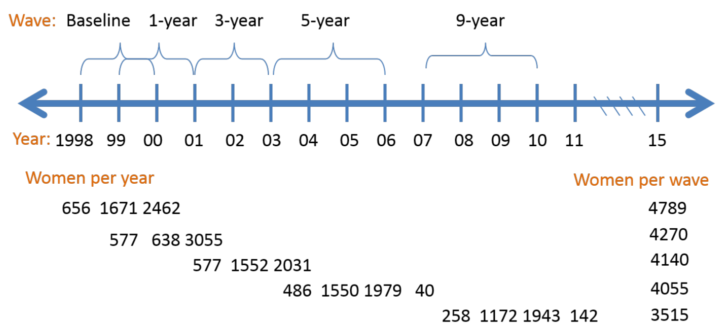

Figure 1: Timeline of Fragile Family Interviews

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 measures of an individual's behaviors and outcomes over time and that these measures be available at uniform intervals. Although the FF data are collected in five surveyed waves that are not equidistant apart (i.e., they contain one-, two-, and four-year gaps), the survey questionnaires include questions about past behaviors or the last time an individual engaged in a behavior, allowing us to fill in behaviors each year in between waves. Hence, we are able to construct one-year lagged behavioral variables for over 65 percent of the participants each year. We discovered, however, that the availability 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 in order to uncover the desired unbiased causal effects of explanatory variables of interest.[4] Other authors using this dataset, and similarly-constructed 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 background on employment, education, 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 results from estimation of a set of correlated structural equations (i.e., demand and production functions) via full information maximum likelihood. We conclude with simulations from the estimated data-generating process to demonstrate the short- and long-term effects of criminal records on physical and mental health via impacts on employment, welfare receipt, and education.

2 Review of Related Literature

In the introduction we briefly summarized the literature's coverage of the health impacts of criminal behavior and outcomes. We now provide an overview of several related literatures relevant to our focused research question. We first describe how a criminal offense history can legally alter one's employment, welfare, and education landscape. Second, we acknowledge the existence of a large literature examining the various bivariate relationships characterized by social determinants of health, with a focus primarily on the roles of employment, welfare receipt, and education. We conclude this section with a brief discussion of econometric approaches toward missing data.

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

2.1 Deterrence and Crime

There are several reviews of the economics and criminology literatures that discuss, as deterrents to crime, the roles of policing, punishment, and (pre-crime) employment and educational opportunities (e.g., Lochner and Moretti, 2004; Levitt and Miles, 2006; Tonry, 2008; Antonovics and Knight, 2009; Durlauf and Nagin, 2011; Abrams, 2012; Nagin , 2013; Aizer and Doyle, 2015; and Chalfin and McCrary, 2017). The literature on crime, generally, is vast and we mention work directly relevant to our study subsequently.

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. With regard to employment, 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.[5]

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 immature

[5]Recent work by Agan et al (2021) suggests that labor market consequences (i.e., unemployment or lower wages) of a criminal record weaken the deterrence effects of first offense misdemeanor crime prosecutions. Consequently, prosecution may increase an individual's future criminal justice system involvement.

and impressionable youth), 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 the respondent 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., 2016).

However, individuals may be unaware of the risks of being caught (i.e., charged) and the collateral consequences of a criminal record. Similarly, they may be unsure of the magnitude, and even direction, of the effects of the consequences. Such risk-perception, both with regard to direct penalties for crimes as well as the collateral consequences, may greatly affect the value of the alternatives that people face. Indeed, policy effectiveness depends upon the extent to which individuals correctly perceive risks (Apel and Nagin, 2011) and the consequences. There are several legally-imposed restrictions that a criminal record places on employment, welfare receipt, and education.

2.2 Legal Consequences: 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 (Holzer, et al. 2006; Kling, 2006, Finlay, 2009; Agan and Starr, 2017). 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, et al., 2006; 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 check 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, 2020). That is, without information, employers are more likely to statistically discriminate (Agan and Starr, 2018).

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 the 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 found 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 Legal Consequences: Social Services and Education

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.

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.

Stewart and Uggen (2019) report that a little over 70 percent of four-year colleges (81 and 55 percent of private and public colleges, respectively) require applicants to report criminal history. Nearly 40 percent of community colleges require criminal history information. They find higher rejection rates among applicants with a felony record. However, racial differences in admission decisions are smaller than such differences in employment offers. Additionally, a 1988 amendment to the Higher Education Act of 1965 delays or denies students with a history of drug offense of federal financial aid. Federal financial aid in the form of Pell grants may also be denied to individuals convicted of forcible or non-forcible sexual offense.

2.4 Social Determinants of Health

Social determinants of health (SDOH), or the factors that shape the conditions in which people live, are correlated with measured health outcomes 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 for poor health than lack of access to medical care or genetic predisposition to disease. This relationship is starkly depicted among disadvantaged 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 contribute 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. Brown and Barbosa (2001) contend that system- and policy-level obstacles make it difficult for disadvantaged women in the U.S. to secure and maintain employment and the economic safety net programs perceived as important for their self-sufficiency. Although studies have depicted the biological mechanisms underlying the psychological distress-poor health association, our understanding of whether and how system-level factors versus other unobserved individual propensities or shocks precipitate the psychological distress experienced by disadvantaged groups has lagged behind.

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 health impacts of employment at its intensive margins (e.g., occupation, hours of work, promotion, job stressors). Identification of causal effects is hampered by two considerations: 1.) initial endowments, education, and health can 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.[6]

There is a vast economics literature examining the correlation between education and health and health behaviors. Beginning with seminal work by Grossman (1972), economists have considered education's impact on health production, allocation of resources to health input behaviors (medical and non-medical inputs), risk aversion, and perceptions (or subjective expectations) of the marginal effects of health inputs. This direct causal relationship can be contrasted with the reverse causality argument that health impacts educational attainment as well. Indeed, health is dynamic and evolves over time. Unobserved individual characteristics, such as how much someone discounts the future, may also explain the strong observed

[6]See Jolivet and Postel-Vinay, 2020.

correlation between education and health. Grossman (2015) summarizes the current state of knowledge.

Much of the economics literature on the health effects of welfare services emphasize its impact on subsequent education or employment. The variety of services examined include income support, child care, housing assistance, food subsidies, medical care, and job training. While the literature is too large to summarize and the results are varying, some findings suggest that social assistance programs are failing to maintain the health of socioeconomically disadvantaged populations (Shahidi et al. 2019).

2.5 Missing Data

The theoretical econometric literature addresses problems with missing endogenous variables. Specifically, underreporting and imputations common in missing data scenarios can introduce measurement error (Bound and Krueger, 1991; Bound, Brown, Duncan, and Rodgers, 1994). The theoretical benefits of maximum likelihood approaches to address missing data in estimation are widely known and supported by simulation studies comparing such algorithms with more traditional approaches. 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, 2019).

If the non-reporting is random, then a researcher may conduct analysis using only the non-imputed subsample. Alternatively, in this case 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 (2019) discuss the inconsistency of the Instrumental Variables (IV) estimator when the endogenous regressor is underreported 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. Using full information maximum likelihood (FIML), we consider a new approach (described in detail in Section 4) that involves jointly estimating an equation(s) explaining the missingness of an endogenous variable(s) that allows for correlation between the missingness of the endogneous explanatory variables, the endogenous variables themselves, and the dependent variable of interest through individual unobserved heterogeneity.[7]

3 Description of Data

In order to study the health impacts of criminal behavior-related interactions with the justice system, 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), among others. 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.[8] Approximately 75 percent of the surveyed sample includes at-risk, or fragile, families headed by unmarried mothers. Because the data we have obtained for this empirical investigation dictates

[7]Engers (2001) discusses several FIML methods that minimize potential bias and increase efficiency.

[8]Center for Research on Child Well-Being. Fragile Families and Child Wellbeing Study: About the Fragile Families and Child Wellbeing Study. 2020; https://fragilefamilies.princeton.edu/about. Accessed October 20, 2020.

some parts of the empirical model we estimate, we describe the data before detailing the theoretical motivation and resulting empirical framework.

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 a 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.[9] Among this sample, 3,515 women (72 percent) are interviewed in wave five (i.e., nine years after baseline interview) and 2,986 (61 percent) participated in all waves.[10] To facilitate the construction of behavior and outcome histories and to retain as much of the sample as possible, we use data from women with three or more waves (4,482) of continuous participation (4,130) from all 20 cities. After removing individuals with missing information on important exogenous variables, the research sample contains 4,033 women with a total of 18,672 *person-wave* observations.[11] Table 1 describes our research sample by the survey participation patterns.

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

Wave: 1	2	3	4	5	Number
Yes	Yes	Yes	Yes	Yes	2,983
Yes	Yes	Yes	Yes	No	607
Yes	Yes	Yes	No	Yes	139
Yes	Yes	Yes	No	No	183
Yes	No	Yes	Yes	Yes	121

At each wave interview, the survey collects information on demographic characteristics, relationships, employment status, welfare receipt, schooling status, criminal records, and the

[9] A sixth wave of the data (at age 15 of the focal child) is currently available, although not used in our "annual" analysis because of the six-year span between waves. FF is also in the field with a seventh wave when the children are age 22.

[10] We drop a few women due to insufficient baseline data that limited their longitudinal participation.

[11] A comparison of the research sample with the original sample by available demographic measures reveals no statistically significant differences.

general and mental health of the child's mother, among other things. Survey questions inquire about current statuses at the time of 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 calendar year, and attrition for those at risk of attriting based on their wave attendance pattern, of the 39,593 *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	1,879	-	-
1999	3,912	-	-
2000	3,926	-	-
2001	3,970	54	1.36
2002	3,979	84	2.11
2003	3,895	270	6.93
2004	3,625	200	5.52
2005	3,425	317	9.26
2006	3,108	4	0.13
2007	3,104	-	-
2008	2,862	-	-
2009	1,811	-	-
2010	97	-	-

Number of person-year observations: 39,593

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 in many years. 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, and we explain this missingness by both observable and unobservable variation (in our subsequent empirical model). We do not observe the employment status of about one-third of the person-year observations over the 14-year period. We note that the wording of the questions suggests that these women are *more* likely to be employed when employment status is not observed.

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 and explain this missingness by jointly estimating the endogenous variable with the full system of endogenous behaviors and outcomes. We do not observe welfare receipt in about five percent of the person-year observations.

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 define her as being enrolled in school in the years between interviews.[12] Enrollment status is missing rarely in the annualized data (around one percent) and we treat it as randomly missing.

While the school enrollment indicator 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.[13]

Charge, Conviction and Incarceration

The FF survey does not elicit information on *participation* in criminal activity. However, it does provide rather detailed information on charges, convictions, and incarceration for those women who are caught committing a crime. The wave 3 survey asks whether the

[12]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.

[13]Specifically, technical school and training program can be combined with any of the other categories. Passing the General Educational Development (G.E.D.) test — which is also referred to as Graduate Equivalency Degree or General Educational Diploma — and some college may also occur simultaneously.

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 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 create 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.[14] Current year charge status is missing for five percent of the person-year observations. We model (i.e., jointly estimate) this missingness along with missing employment and welfare receipt statuses.

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). To explain variation in health by observed and unobserved heterogeneity, we use the responses from the interview years as the dependent variable. When health entering the period is an explanatory variable, we fill in the values of health for

[14] In concurrent work (Kneipp et al., 2017), we are exploring imputations to correct for underreporting of criminal activity. Our work to date suggests that criminal records are likely among 20 percent or more of the sample, rather than the eight percent that we observe (for being ever charged by wave 5). While we are able to impute indicators for having ever been charged, convicted, or incarcerated by each interview wave, we cannot impute the yearly information on charges, convictions, and incarcerations for use in our "annual" analyses.

the years between interviews with interpolated (within individual) values based on reported health in the nearest preceding and following interviews.

A woman's mental health is evaluated in waves 2 through 5 at two levels — a conservative measure and a liberal measure — of depression criteria. A depression indicator, based the liberal measure, serves as the dependent variable for a women's mental health in each of the interview years. When mental health enters the empirical models as an explanatory variable, we fill in the values for the years between interviews using the nearest subsequent interview.[15]

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 ($t = 1$) that cannot be explained by a dynamic equation since lagged values are not available.

Table 3: Descriptive Statistics for Dependent Variables

	Variable name	Mean	Std Dev	Min	Max
Behaviors	Nonemployment at t (conditional on knowing info)	0.394	0.489	0	1
	Welfare receipt at t (conditional on knowing info)	0.188	0.391	0	1
	School enrollment at t	0.262	0.440	0	1
Caught	Charged at t (conditional on knowing info)	0.022	0.147	0	1
	Convicted at t (conditional on being charged)	0.620	0.486	0	1
Health	General health at t	3.721	0.970	1	5
	Depression at t	0.175	0.380	0	1
Selection	Do not know employment status at t	0.343	0.475	0	1
	Do not know welfare status at t	0.056	0.231	0	1
	Do not know charge status at t	0.055	0.229	0	1
	Attrition at the end of t	0.124	0.329	0	1
Initial	Ever charged, convicted, or incarcerated at $t = 1$	0.035	0.183	0	1
	General health at $t = 1$	3.912	0.941	1	5
	Depression at $t = 1$	0.156	0.363	0	1

Probabilities/densities of these correlated dependent variables form the likelihood function, which is estimated via full information maximum likelihood (FIML) using discrete factor random effects (DFRE) to flexibly model the potential correlation.

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

The observed variables that explain variation in these dependent variables include endogenous explanatory variables and exogenous explanatory variables (as well as individual unobservables that are 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 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 for Environmental Information; and the Department of Education. Per-year variables of interest include average unemployment rates (by county); average TANF benefit levels (by state and family size); and the number of criminal arrests (by state), 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).[16]

4 Theoretical Motivation and Empirical Framework

4.1 Dynamic Forward-looking Decisionmaking

To motivate the empirical analysis, we begin by describing an individual's optimization problem regarding four jointly-chosen behaviors, or actions, over time: 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, or combination of actions, in period t, but have no intention of parameterizing the utility function, solving the model, and estimating the structural parameters of the optimization problem. Data limitations

[16] 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.

Table 4: Descriptive Statistics for Endogenous Individual Explanatory Variables

Variable name	Mean	Std Dev	Min	Max
Employment history				
Employed in $t-1$	0.576	0.494	0	1
Employment in $t-1$ missing	0.416	0.493	0	1
Welfare receipt history				
Received welfare in $t-1$	0.187	0.390	0	1
Welfare receipt in $t-1$ missing	0.077	0.266	0	1
Schooling history				
Enrolled in school in $t-1$	0.249	0.433	0	1
School enrollment in $t-1$ missing	0.015	0.121	0	1
Less than eight years of education entering t	0.040	0.196	0	1
Some high school entering t	0.259	0.438	0	1
High school degree entering t	0.252	0.434	0	1
GED degree entering t	0.064	0.245	0	1
Some college entering t	0.217	0.412	0	1
Technical school entering t	0.088	0.283	0	1
Bachelor's degree entering t	0.084	0.277	0	1
Graduate degree entering t	0.056	0.229	0	1
Training program entering t	0.079	0.270	0	1
Criminal history				
Ever charged status entering t missing	0.105	0.307	0	1
Ever convicted status entering t missing	0.087	0.281	0	1
Ever incarcerated status entering t missing	0.065	0.246	0	1
Conditional on knowing ever charged status:				
Ever charged entering t	0.110	0.313	0	1
Charge status in $t-1$ missing	0.026	0.160	0	1
Charged in $t-1$	0.022	0.145	0	1
Conditional on knowing ever convicted status:				
Ever convicted entering t	0.074	0.261	0	1
Conviction status in $t-1$ missing	0.053	0.225	0	1
Convicted in $t-1$	0.196	0.397	0	1
Years since last conviction entering t missing	0.136	0.343	0	1
Years since last conviction entering t	4.615	4.256	1	31
Convicted in last five years	0.282	0.450	0	1
Convicted in $t-1$	0.214	0.410	0	1
Conditional on knowing ever incarcerated status:				
Ever incarcerated entering t	0.053	0.224	0	1
Incarceration status in $t-1$ missing	0.084	0.277	0	1
Incarcerated in $t-1$	0.196	0.397	0	1
Years since last incarceration entering t missing	0.154	0.361	0	1
Years since last incarceration entering t	4.097	3.033	1	24
Incarcerated in last five years	0.260	0.439	0	1
Incarcerated in $t-1$	0.212	0.409	0	1
General health and depression history				
Bad general health entering t	0.097	0.295	0	1
Depression entering t	0.173	0.378	0	1
Bad general health and depression entering t	0.035	0.185	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	0.503	0.500	0	1
Other race	0.180	0.384	0	1
Hispanic ethnicity	0.251	0.434	0	1
Demographic characteristics missing	0.016	0.126	0	1
Respondent's mother highest grade completed	11.690	2.935	0	18
Respondent's mother highest grade completed missing	0.112	0.315	0	1
Respondent's father highest grade completed	11.902	2.997	0	18
Respondent's father highest grade completed missing	0.325	0.468	0	1
Respondent's mother deceased	0.065	0.246	0	1
Respondent's mother deceased missing	0.166	0.372	0	1
Respondent's father deceased	0.131	0.337	0	1
Respondent's father deceased missing	0.170	0.376	0	1
Time-variant individual variables over all person-years				
Age	29.020	6.802	14	52
Married	0.292	0.455	0	1
× White race	0.472	0.499	0	1
× Black race	0.092	0.290	0	1
× Other race	0.059	0.236	0	1
× Hispanic ethnicity	0.079	0.270	0	1
Marriage status missing	0.094	0.291	0	1
Number of children	2.186	1.421	0	11
Number of children missing	0.531	0.499	0	1
Time trend	5.234	3.174	0	12

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, low SES **	12.684	23.630	3.13	249.40
Quarterly employment: female, low education **	28.234	1.598	23.10	35.76
New hire rate: female, low SES *	0.438	0.259	0.09	1.38
New hire rate: female, 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, low SES	15.447	2.395	8.14	22.69
Hiring rate as % of quarterly employment: female, low 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, low SES (in 000s)	1.801	0.454	1.00	2.83
Average monthly earnings: female, 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: female, white	4.332	1.256	1.70	11.20
Unemployment rate: female, white missing	0.038	0.191	0.00	1.00
Unemployment rate: female, Black	8.578	2.502	3.30	23.10
Unemployment rate: female, Black missing	0.044	0.205	0.00	1.00
Unemployment rate: female, Hispanic Black	7.269	2.291	2.20	20.40
Unemployment rate: female, Hispanic Black 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 for first offense	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 ($/pack)	3.448	0.682	1.941	7.921
State and federal cigarette taxes (% of average retail price)	28.039	8.797	10.500	57.789
Average wine price ($/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.

prevent such an approach from being feasible. Yet, the theoretical set up lends guidance to specification and identification of our multiple structural equations approach (i.e., jointly estimated demand and production functions and stochastic realizations). For simplicity, we model each behavior as a dichotomous action. The discrete employment actions 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 actions are participation in an educational activity ($s = 1$) or not ($s = 0$).[17] Individuals may also participate in illegal, or criminal, activity ($c = 1$) or not ($c = 0$).[18] Let d_t^{ersc} indicate the mutually-exclusive joint combinations of the employment (e), welfare receipt (r), schooling (s), and crime (c) actions in period t.

Each action alternative may not be available to an individual in every period. Rather, the employment alternative 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 (or experience in different areas): employment experience (X_t^E), educational attaintment (X_t^S), and criminal record history (CR_t).[19] Eligibility for social services is also a stochastic function of accumulated past behaviors: previous earned income (Y_{t-1}^E), welfare experience (X_t^R), and criminal record history (CR_t).[20] We allow a criminal record to impact job offer probabilities as well as eligibility for social services; in reality, this dependence varies by state and local jurisdictions over time. 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 behaviors we do model.

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

[18]Each of the dichotomous actions 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 choice. We could specify the particular type of crime committed. Such levels of specificity are not necessary to demonstrate the channels through which a criminal record may impact behaviors and subsequent health outcomes.

[19]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.

[20]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 X_t^R.

Next we define the per-period utility associated with each combination of actions. 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, the per-period 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) may 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. Being caught may result in a charge, a conviction, and/or incarceration. This caught state indicates reduced time available for activities (via court time or jail time); it may also involve pecuniary fines or community service. If $C_t = 1$, then by default the individual — who committed criminal activity last period, was caught by the end of the period, and is in the caught state in the current period — has a criminal record entering period t (CR_t). The purpose of specifying both vectors (C_t, CR_t) in the information set is to distinguish between recent caught criminal activity and a history of past caught criminal activity. The vector $C_t = [C_t^1, C_t^2, C_t^3]$ indicates a charge, conviction, or incarceration in period t as a result of being caught for criminal activity in period $t-1$. Being charged, convicted, or incarcerated activates a criminal record, denoted by the vector $CR_t = [CR_t^1, CR_t^2, CR_t^3]$ (i.e., each indicator equal to one if *ever* charged, convicted or incarcerated entering period t; zero otherwise). This vector of criminal record variables also includes the number of years since the last conviction or incarceration.[21]

Consumption and leisure are defined by the budget and time constraints, respectively. Individuals receive income from legal employment, illegal activity, and social programs if eligible, where Y_t^E is per-period employment income, Y_t^C is income from criminal activity, and Y_t^R is cash assistance from the welfare program. These income values depend on experience in each of the activities, among other things. They spend their income on: private or public housing accommodations (A_t, assumed a necessity); family food consumption (F_t, assumed

[21]Note that individuals who are convicted are also charged, and those incarcerated have been charged and convicted. While we have years since last conviction and incarceration in our data, which by definition defines whether the criminal record is recent, we do not know years since last charge.

a necessity) which depends on the number of children (K_t) and marital status (M_t); health care inputs (HC_t) comprised of both medical and non-medical inputs; schooling/training after high school (s_t); crime costs if caught; and other consumption (X_t).[22] That is,

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

where pecuniary prices (of accommodations, food, health care, schooling, costs for caught criminal activity, and other consumption) 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 the 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 (a necessity if children are present). Specifically,

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

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 required for each behavior.[23] With regard to criminal activity, participation in crime in period t (c_t) takes time. Additionally, being in a caught state in period t (C_t) (for previous criminal activity) may result in lost time (e.g., court appearance, community service, jail time).

Our model of optimal decisionmaking allows individuals to be forward looking (with discount factor β). Individuals evaluate the different combinations of current period behavior alternatives (i.e., employment, welfare receipt, schooling, and criminal activity) to maximize

[22] We specify, in this theoretical motivation, that something is a necessity simply to indicate that we are not modeling it as a decision variable (here, or in our empirical model).

[23] We assume child care time is a function of the time prices, the number of children, and marital status. Individuals could also pay someone to care for children.

discounted expected utility over one's lifetime. Job offers (O_t) determine whether or not legal employment is an available alternative each period. Eligibility for welfare (R_t) determines whether or not it is an available alternative in each period. The non-random availability of employment and welfare options depends, importantly, on one's recent activities and her accumulated histories of actions. Similarly, a criminal record is non-random and depends on whether or not an individual who commits illegal activity in t is caught in $t+1$ (C_{t+1}), which may depend on one's history of behaviors. We represent these stochastic outcomes by the following probabilities:

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

that may vary by demographics (D_t) and exogenous characteristics of the employment, welfare, criminal justice/law enforcement, and health systems (denoted by the vector $Z_t = [Z_t^E, Z_t^R, Z_t^C, Z_t^H]$, which includes pecuniary and time prices, P_t and Q_t , associated with related activities).

Health in period t shifts the per-period utility of behaviors and the pecuniary and time prices of health care consumption may vary by one's health. While health is known (i.e., updated) entering period t, future health is uncertain. Importantly, health in period $t+1$ in future periods is stochastic and depends on current health and health inputs in period t (first line of equation below). Health evolution, or the health production function, is modeled as

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

Because we do not model health care consumption and time allocated to health behaviors (HC_t) explicitly, we substitute the determinants of demand for this input into the health production function (second line of health production equation above). 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, Q_t, and Z_t) do not independently impact health transitions conditional on the observed behaviors (i.e., they can be used as exclusion restrictions for identification).

As one can see from this stylized (and somewhat simplified) model of individual decision-making, criminal activity and the resulting criminal record if caught impact the optimization problem through several channels. First, criminal behaviors may provide utility (or disutility) and individuals may have heterogenous preferences over these activities. Second, a criminal record may affect the availability of other actions such as employment (via offers) or welfare (via eligibility). Third, individuals may face different probabilities of being caught depending on their histories of criminal behavior and criminal record. Fourth, caught criminal activity may impose pecuniary and time costs that reduce available income and time. Fifth, criminal behavior or the consequences of being caught may impact physical and mental health directly. And lastly, the reallocation of behaviors and dynamic health outcomes resulting from a criminal history may indirectly influence future health transitions.

Because we do not explicitly solve and estimate the individual's optimization problem, we cannot quantify each of these channels. However, our approximation to the derived demand functions (for employment, welfare receipt, and schooling) and health production functions allow us to decompose the total effect of criminal record on health into several identifiable channels. Namely, we can determine the extent to which a criminal record impacts health directly given observed employment, welfare receipt, and schooling behaviors (which we call the *direct* effect). We can also determine the indirect effect on health of these simultaneously chosen behaviors (which we call the *indirect contemporaneous* effect). And we can quantify how a less recent criminal history has impacted past health, which, in turn, influences current health evolution (which we term the *indirect dynamic* effect).

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

and caught state $C_t = j$ as

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

Given parameterized functional forms for the utility function and stochastic probabilities (as well as a terminal value function), a researcher could form a likelihood of observing the behaviors and outcomes in the data as the joint probabilities of each of the behavior combinations and probabilities or densities of the stochastic outcomes. Variation in the values of each observed behavior combination depends explicitly on information available to the individual at the point of decisionmaking, namely $\Omega_t = [C_t, CR_t, H_t, X^E_t, X^R_t, X^S_t, D_t, Z_t]$. The information known by the individual includes her endogenous record of criminal activity up to period t, health entering period t, and experience in each of the behavior areas entering period t as well as exogenous demographics (including income, number of kids and marital status), prices and supply-side determinants, and system characteristics. Under an assumption that the alternative-specific preference error term (ϵ^u_t) is additive and Extreme-value distributed, the probabilities of the jointly-chosen behaviors given values of the health and caught states entering t (i.e., $H_t = h, C_t = j$) are

$$\begin{aligned}
p(e_t = e, r_t = r, s_t = s, c_t = c | \Omega_t) \quad &= \quad p(d^{ersc}_t = 1 | \Omega_t) \\
&= \quad \frac{\exp \overline{V}^{hj}_{ersc}(\Omega_t)}{\sum_{e'=0}^{1} \sum_{r'=0}^{1} \sum_{s'=0}^{1} \sum_{c'=0}^{1} \exp \overline{V}^{hj}_{e'r's'c'}(\Omega_t)} \ \forall t
\end{aligned}$$

where $\overline{V}^{hj}_{ersc}(\Omega_t) = V^{hj}_{ersc}(\Omega_t, \epsilon^u_t) - \epsilon^u_{ersc,t}$ is the deterministic part of the value function (i.e., the time t lifetime value of alternative $ersc$ given information set Ω_t).

4.2 Empirical Model

To move from the theory to the empirical model, we discuss in detail several econometric issues that must be dealt with properly in estimation. These issues include data limitations that do not allow us to solve and estimate the theoretical model, dependence of current behaviors on lagged behaviors, simultaneity of behaviors, missingness of dependent variables, stochastic probabilities of being observed to be caught, unobserved criminal activity, and endogenous initial conditions.

Data Limitations

There are a number of aspects of the theoretical model that are unobserved in our data, and in most datasets for that matter, that make it difficult to estimate the decisionmaking problem described above. These unobserved variables include criminal activity (i.e., the action (c_t) and, hence, the probability of being caught ($p(C_{t+1} = 1)$), but not the criminal record (CR_{t+1}) if caught); employment offers (which help explain the offer probability, $p(O_t = 1)$); and all the determinants of eligibility for public assistance (which would allow us to frame welfare as a probabilistic option, $p(R_t = 1)$). Although we do not have the necessary data to estimate offer rates, welfare eligibility, and being caught, we use the theoretical model to derive (linearized) demand equations for the observed (i.e., optimal) employment, welfare receipt, and schooling behaviors that depend on the determinants of preferences, constraints, and uncertain future outcomes of an individual's forward-looking optimization problem. In this section we describe the resulting set of approximated structural equations representing demand for the observed actions/behaviors, the stochastic probabilities of "caught" criminal activities resulting in a criminal record, and the production of health. The theory also provides meaningful guidance regarding variables for empirical identification.

Dynamic Demand and Serial Dependence

The resulting demand function for the per-period actions depends on pre-determined variables (i.e., the histories of one's actions/behaviors) as well as period t exogenous individual and system-specific variables. Here, we focus on one action specifically — welfare receipt — in order to explain its determinants. Since the other behaviors (employment, schooling, and crime activities) are chosen jointly, they depend on the same set of determinants. The latent variable describing the demand for each welfare alternative, or welfare participation,

R_t^*, is

$$R_{rt}^* = R_r(C_t, CR_t, H_t, e_{t-1}, r_{t-1}, s_{t-1}, D_t, Z_t) + u_t^{R_r} \quad r = 0, 1$$

where $u_t^{R_r}$ represents unobserved determinants of welfare receipt alternative r. Demand in period t depends on whether or not she has recently been caught and her criminal record (which includes the histories of charge, conviction, and incarceration); health; the observable histories of employment, welfare receipt, and schooling; demographics; and the vector of price and supply-side, or system-level, variables (Z_t).

While current welfare eligibility, and hence observed receipt, depends on cumulative and consecutive years of welfare receipt (i.e., one's history of behavior), we include only the one-period lagged behavior (i.e., welfare receipt 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 welfare behavior in period t on one's welfare behavior in period $t-1$ may reflect persistence but, in order to uncover causal effects of this history, it also requires that an econometrician account for unobserved determinants of participation in period t that could be correlated with unobserved determinants of participation in period $t-1$.

To allow for serial correlation in unobservables, we decompose the error terms, u_t^j, which capture the unobserved determinants of each behavior j (with other equations described below), into a permanent individual component (μ^j), a time-varying serially-independent individual component (ν_t^j), and an idiosyncratic component (ϵ_t^j); specifically, $u_t^j = \mu^j + \nu_t^j + \epsilon_t^j$. Each idiosyncratic error (ϵ_t^j) is assumed to be uncorrelated over time and independent of the errors in other equations. Its distribution dictates the probability or density of the outcome variable of interest, conditional on the other delineated unobserved heterogeneity terms.

Replacing u_t^R with its decomposition, the probabilities of welfare receipt ($r_t = 1$), relative to not receiving welfare ($r_t = 0$), in period t are

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

under the assumption that $\epsilon_t^{R_r}$ is Extreme value-distributed (with its difference being logistically distributed). The permanent component μ^j captures correlation in actions over time via unobservable individual characteristics.

Simultaneity and Cross Behavior Dependence

The theoretical framework suggests that employment and schooling are chosen jointly with welfare receipt 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 these behaviors are chosen simultaneously, their derived demand functions depend on the same set of determinants including the full vector of price and supply-side variables to capture potential cross price effects exhibited by substitutes or complements. The jointly-determined employment and schooling probabilities, in log odds, are

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

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

where we model the probability of non-employment since employment is the most-frequently observed behavior. Two theory-driven properties of these jointly-chosen dynamic behaviors, namely dependence on lagged outcomes (discussed above) and simultaneity, are captured by the empirical specification and assumptions about correlation in unobserved determinants. Specifically, the observed outcomes may be correlated through observed explanatory variables, denoted $\Omega_t = [C_t, CR_t, H_t, e_{t-1}, r_{t-1}, s_{t-1}, D_t, Z_t]$, and through common individual-level unobserved heterogeneity, denoted by the vectors μ and ν_t. The specification of the error structure allows the behaviors to be correlated (within a time period) through permanent unobserved heterogeneity of individuals (μ), which also enables us to distinguish between persistence and causal influence of the lagged behavior. The error decomposition also includes an unobserved component (ν_t) that varies over time and is serially uncorrelated, yet may be correlated across behaviors within the same time period. The joint probability of the three behaviors, explicitly conditional on the observable explanatory variable vector

Ω_t and the unobserved correlated components μ and ν_t, is

$$p(e_t = e, r_t = r, s_t = s|\Omega_t, \mu, \nu_t) = p(e_t = e|\Omega_t, \mu, \nu_t) \cdot p(r_t = r|\Omega_t, \mu, \nu_t) \cdot p(s_t = s|\Omega_t, \mu, \nu_t)$$

since the remaining components of the error terms, ϵ_t^j, are independent.

To recap, the permanent unobservables (μ) capture correlation across equations as well as over time, which allows the unobserved determinants of lagged behaviors to be correlated with the unobserved determinants of current behaviors. The time-varying unobserved heterogeneity (ν_t) allows for additional contemporaneous correlation in unobserved determinants 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.[24] Note that the entire policy vector impacts the behavioral decisions at the beginning of the period. Subsequent outcomes may not depend on the full vector of prices/supply side variables conditional on the observed chosen behaviors. These variables provide the theoretical justification for identification of the empirical model.

Missingness

Often a researcher encounters an empirical specification where an endogenous variable is underreported or imputed, but the instrumental variable is not underreported or imputed. As explained in Section 4, welfare receipt (and employment) are not observed for all individuals in every time period. Consider our equation 1 where current welfare receipt depends on lagged welfare receipt. Hence, as a behavior that we explain, the dependent variable is

[24] To avoid modeling beliefs about how these policy variables evolve, we assume all current and future values are known at the beginning of each period, and a woman believes that the values will not change over time. The values of endogenous variables 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 in order to estimate a parameterized version of the model, so an assumption about beliefs is only necessary to the extent that it impacts our identification strategy.

observed for a selected group of individuals. Additionally, as an endogenous explanatory variable it is missing non-randomly. To deal with this econometric issue, we define a variable for each period t that indicates whether information is missing, m_t^j, about the endogenous time t variable j (in our example case, welfare receipt in t, which becomes an endogenous explanatory variable for outcomes at the end of the period and behaviors in the next period). Here, $m_t^j = 1$ indicates that a value of behavior/activity j is not observed by the econometrician in period t and $m_t^j = 0$ indicates that the activity status (i.e., 0/1) is observed. Specifically, the marginal probabilities of not knowing employment and welfare receipt are estimated by

$$\ln\left[\frac{p(m_t^j = 1)}{p(m_t^j = 0)}\right] = f^{M_j}(C_t, CR_t, H_t, e_{t-1}, r_{t-1}, s_{t-1}, m_{t-1}, D_t, Z_t, W_t) + \mu^{M_j} + \nu_t^{M_j} \; j = R, E \tag{4}$$

where W_t indicates the most recent survey wave of an individual at year t. We include these recent wave indicators as exogenous shifters of whether we, as the econometricians, observe particular behaviors. These variables capture the differences in questions asked at different waves, which exogenously determines observability of some variables. Additionally, we include the histories of behaviors as determinants of missingness because the endogenous responses to some survey questions impact whether behaviors are observed in year t (i.e., the endogeniety of the missingness).

Within any period t, then, we only have observations on behavior/activity j conditional on it being known (i.e., $m_t^j = 0$). The probabilities of behaviors must reflect this conditioning on missingness in estimation. The welfare receipt and employment probabilities, conditional on knowing the dependent variable status, and the schooling probability (which is observed in all periods) are

$$\begin{aligned}
\ln\left[\frac{p(r_t = 1|m_t^R = 0)}{p(r_t = 0|m_t^R = 0)}\right] &= f^R(C_t, CR_t, H_t, e_{t-1}, r_{t-1}, s_{t-1}, m_{t-1}, D_t, Z_t) + \mu^R + \nu_t^R \\
\ln\left[\frac{p(e_t = 0|m_t^E = 0)}{p(e_t = 1|m_t^E = 0)}\right] &= f^E(C_t, CR_t, H_t, e_{t-1}, r_{t-1}, s_{t-1}, m_{t-1}, D_t, Z_t) + \mu^E + \nu_t^E \\
\ln\left[\frac{p(s_t = 1)}{p(s_t = 0)}\right] &= f^S(C_t, CR_t, H_t, e_{t-1}, r_{t-1}, s_{t-1}, m_{t-1}, D_t, Z_t) + \mu^S + \nu_t^S
\end{aligned} \tag{5}$$

where m_{t-1} is a vector of indicators of missing lagged $(t-1)$ endogenous variables, which are themselves endogenous.

Consider that the underreporting (or missingness due to not knowing the status) could be random or non-random. When a variable 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 further consider whether selection is on observables only or whether selection may depend 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 selection equations, $p(m_t^j = 1), j = R, E$, and the outcomes of interest, $r_t | m_t^R = 0$ and $e_t | m_t^E = 0$. Note that equation 4 includes the permanent and time-varying unobserved heterogeneity terms that also influence the (conditional) period t behaviors. The availability of information (to the researcher) depends both on observed and unobserved individual characteristics (that determine behaviors at t) as well as differences in wording of the questions across survey waves (i.e., exogenous, random variation).

Stochastic Criminal Record Outcomes: Charge, Conviction, and Incarceration

What is uncertain to an individual when she is making her period t decisions about the behaviors (including 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 $t + 1$. For the researcher, an observed charge, conviction or incarceration defines "having been caught". The wording of survey questions in each wave determines whether one's "caught" status can be determined annually. The data allow us to observe new convictions and incarcerations, but we are unable to date all observed charges. Additionally, we assume that a conviction occurs conditional on being charged, and an incarceration occurs conditional on being convicted (and charged). Using information on timing of new offense records, we model the conditional probabilities of observing a new charge (conditional on not missing), conviction (conditional on being charged), and incarceration (conditional on being convicted) entering period $t+1$ ($C^1_{t+1}, C^2_{t+1}, C^3_{t+1}$, respectively) as

$$\begin{aligned}
\ln\left[\frac{p(C^1_{t+1}=1|m^{C^1}_{t+1}=0)}{p(C^1_{t+1}=0|m^{C^1}_{t+1}=0)}\right] &= f^{C^1}(C_t, CR_t, H_t, e_t, r_t, s_t, m_t, D_t, Z^C_t) + \mu^{C^1} + \nu^{C^1}_t \\
\ln\left[\frac{p(C^2_{t+1}=1|C^1_{t+1}=1)}{p(C^2_{t+1}=0|C^1_{t+1}=1)}\right] &= f^{C^2}(C_t, CR_t, H_t, e_t, r_t, s_t, m_t, D_t, Z^C_t) + \mu^{C^2} + \nu^{C^2}_t \\
\ln\left[\frac{p(C^3_{t+1}=1|C^2_{t+1}=1)}{p(C^3_{t+1}=0|C^2_{t+1}=1)}\right] &= f^{C^3}(C_t, CR_t, H_t, e_t, r_t, s_t, m_t, D_t, Z^C_t) + \mu^{C^3} + \nu^{C^3}_t \ .
\end{aligned} \tag{6}$$

and the probabilities of not observing charge status are

$$\ln\left[\frac{p(m^{C^1}_{t+1}=1)}{p(m^{C^1}_{t+1}=0)}\right] = f^{M_{C^1}}(C_t, CR_t, H_t, e_t, r_t, s_t, m_t, D_t, Z^C_t, W_t) + \mu^{M_{C^1}} + \nu^{M_{C^1}}_t \tag{7}$$

Note that individual unobserved heterogeneity determinants (μ and ν_t) enter each equation. Hence, any correlation between observed behaviors (i.e., employment, welfare receipt, and schooling) and observed charges, convictions, and/or incarcerations is picked up through estimation of the distributions of the individual permanent and time-varying unobservables, μ and ν_t. We assume that an individual's "caught" statuses are observed at the end of the period (or entering the next period) after realizations of her chosen behaviors in period t. Thus, conditional on those observed behaviors, some determinants of Z_t are theoretically excluded (such as Z^E_t, Z^R_t, and Z^S_t) yet these charge, conviction, and incarceration probabilities still depend on Z^C_t.

Stochastic Health Outcomes: Health Production

Ultimately, we are interested in the short- and long-run impacts of a criminal record on health outcomes. In section 4.1, we specified the health production function, substituting in the determinants of (non-observed) health care inputs, which produces the stochastic health equation below (with the decomposed error structure that demonstrates potential correlation through permanent and time-varying unobserved heterogeneity components). Recall that criminal activity during period t (c_t) is not observed (so we cannot model the effects of participation in crime generally (first line of health production equation below). However, we can determine whether a charge, conviction, or incarceration as a result of such criminal activity (which defines the caught state in the subsequent period, C_{t+1}) impacts health directly (second line of health production equation below). The stochastic health outcome entering period $t+1$ is

$$
\begin{aligned}
H_{t+1} &= g^H(H_t, CR_t, e_t, r_t, s_t, c_t, D_t, Z_t^H) + \mu^H + \nu_t^H + \epsilon_t^H \\
&= h^H(H_t, CR_t, e_t, r_t, s_t, m_t, C_{t+1}, D_t, Z_t^H) + \mu^H + \nu_t^H + \epsilon_t^H \ . \qquad (8)
\end{aligned}
$$

The production function $h(\cdot)$ includes the observed updated outcomes C_{t+1} to reflect the effects of being caught (for criminal activity in period t) on subsequent health. Note that a history of criminal behavior, captured by CR_t, may also impact health evolution. Exogenous health determinants, including location and time-varying weather variables and the pecuniary and time prices of health care inputs (e.g., medical care, cigarettes, exercise), are included in Z_t^H.[25] The equation also includes the indicator (m_t) for missing endogenous behaviors or recent charges.

In our empirical model we include two measures of health: physical health and mental health. Physical health (ranging from excellent to poor) is modeled as a continuous variable with larger values indicating better health. Mental health is a dichotomous indicator of satisfying the criteria for a (liberal) validated measure of depression.

Correlated Initial Conditions

Each of the equations defined above depend on lagged dependent variables. Our data begin following women as young as age 14, and previous values of endogenous variables are likely to vary. That is, health and criminal record entering the first period of the data are endogenous (i.e., depend on both observable and unobservable individual variation that might be correlated with current behaviors and outcomes). To account for this correlation we model initial condition equations for having ever been charged, convicted or incarcerated upon entering the survey and initially-observed physical and mental health at $t = 1$. We allow these equations to depend on the permanent individual unobserved heterogeneity μ and a vector

[25] Conditional on employment, welfare receipt, schooling, and criminal record, other determinants of the vector of price/supply/system characteristics (Z_t) do not independently influence health transition.

of variables that may shift initially-observed outcomes, but that do not affect subsequent outcomes conditional on lagged endogenous variables.[26]

4.3 Estimation and Identification

Equations 5-8 and the initial condition equations 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_k, and accompanying probability weights, θ_k , $k = 1, \ldots, K$, where K 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 K and L. We then vary the size of K 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. Our estimated model includes eight mass points for each of the discrete distributions, with estimated mass point vectors and their estimated weights detailed in Appendix Tables A16-A18.

[26]We do not model initial employment, welfare receipt, or schooling but do construct variables for annual behaviors back to 1997, at least one year prior to the wave one interview. Thus, the dynamic behavior equations include year 1998 behaviors as a function of year 1997 behaviors, while the outcome variables (criminal record and health) begin in 1999 and are a function of 1998 behaviors.

Each of the estimated probabilities and densities of the likelihood function contain endogenous and exogenous variables. Specifically, the exogenous variation that identifies the model includes individual-specific variables in the vector D_t that may be time invariant or time-varying (and are listed in Table 5. Also included in $D_{t=1}$ are additional exogenous variables (e.g., mother's and father's highest grade completed and deceased status) that enter the initial condition equations only. Exogenous variation in vector Z_t includes market shifters (such as local sector-specific average wages, state welfare eligibility cutoffs, or average tuition rates of state public colleges) that are location- and time-specific (and are listed in Table 6). These vectors of variables provide two sources of identification of the marginal effects of lagged endogenous variables on current behaviors or outcomes. First, in addition to the cross-section variation in individual variables, the histories of exogenous time-varying individual variables creates variation across individuals over time (Arellano and Bond, 1991). Second, the time-varying location variables provide identifying instruments through the lagged endogenous variables, where, for example, 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.[27] We refer the reader back to Table 3 to summarize the observed behavior, caught, health, selection, and initial condition probabilities and densities (conditional on observed variables and unobserved heterogeneity) that form the unconditional likelihood function, in which we integrate over the estimated discrete distributions of the permanent and time-varying individual unobserved heterogeneity.

4.4 Defining the Effects of Criminal Record on Health

At this point, we have the notation to describe the effects of a criminal history on health that we wish to measure. Recall that one's criminal history is defined by the vectors CR_t and C_t, where the former describes an individual's charge, conviction, and incarceration history (i.e., ever and years since last) and the latter describes a recent (last period) charge,

[27] Here, identification is assumed theoretically, yet we perform empirical tests to support this assumption. Specifically, joint t-tests show that these lagged exogenous variables have no statistically significant effects on current behaviors and outcomes conditional on the lagged endogenous variables. Results are available from the authors.

conviction, or incarceration. For simplicity of exposition, we use CR_t to reflect both recent and historical criminal record in the following derivation of the effect of criminal record on health. Specifically,

$$
\begin{aligned}
\frac{dH_{t+1}}{dCR_t} \;=\; & \frac{\partial h^H(H_t, CR_t, e_t, r_t, s_t, D_t, Z_t^H, \mu, \nu_t)}{\partial CR_t} \\
& + \sum_{e=0}^{1}\sum_{r=0}^{1}\sum_{s=0}^{1} h^H(H_t, CR_t, e, r, s, D_t, Z_t^H, \mu, \nu_t)\frac{\partial p(e_t = e, r_t = r, s_t = s)}{\partial CR_t} \\
& + \frac{\partial h^H(H_t, CR_t, e_t, r_t, s_t, D_t, Z_t^H, \mu, \nu_t)}{\partial H_t}\frac{\partial H_t}{\partial CR_t}\,. \qquad (9)
\end{aligned}
$$

The first line of the derivative captures the direct effect of a criminal record on health. The second line captures the indirect effects of a criminal record through its impact on employmnet, welfare receipt, and schooling. Because our model distinguishes between a previous history of being caught and being caught at the end of t (i.e., prior to period $t+1$) for criminal behavior during period t, the first two lines of equation 9 measure the effect of recent and historical criminal outcomes (either directly or through behaviors), while the third line captures the effect of historical criminal outcomes 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.

It remains to define the joint probabilities of the behaviors, $p(e_t = e, r_t = r, s_t = s)$ for each combination of e, r, and s. We use the marginal and conditional probabilities in 4 and 5 to form the joint probabilities

$$p(e_t = e, r_t = r, s_t = s) = p(e_t = e|m_t^E = 0)p(m_t^E = 0)\times p(r_t = r|m_t^R = 0)p(m_t^R = 0)\times p(s_t = s)$$

for the eight combinations of the dichotomous behaviors e, r, and s. The observed criminal outcomes of $[C_{t+1}^1, C_{t+1}^2, C_{t+1}^3]$ include $\{0,0,0\}, \{1,0,0\}, \{1,1,0\}, \{1,1,1\}$; their joint probabilities, accounting for both missingness and selection, are

$$
\begin{aligned}
p(C^1_{t+1}=0,C^2_{t+1}=0,C^3_{t+1}=0) &= (1-p(C^1_{t+1}=1|m^{C^1}_{t+1}=0))p(m^{C^1}_{t+1}=0)
\end{aligned}
$$

$$
\begin{aligned}
p(C^1_{t+1}=1,C^2_{t+1}=0,C^3_{t+1}=0) &= p(C^1_{t+1}=1|m^{C^1}_{t+1}=0)p(m^{C^1}_{t+1}=0)\\
&\quad \times(1-p(C^2_{t+1}=1|C^1_{t+1}=1))\\
p(C^1_{t+1}=1,C^2_{t+1}=1,C^3_{t+1}=0) &= p(C^1_{t+1}=1|m^{C^1}_{t+1}=0)p(m^{C^1}_{t+1}=0)\\
&\quad \times p(C^2_{t+1}=1|C^1_{t+1}=1)\times(1-p(C^3_{t+1}=1|C^2_{t+1}=1))\\
p(C^1_{t+1}=1,C^2_{t+1}=1,C^3_{t+1}=1) &= p(C^1_{t+1}=1|m^{C^1}_{t+1}=0)p(m^{C^1}_{t+1}=0)\\
&\quad \times p(C^2_{t+1}=1|C^1_{t+1}=1)\times p(C^3_{t+1}=1|C^2_{t+1}=1)
\end{aligned}
$$

After equations 5 through 8 have been estimated, the joint probabilities above are used to simulate the correlated jointly-chosen behaviors, criminal record outcomes, and health outcomes over time.

5 Estimation Results

In this section we present and discuss findings from estimation of the 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 fourteen year span), and jointly models the endogenous probabilities of variable missingness (i.e, in employment, welfare receipt, and charges in some years). 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; see Table reftable:dep) 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. That is, we use the model (i.e., the equation specifications, the estimated parameters, and the exogenous variables) to predict endogenous variables each year, replace observed endogenous behaviors with the simulated values (i.e., update), simulate subsequent outcomes at the end of the year, and update all pre-determined variables entering into the next simulated year. We demonstrate in Figures 2-4 that the estimated model produces a data generating process that fits the observed data very well. In fact, we fit the data well when we use the observed pre-determined explanatory variables directly (i.e., no updating, but bias-corrected parameter estimates via the modeling of unobserved heterogeneity (labeled "Simulated: UH, no UPDATE") 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: UH, UPDATE").[28] The results from estimation of each probability or density equation by itself and, hence, without the correlated unobserved heterogeneity (labeled "Simulation: no UH, no UPDATE") are also included in the figures.

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, welfare receipt, and charges) in order to recover causal impacts of a criminal record on

[28]Here, "UH" indicates the jointly estimated model allowing for correlated unobserved heterogeneity and "UPDATE" indicates that the simulations are updated dynamically.

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

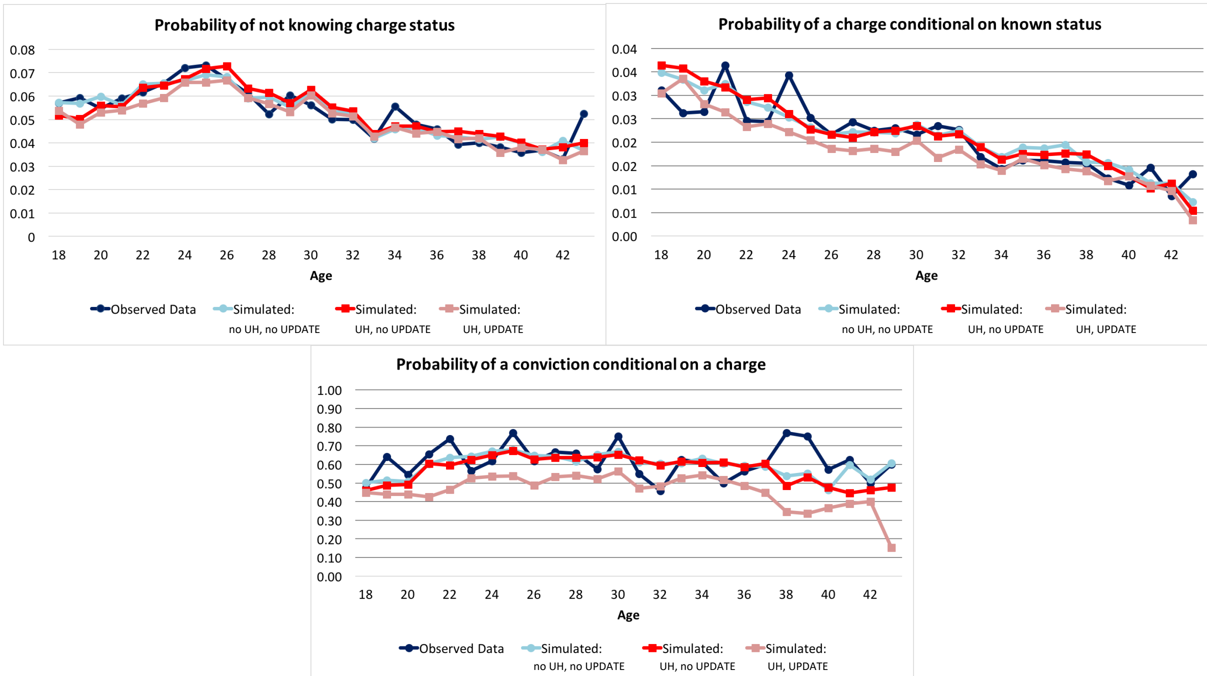

Figure 3: Graphical Comparison of Charge and Conviction:
Observed Data vs. Estimated Data Generating Process

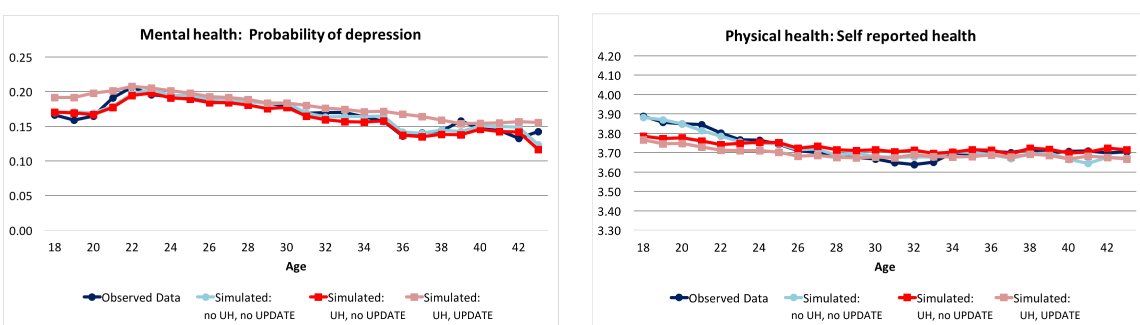

Figure 4: Graphical Comparison of Health Outcomes:
Observed Data vs. Estimated Data Generating Process

health outcomes. To calculate these effects we simulate the behaviors and outcomes for R replications of each individual in the sample, where R=500. 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.[29]

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). A baseline simulation, for comparison, imposes a history of no criminal offenses. In Scenario 1 of Table 7, for example, we assume individuals have been charged in t, 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 criminal history variables enter directly and are interacted with a dichotomous indicator of bad health and the depression indicator entering the current period. Given these interactions, we report the average marginal effect calculated through simulations (i.e., $\frac{\partial h^H(H_t,CR_t,e_t,r_t,s_t,D_t,Z_t^H,\mu,\nu_t)}{\partial CR_t}$, or the direct effect portion of the total effect of criminal record on health defined in equation 9). We find that a recent charge alone (with no conviction or incarceration, scenario 1) appears to slightly improve health yet increases the probability of depression by nearly four percentage points. A recent charge and conviction (scenario 2) reduces health, with a drug-related conviction (scenario 3) reducing health even more; depression is seven percentage points more likely. Charges and convictions in the past (scenarios 5 and 6) also reduce health and increase the probability of depression slightly. Incarceration (scenarios 4 and 7) has no statistically significant impact on health.

[29]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 is one that includes eight discrete mass points to capture the permanent unobserved heterogeneity distribution and eight discrete mass points for the time-varying unobserved heterogeneity distribution.

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

Comparison Scenarios Entering t	Charged		Convicted				Incarcerated			Average Outcomes in $t+1$		Contemporaneous ME (scenario - baseline)	
	in t	ever	in t	ever	years ago	drug related	in t	ever	years ago	health	depression	health	depression
Baseline	0	0	0	0	0	0	0	0	0	3.687	0.178		
										(0.033)	(0.113)		
Scenario 1	1	1	0	0	0	0	0	0	0	3.696	0.217	**0.009*** **	**0.039***
										(0.033)	(0.130)	0.001)	0.021)
Scenario 2	1	1	1	1	1	0	0	0	0	3.668	0.250	**-0.019*** **	**0.072** **
										(0.034)	(0.143)	(0.005)	(0.035)
Scenario 3	1	1	1	1	1	1	0	0	0	3.631	0.201	**-0.056*** **	0.023
										(0.034)	(0.123)	(0.007)	(0.015)
Scenario 4	1	1	1	1	1	0	1	1	1	3.681	0.213	-0.005	0.035
										(0.034)	(0.137)	(0.007)	(0.046)
Scenario 5	0	1	0	0	0	0	0	0	0	3.686	0.191	**-0.001*** **	**0.013***
										(0.033)	(0.119)	(0.000)	(0.007)
Scenario 6	0	1	0	1	5	0	0	0	0	3.673	0.190	**-0.014*** **	**0.012***
										(0.034)	(0.119)	(0.005)	(0.007)
Scenario 7	0	1	0	1	5	0	0	1	5	3.684	0.185	-0.003	0.007
										(0.034)	(0.121)	(0.007)	(0.031)

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., $\frac{\partial p(e_t=e, r_t=r, s_t=s)}{\partial CR_t}$ of the total effect of criminal record on health defined in equation 9). 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 recently charged and convicted (scenarios 2, 3, and 4) are more likely to be enrolled. Those ever charged (scenario 2) are also more likely to receive welfare. These positive (and perhaps counterintuitive) findings may reflect a possible outcome of contact with the criminal justice system: namely, the required (or promoted or provided) resources for employment and social support services that were unknown prior to contact with the system. Another explanation may be related to sentencing. While sentencing for criminal convictions can involve probation, fines, restitution, and community service, the offender 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. For example, we find that a criminal conviction for a drug-related offense in one period increases employment next period (scenario 3). Even a past charge, conviction, or incarceration (scenarios 5, 6, and 7) increases welfare receipt and schooling/training. However, past convictions and incarcerations (5 years ago, scenarios 6 and 7) reduce employment.

Table 8: Contemporaneous Marginal Effects of Crime Record on Behaviors

Comparison Scenarios Entering t	Charged		Convicted				Incarcerated			Average Outcomes in t			Contemporaneous ME (scenario - baseline)		
	in $t-1$	ever	in $t-1$	ever	years ago	drug related	in $t-1$	ever	years ago	employed	welfare	enrolled	employed	welfare	enrolled
Baseline	0	0	0	0	0	0	0	0	0	0.633	0.250	0.225			
										(0.138)	(0.222)	(0.096)			
Scenario 1	1	1	0	0	0	0	0	0	0	0.607	0.280	0.251	-0.026	**0.055****	**0.026***
										(0.141)	(0.238)	(0.102)	(0.023)	(0.024)	(0.014)
Scenario 2	1	1	1	1	1	0	0	0	0	0.635	0.207	0.279	0.002	-0.019	**0.054*****
										(0.148)	(0.224)	(0.108)	(0.054)	(0.024)	(0.020)
Scenario 3	1	1	1	1	1	1	0	0	0	0.771	0.223	0.324	**0.138***	-0.002	**0.098*****
										(0.136)	(0.224)	(0.116)	(0.072)	(0.045)	(0.032)
Scenario 4	1	1	1	1	1	0	1	1	1	0.610	0.232	0.254	-0.023	0.007	0.028
										(0.155)	(0.229)	(0.104)	(0.071)	(0.025)	(0.020)
Scenario 5	0	1	0	0	0	0	0	0	0	0.628	0.279	0.268	-0.005	**0.053*****	**0.042*****
										(0.138)	(0.227)	(0.104)	(0.006)	(0.012)	(0.009)
Scenario 6	0	1	0	1	5	0	0	0	0	0.613	0.258	0.270	**-0.020*****	**0.032****	**0.045*****
										(0.140)	(0.224)	(0.105)	(0.007)	(0.016)	(0.014)
Scenario 7	0	1	0	1	5	0	0	1	5	0.593	0.269	0.253	**-0.040****	**0.043****	**0.028****
										(0.142)	(0.226)	(0.103)	(0.020)	(0.018)	(0.014)

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

To understand the effects of these resulting changes in behaviors on health (via a criminal record), we calculate the marginal effects of each behavior on health (i.e., $\frac{\partial H_{t+1}}{\partial b_t}$ where b_t represents e_t, r_t, or s_t). Table 9 suggests that there are no statistically significant effects, on average, of employment, welfare receipt, and schooling on health or depression. In light of the abundant literature demonstrating causal effects of employment, welfare receipt, and schooling on health, we were perplexed by this result initially. Upon further investigation, we realized these findings were average effects. That is, the numbers report in Table 9 are the impacts of employment in t, for example, on health in $t + 1$, averaged over all health values entering period t. Put differently, the marginal effects of employment on future health vary by one's health in period t.

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

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	3.684	0.184		
	(0.033)	(0.128)		
Scenario: Employed	3.687	0.181	0.003	-0.003
	(0.033)	(0.085)	(0.003)	(0.047)
Baseline: Not Receiving Welfare	3.687	0.176		
	(0.033)	(0.111)		
Scenario: Receiving Welfare	3.686	0.187	0.000	0.012
	(0.033)	(0.124)	(0.001)	(0.015)
Baseline: Not enrolled	3.685	0.177		
	(0.033)	(0.108)		
Scenario: Enrolled	3.683	0.183	-0.003	0.006
	(0.033)	(0.127)	(0.002)	(0.025)

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	3.618	0.206				
		(0.060)	(0.362)				
scenario 1	charged and convicted in 1997, never again	3.595	0.243	**-0.023*** **	**0.037** **		
		(0.061)	(0.367)	(0.005)	(0.019)		
scenario 2	charged and convicted in 1997, never again; for employment, act as if no crime ever	3.595	0.243	**-0.023*** **	**0.037** **	0.000	0.000
		(0.061)	(0.366)	(0.005)	(0.018)	(0.000)	(0.001)
scenario 3	charged and convicted in 1997, never again; for welfare, act as if no crime ever	3.595	0.242	**-0.023*** **	**0.035** **	0.000	-0.002
		(0.061)	(0.366)	(0.005)	(0.017)	(0.000)	(0.002)
scenario 4	charged and convicted in 1997, never again; for school, act as if no crime ever	3.595	0.243	**-0.023*** **	**0.037** **	**0.000** **	0.000
		(0.061)	(0.366)	(0.005)	(0.018)	(0.000)	(0.001)

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. We need to examine these results further to uncover potential heterogeneous effects.

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, 2020). 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	0.633	0.256	0.139						
		(0.137)	(0.272)	(0.129)						
scenario 1	charged and convicted in 1997, never again	0.619	0.289	0.196	**-0.014***	**0.033****	**0.056****			
		(0.138)	(0.275)	(0.146)	(0.008)	(0.017)	(0.025)			
scenario 2	charged and convicted in 1997, never again; for employment, act as if no crime ever	0.631	0.289	0.196	-0.002	**0.033****	**0.056****	**0.012***	0.000	0.000
		(0.137)	(0.275)	(0.146)	(0.002)	(0.017)	(0.025)	(0.007)	(0.000)	(0.000)
scenario 3	charged and convicted in 1997, never again; for welfare, act as if no crime ever	0.622	0.286	0.140	-0.011	**0.031***	0.000	**0.003****	**-0.003***	**-0.056****
		(0.138)	(0.275)	(0.130)	(0.007)	(0.016)	(0.001)	(0.001)	(0.001)	(0.025)
scenario 4	charged and convicted in 1997, never again; for school, act as if no crime ever	0.617	0.258	0.195	**-0.016****	0.003	**0.056****	**-0.002***	**-0.031***	0.000
		(0.138)	(0.273)	(0.146)	(0.008)	(0.002)	(0.025)	(0.001)	(0.016)	(0.000)

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

6 Conclusion

There are two big takaways from our findings. First, our finding of positive impacts of a drug-related conviction on employment, and of a charge or conviction on enrollment, in the next year was initially counter intuitive. However, these findings are very robust to different specifications. We believe that, among this group of disadvantaged women, contact with the criminal justice system may improve awareness of opportunities and services. Alternatively, it may bring to light the importance of making positive changes in their lives so as to avoid harsher penalities in the future, such as removal of custody of children or jail time. Second, the health impacts of employment, welfare receipt, and schooling differ by the health of women participating in these activities. For example, employment can have a positive impact on subsequent health among those with above average health. Conversely, women in fair or poor health or who are depressed experience negative impacts of employment on subsequent physical and mental health. Hence, any changes in the criminal justice system that promote employment, welfare participation, or schooling/training should consider the health of the individual in conjunction with expected behavioral changes.

References

Abrams, DS. 2012. "Estimating the Deterrent Effect of Incarceration Using Sentencing Enhancements." *American Economic Journal: Applied Economics* 4 (4): 32–56.

Agan, A., J. Doleac, and A. Harvey. 2021. "Misdemeanor Prosecution." NBER Working Paper 28600.

Agan, A. and S. Starr. 2017. "The Effect of Criminal Records on Access to Employment." *American Economic Review*, 107 (5): 560-64.

Agan, A. and S. Starr. 2018. "Ban the Box, Criminal Records, and Racial Discrimination: A Field Experiment." *The Quarterly Journal of Economics*, 133 (1): 191?235.

Aizer, A. and J. Doyle. 2015. "Juvenile Incarceration, Human Capital, and Future Crime: Evidence from Randomly Assigned Judges." *The Quarterly Journal of Economics*130 (2): 759–804.

Antonovics, K. and B. Knight. 2009. "A New Look at Racial Profiling: Evidence from the Boston Police Department." *Review of Economics and Statistics* 91 (1): 163–177.

Apel, R. 2013. "Sanctions, Perceptions, and Crime: Implications for Criminal Deterrence." *Journal of Quantitative Criminology* 29 (1): 67–101.

Bencsik, P . 2020. "Stress on the Sidewalk: The Mental Health Costs of Close Proximity Crime." working paper.

Bor, J., A. S. Venkataramani, D. R. Williams, and A. C. Tsai. 2018. "Police killings and their spillover effects on the mental health of Black Americans: a population-based, quasi-experimental study." *The Lancet* 392 (10144), 302–310.

Braveman P. 2011. "Accumulating Knowledge on the Social Determinants of Health and Infectious Disease." *Public health reports* 126 Suppl 3:28-30; Sep–Oct.

Braveman P, S. Egerter, D.R. Williams. 2011. "Determinants of Health: Coming of Age." *Annual Review of Public Health* (32):381398.

Brown, S.G. and G. Barbosa. 2001. "Nothing is Going to Stop Me Now: Obstacles Perceived by Low-income Women as They Become Self-sufficient." *Public Health Nursing* 18:364–372.

Bureau of Justice Statistics. 2011. "Plea and Charge Bargaining." Washington, DC: U.S. Department of Justice.

Chalfin, A. and J. McCrary. 2017. "Criminal Deterrence: A Review of the Literature." *Journal of Economic Literature* 55 (1), 5–48.

Cornaglia, F., N.E. Feldman, and A. Leigh. 2014. "Crime and mental well-being." *Journal of Human Resources* 49 (1), 110–140.

Currie, J. and B.C. Madrian. 1999. "Health, Health Insurance and the Labor Market" in Handbook of Labor Economics 3: 3309–3416.

Doleac, J. and B. Hansen. 2020. "The Unintended Consequences of ?Ban the Box?: Statistical Discrimination and Employment Outcomes When Criminal Histories Are Hidden." *Journal of Labor Economics* 38 (2): 321–374.

Durlauf, S. and D. Nagin. 2011. "Imprisonment and Crime: Can Both Be Reduced?" *Criminology and Public Policy* 10 (1): 13–54.

Enders, C. 2001. "A Primer on Maximum Likelihood Algorithms Available for Use With Missing Data." *Structural Equation Modeling* 8 (1): 128–141.

Equal Employment Opportunity Commission. 2012. "Consideration of Arrest and Conviction Records in Employment Decisions Under Title VII of the Civil Rights Act of 1964." EEOC Enforcement Guidance, 04/25/2012
(`https://www.eeoc.gov/laws/guidance/arrest_conviction.cfm`).

Finlay, K. 2009. "Effect of Employer Access to Criminal History Data on the Labor Market Outcomes of Ex-Offenders and Non-Offenders." In David H. Autor, editor, Studies of Labor Market Interm pp. 89?125. University of Chicago Press.

Graetz B. 1993. "Health Consequences of Employment and Unemployment: Longitudinal Evidence for Young Men and Women." *Social science and medicine* 36(6):715–724.

Grossman, M. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 80 (2): 223–255.

Grossman, M. 2015. "The Relationship between Health and Schooling: What's New?" NBER working paper no. 21609.

Grzywacz, J.G., D.M. Almeida, S.D. Neupert, and S.L. Ettner. 2004. "Socioeconomic Status and Health: A Micro-Level Analysis of Exposure and Vulnerability to Daily Stressors." *Journal of Health and Social Behavior*. 45: 1–16.

Holzer, H.J., S. Raphael, and M.A. Stoll. 2006. "Perceived criminality, criminal background checks, and the racial hiring practices of employers." *Journal of Law and Economics* 49 (2): 451?80.

Institute of Medicine. 2012. "How Far Have We Come in Reducing Health Disparities? Progress Since 2000." Washington, D.C.: National Academy of Science.

Janke, K.M., C. Propper, and M.A. Shields. 2016. "Assaults, murders and walkers: The impact of violent crime on physical activity." *Journal of Health Economics* 47: 34–49.

Jolivet, Grgory and Fabien Postel-Vinay. 2020. "A Structural Analysis of Mental Health and Labor Market Trajectories." IZA DP No. 13518.

Kaeble, D. and L. Glaze. 2016. "Correctional Population in the United States, 2015." U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics; December.

Kalil, A., C.E. Born, J. Kunz, and P.J. Caudill. 2001. "Life Stressors, Social Support, and Depressive Symptoms Among First-Time Welfare Recipients." *American Journal of Community Psychology* 29: 355–369.

Karlamangla, A.S., B.H. Singer, B.S. McEwen, J.W. Rowe, and T.E. Seeman. 2002. "Allostatic Load as a Predictor of Functional Decline. Macarthur Studies of Successful Aging." *Journal of Clinical Epidemiology* 55: 696–710.

Kling, J.R. 2006. "Incarceration length, employment, and earnings." *American Economic Review* 96 (3): 863?76.

Kneipp S. 2000. "The Health of Women in Transition from Welfare to Employment." *Western Journal of Nursing Research.* 22: 8–34.

Kneipp S.M., J.A. Kairalla JA, A.L. Sheely. 2012. "A Randomized Controlled Trial to Improve Health Among Women Receiving Welfare in the U.S.: The Relationship Between Employment Outcomes and the Economic Recession." *Social Science and Medicine* .

Levitt, S. and T. Miles. 2006. "Economic Contributions to the Understanding of Crime." *Annual Review of Law and Social Science* 2: 147–164.

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

Lochner, L. 2007. "Individual Perceptions of the Criminal Justice System." *American Economic Review* 97 (1): 444–460.

Lochner, L. and E. Moretti. 2004. "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports." *American Economic Review* 94 (1): 155–189.

Marmot, M. 2000. "Multilevel Approaches to Understanding Social Determinants." In: Berkman LF, Kawachi I, eds. Social Epidemiology. New York: Oxford University Press; p.347–367.

Marmot, M. and R.G. Wilkinson. 2000. Social Determinants of Health. Oxford: Oxford University Press.

Mayson, Sandra and Megan T. Stevenson. 2018. "The Scale of Misdemeanor Justice,." *Boston University Law Review* 98: 731–777.

McEwen, B. 2003. "Mood Disorders and Allostatic Load." *Biological Psychiatry* 54: 200–207.

Merlo A. and K. Wolpin. 2015 "The Transition from School to Jail: Youth Crime and High School Completion Among Black Males." *European Economic Review* 79: 234–251.

National Center for Health Statistics. 2012. "Health, United States, 2011: With Special Feature on Socioeconomic Status and Health." Hyattsville, MD.

Nowotny, K., Z. Bailey, M. Omori, and L. Brinkley-Rubinstein. 2020. "COVID-19 Exposes Need for Progressive Criminal Justice Reform." *American Journal of Public Health* 110: 967–968.

Mancino, A., S. Navarro, and D. Rivers. 2016. "Separating State Dependence, Experience, and Heterogeneity in a Model of Youth Crime and Education." *Economics of Education Review* 54: 274-305.

Roelfs, D.J., E. Shor, K.W. Davidson, and J.E. Schwartz. 2011. "Losing Life and Livelihood: A Systematic Review and Meta-Analysis of Unemployment and All-Cause Mortality." *Social science and medicine* 72(6): 840–854.

Sabol, W. 2014. "Survey of State Criminal History Information Systems, 2012." U.S. Department of Justice, Office of Justice Programs, Bureau of Justice Statistics; January.

Schnittker, J. and A. John. 2007. "Enduring Stigma: The Long-Term Effects of Incarceration on Health." *Journal of Health and Social Behavior* 48 (2): 115–130.

Semykina, A. and J.M. Wooldridge. 2013. "Estimation of Dynamic Panel Data Models with Sample Selection." *Journal of Applied Econometrics*, 28 (1): 47–61.

Shahidi, F.V., C. Ramraj, O. Sod-Erdene, et al. 2019. "The impact of social assistance programs on population health: a systematic review of research in high-income countries." *BMC Public Health* 19 (2).

Sheely, A. and S. Kneipp. 2015. "The Effects of Collateral Consequences of Criminal Involvement on Employment, Use of Temporary Assistance for Needy Families, and Health." *Women and Health* 55 (5): 548–565.

Shannon, S., C. Uggen, J. Schnittker, M. Thompson, S. Wakefield, and M. Massoglia. 2017. "The Growth, Scope, and Spatial Distribution of People with Felony Records in the United States, 1948 to 2010." *Demography* 54 (5): 1795–1818.

Steptoe, A., P.J. Feldman, S. Kunz, N. Owen, G. Willemsen, and M. Marmot. 2002. "Stress Responsitivity and Socioeconomic Status: A Mechanism for Increased Cardiovascular Disease Risk?" *Eur Heart J.* 23:1757–1763.

Stephens, Jr., Melvin and Takashi Unayama. 2019. "Estimating the Impacts of Program Benefits: Using Instrumental Variables with Underreported and Imputed Data." *The Review of Economics and Statistics* 101(3): 468–475.

Tonry, M. 2008. "Learning from the Limitations of Deterrence Research." *Crime and Justice* 37 (1): 279–311.

U.S. Census Bureau. 2012. Statistical Abstract of the United States: 2012. 131 ed. Washington, D. C.: U.S. Government Printing Office.

Williams, D.R., D. A. John, D. Oyserman, J. Sonnega, S.A. Mohammed, and J.S. Jackson. 2012. "Research on Discrimination and Health: An Exploratory Study of Unresolved Conceptual and Measurement Issues." *American Journal of Public Health* 102 (5): 975–978.

Woolf, S.H. and P. Braveman. 2011. "Where Health Disparities Begin: The Role of Social and Economic Determinants — And Why Current Policies May Make Matters Worse." *Health Affairs* 30 (10): 1852–1859.

A Appendix: Estimation Results

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

Variable Description	Source
Employment variables	
Full quarter employment: female, low SES **	BLS
Full quarter employment: female, low education **	BLS
New hire rate: female, low SES *	BLS
New hire rate: female, low education *	BLS
End of quarter hiring rate as % of quarterly employment: female, low SES	BLS
End of quarter hiring rate as % of quarterly employment: female, low education	BLS
Average monthly earnings of new hires: female, low SES (in 000s)	BLS
Average monthly earnings of new hires: female, low education (in 000s)	BLS
Unemployment rate: female, white	BLS
Unemployment rate: female, Black	BLS
Unemployment rate: female, Hispanic	BLS
Welfare variables	
TANF monthly benefit: three person family	UI
Sanction severity for first offense: adult portion or full family	
Drug felony eligibility: lifetime ban or compliance restrictions	
Schooling variables	
Average public 4-year college tuition (in 000s)	NCES
Average private 4-year college tuitions (in 000s)	NCES
Average public 2-year college tuitions (in 000s)	NCES
Crime-related variables	
Number of female prisoners **	
Violent offenses ***	UCR
State and local expenditure: police protection ****	BJS
State and local expenditure: judicial and legal ****	BJS
State and local expenditure: corrections ****	BJS
Health-related variables	
Annual average temperature	NCEI
Annual lowest temperature	NCEI
Annual highest temperature	NCEI
Annual precipitation (in inches)	NCEI
Number of non-elderly,non-disabled adults with Medicaid *	NCEI
Percent of counties HPSA designated: primary care	HRSA
Percent of counties HPSA designated: mental health care	HRSA
Average cigarette price ($/pack)	ACCRA
State and federal cigarette taxes (% of average retail price)	ACCRA
Average wine price ($/bottle)	ACCRA
Average beer price ($/6-pack)	ACCRA

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.

Sources: ACCRA (American Chamber of Commerce Research Association, now Council for Community and Economic Research); BJS (Bureau of Justice Statistics); BLS (Bureau of Labor Statistics); HRSA (Health Resources and Services Administration); NCEI (National Center for Environmental Information); NCES (National Center for Education Statistics); UCR (Uniform Crime Report); UI (Urban Institute, Welfare Rule Database).

Table A2: Estimation Results: Employment Status Not Known

Variable name	Coeff	Std Err	
Ever charged entering t	-0.08399	0.1995	
Ever convicted entering t	-0.32207	0.3604	
Ever incarcerated entering t	-0.20391	0.3869	
Last conviction within 5 years entering t	-0.42738	0.2721	
Last incarceration within 5 years entering t	0.47723	0.3078	
Charged in $t-1$	0.16135	0.3050	
Convicted in $t-1$	-0.37395	0.4077	
Incarcerated in $t-1$	0.19585	0.3261	
Drug-related conviction in $t-1$	0.71431	0.4528	
Enrolled in school in $t-1$	-0.01192	0.0613	
Received welfare in $t-1$	-0.17436	0.0738	**
Less than eight years of education entering t	-1.09674	0.3012	***
Some high school entering t	-0.92926	0.2672	***
High school degree entering t	-0.16081	0.2582	
GED degree entering t	-0.64943	0.2958	**
Some college entering t	-0.01648	0.2576	
Technical school entering t	0.11286	0.1360	
Bachelor's degree entering t	0.05930	0.2683	
Graduate degree entering t	0.15628	0.2720	
Training program entering t	0.12729	0.1256	
Poor/fair health entering t	-0.07061	0.1032	
Depressed entering t	0.01038	0.0891	
Poor/fair health×Depressed entering t	-0.37614	0.1461	***
Last interviewed in wave 1 entering t	0.68319	0.3156	**
Last interviewed in wave 2 entering t	2.20495	0.3498	***
Last interviewed in wave 3 entering t	2.88637	0.4104	***
Last interviewed in wave 4 entering t	1.69108	0.4500	***
Age - 18	0.13328	0.0307	***
Age - 18 squared/100	-1.14995	0.2350	***
Age - 18 cubic/1000	0.23406	0.0559	***
Black race	0.30461	0.1187	**
Non-white non-black	0.02043	0.1677	
Hispanic	-0.21684	0.1509	
Married	-0.37572	0.1173	***
Black race×married	0.11635	0.1481	
Non-white non-black×married	-0.00322	0.2036	
Hispanic×married	0.06375	0.1842	
Number of children	-0.54775	0.1691	***
Number of children squared	0.07715	0.0194	***

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 A2: Estimation Results (continued): Employment Status Not Known

Variable name	Coeff	Std Err	
Violent offenses ***	0.09745	0.0266	***
Number of female prisoners **	0.15159	0.1802	
State and local expenditure: police protection ****	-0.62225	0.1667	***
State and local expenditure: judicial and legal ****	0.86404	0.3033	***
State and local expenditure: corrections ****	-0.02621	0.1714	
New hire rate: female, low SES *	1.52193	0.4627	***
New hire rate: female, low education *	-2.80602	0.8833	***
Hiring rate as % of quarterly employment: female, low SES	-0.13323	0.0402	***
Hiring rate as % of quarterly employment: female, low education	0.17539	0.0553	***
Quarterly employment: female, low SES **	-0.00476	0.0014	***
Quarterly employment: female, low education **	0.08340	0.0409	**
Average monthly earnings: female, low SES (in 000s)	0.29759	0.1864	
Average monthly earnings: female, low education (in 000s)	-0.48347	0.4391	
Unemployment rate: female, white	-0.29614	0.0550	***
Unemployment rate: female, Black	-0.06355	0.0155	***
Unemployment rate: female, Hispanic Black	0.00626	0.0124	
Average public 4-year college tuition (in 000s)	0.01058	0.0576	
Average private 4-year college tuition (in 000s)	0.03491	0.0265	
Average public 2-year college tuition (in 000s)	-0.32903	0.1287	**
Sanction severity for first offense	-0.15720	0.1040	
Drug felony eligibility	-0.10188	0.0925	
TANF monthly benefit: three person family	-0.00130	0.0008	*
Annual lowest temperature	-0.02092	0.0132	
Annual precipitation (in inches)	-0.48371	0.3936	
Number of non-elderly, non-disabled adults with Medicaid *	-0.2151	0.1745	
Percent of counties HPSA designated: primary care	0.00536	0.0036	
Percent of counties HPSA designated: mental health care	0.00825	0.0053	
Average cigarette price ($/pack)	0.51139	0.1233	***
State and federal cigarette taxes (% of average retail price)	-0.02487	0.0089	***
Average wine price ($/bottle)	-0.11973	0.0724	*
Average beer price ($/6-pack)	-0.07446	0.0943	
Time trend (1=2001)	-0.50301	0.1632	***
Time trend squared	0.12030	0.0454	***
Time trend cubic	-0.00450	0.0035	
Constant	-8.45273	1.0200	***

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 | Status Known

Variable name	Coeff	Std Err	
Ever charged entering t	0.03245	0.1301	
Ever convicted entering t	0.02508	0.2417	
Ever incarcerated entering t	0.28030	0.2623	
Last conviction within 5 years entering t	0.07690	0.2009	
Last incarceration within 5 years entering t	-0.15218	0.2012	
Charged in $t-1$	0.17849	0.2455	
Convicted in $t-1$	-0.28459	0.3719	
Incarcerated in $t-1$	0.03356	0.2551	
Drug-related conviction in $t-1$	-1.29685	0.6633	*
Drug-related conviction in $t-1\times$drug felony eligibility	0.62068	0.7940	
Any crime in $t-1\times$severe financial sanction for first offense	0.19196	0.2268	
Enrolled in school in $t-1$	-0.38239	0.0535	***
Received welfare in $t-1$	0.39881	0.0658	***
Enrolled in $t-1\times$any crime in $t-1$	-0.59032	0.2756	**
Received welfare in $t-1\times$any crime in $t-1$	-0.03554	0.2409	
Enrolled in $t-1\times$drug-related conviction in $t-1$	3.66017	0.8885	***
Received welfare in $t-1\times$drug-related conviction in $t-1$	-0.89723	0.9044	
Less than eight years of education entering t	1.00313	0.2174	***
Some high school entering t	0.79150	0.1957	***
High school degree entering t	0.26564	0.1848	
GED degree entering t	0.42695	0.2096	**
Some college entering t	0.07153	0.1854	
Technical school entering t	-0.01498	0.0949	
Bachelor's degree entering t	0.05306	0.2004	
Graduate degree entering t	0.00392	0.2030	
Training program entering t	-0.01928	0.0893	
Poor/fair health entering t	0.24799	0.0941	***
Depressed entering t	-0.02778	0.0747	
Poor/fair health$\times$Depressed entering t	0.12244	0.1308	
Poor/fair health coming into $t\times$enrolled in $t-1$	0.20329	0.1320	
Poor/fair health coming into $t\times$received welfare in $t-1$	0.00859	0.1343	
Depressed coming into $t\times$enrolled in $t-1$	0.31037	0.0999	***
Depressed coming into $t\times$received welfare in $t-1$	-0.13171	0.1025	
Age - 18	-0.04357	0.0243	*
Age - 18 squared/100	0.59026	0.1848	***
Age - 18 cubic/1000	-0.12979	0.0425	***
Black race	-0.32409	0.0908	***
Non-white non-black	-0.02595	0.1269	
Hispanic	0.27328	0.1116	**
Married	0.61015	0.0891	***
Black race$\times$married	-0.54646	0.1056	***
Non-white non-black$\times$married	0.03183	0.1403	
Hispanic$\times$married	-0.29387	0.1311	**
Number of children	0.05466	0.0419	
Number of children squared	-0.00107	0.0062	

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 (continued): Non-employment Status | Status Known

Variable name	Coeff	Std Err	
Violent offenses ***	0.03335	0.0189	*
Number of female prisoners **	0.31514	0.1324	**
State and local expenditure: police protection ****	0.17100	0.0956	*
State and local expenditure: judicial and legal ****	0.13197	0.2123	
State and local expenditure: corrections ****	-0.60490	0.1205	***
New hire rate: female, low SES *	-0.86440	0.3340	***
New hire rate: female, low education *	0.24037	0.5559	
Hiring rate as % of quarterly employment: female, low SES	0.12637	0.0300	***
Hiring rate as % of quarterly employment: female, low education	-0.10784	0.0401	***
Quarterly employment: female, low SES **	0.00195	0.0011	*
Quarterly employment: female, low education **	-0.06681	0.0317	**
Average monthly earnings: female, low SES (in 000s)	0.00932	0.1411	
Average monthly earnings: female, low education (in 000s)	-0.22250	0.3055	
Unemployment rate: female, white	0.02154	0.0404	
Unemployment rate: female, Black	0.04213	0.0115	***
Unemployment rate: female, Hispanic Black	0.01764	0.0116	
Average public 4-year college tuition (in 000s)	0.04138	0.0396	
Average private 4-year college tuition (in 000s)	-0.07155	0.0181	***
Average public 2-year college tuition (in 000s)	0.25224	0.0917	***
Sanction severity for first offense	-0.08756	0.0737	
Drug felony eligibility	0.10844	0.0687	
TANF monthly benefit: three person family	0.00179	0.0005	***
Annual lowest temperature	0.00740	0.0091	
Annual precipitation (in inches)	-0.02275	0.3172	
Number of non-elderly, non-disabled adults with Medicaid *	0.10601	0.1432	
Percent of counties HPSA designated: primary care	-0.01048	0.0027	***
Percent of counties HPSA designated: mental health care	-0.00778	0.0038	**
Average cigarette price ($/pack)	0.07138	0.0914	
State and federal cigarette taxes (% of average retail price)	-0.01327	0.0071	*
Average wine price ($/bottle)	0.13452	0.0507	***
Average beer price ($/6-pack)	-0.06488	0.0557	
Time trend (1=2001)	0.20343	0.0769	***
Time trend squared	0.01789	0.0228	
Time trend cubic	-0.00581	0.0018	***
Constant	0.75788	0.6853	

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	
Ever charged entering t	0.21623	0.1464	
Ever convicted entering t	0.50675	0.2579	**
Ever incarcerated entering t	-0.56569	0.3068	*
Last conviction within 5 years entering t	-0.73102	0.2569	***
Last incarceration within 5 years entering t	0.39567	0.3136	
Charged in $t-1$	-0.20042	0.3587	
Convicted in $t-1$	0.70710	0.5990	
Incarcerated in $t-1$	-0.21678	0.4403	
Drug-related conviction in $t-1$	0.04648	0.5951	
Enrolled in school in $t-1$	-0.12694	0.0754	*
Received welfare in $t-1$	0.05152	0.0886	
Less than eight years of education entering t	0.27392	0.2115	
Some high school entering t	0.24181	0.1772	
High school degree entering t	0.17732	0.1756	
GED degree entering t	0.19803	0.1850	
Some college entering t	-0.01134	0.1751	
Technical school entering t	0.11175	0.1044	
Bachelor's degree entering t	-0.35492	0.2175	
Graduate degree entering t	-0.00502	0.2230	
Training program entering t	-0.03730	0.0939	
Poor/fair health entering t	0.16312	0.1069	
Depressed entering t	0.04596	0.0796	
Poor/fair health×Depressed entering t	-0.02929	0.1730	
Last interviewed in wave 1 entering t	0.64608	0.2425	***
Last interviewed in wave 2 entering t	1.24830	0.2571	***
Last interviewed in wave 3 entering t	3.29562	0.3541	***
Last interviewed in wave 4 entering t	5.17672	0.4140	***
Age - 18	-0.03076	0.0055	***
Black race	0.09754	0.0798	
Non-white non-black	-0.03882	0.1106	
Hispanic	-0.03383	0.1005	
Married	-0.66212	0.1525	***
Black race×married	0.46629	0.1872	**
Non-white non-black×married	0.14024	0.2574	
Hispanic×married	0.35323	0.2131	*
Number of children	-0.05042	0.1195	
Number of children squared	-0.01227	0.0209	

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 (continued): Welfare Receipt Status Not Known

Variable name	Coeff	Std Err	
Violent offenses ***	0.07091	0.0248	***
Number of female prisoners **	0.41229	0.1706	**
State and local expenditure: police protection ****	-0.34460	0.2215	
State and local expenditure: judicial and legal ****	1.44567	0.3436	***
State and local expenditure: corrections ****	-0.03049	0.1773	
New hire rate: female, low SES *	1.46918	0.6976	**
New hire rate: female, low education *	-1.83887	1.1266	
Hiring rate as % of quarterly employment: female, low SES	0.05558	0.0654	
Hiring rate as % of quarterly employment: female, low education	-0.11376	0.0829	
Quarterly employment: female, low SES **	-0.00645	0.0020	***
Quarterly employment: female, low education **	-0.07028	0.0410	*
Average monthly earnings: female, low SES (in 000s)	1.29471	0.2804	***
Average monthly earnings: female, low education (in 000s)	-3.03160	0.5689	***
Unemployment rate: female, white	-0.27749	0.0692	***
Unemployment rate: female, Black	-0.03139	0.0221	
Unemployment rate: female, Hispanic Black	0.05518	0.0220	**
Average public 4-year college tuition (in 000s)	0.04517	0.0578	
Average private 4-year college tuition (in 000s)	0.01624	0.0265	
Average public 2-year college tuition (in 000s)	-0.06971	0.1440	
Sanction severity for first offense	-0.05993	0.1065	
Drug felony eligibility	0.20579	0.1045	**
TANF monthly benefit: three person family	-0.00331	0.0008	***
Annual lowest temperature	-0.03548	0.0148	**
Annual precipitation (in inches)	-1.06391	0.5230	**
Number of non-elderly, non-disabled adults with Medicaid *	0.42216	0.2378	*
Percent of counties HPSA designated: primary care	-0.00947	0.0040	**
Percent of counties HPSA designated: mental health care	-0.00832	0.0054	
Average cigarette price ($/pack)	0.88064	0.1816	***
State and federal cigarette taxes (% of average retail price)	-0.06333	0.0128	***
Average wine price ($/bottle)	-0.08348	0.0891	
Average beer price ($/6-pack)	-0.21072	0.1083	*
Time trend (1=2001)	-0.71091	0.1806	***
Time trend squared	0.07446	0.0543	
Time trend cubic	-0.00460	0.0043	
Constant	-6.49064	1.1623	***

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 | Status Known

Variable name	Coeff	Std Err	
Ever charged entering t	0.45770	0.1259	***
Ever convicted entering t	-0.21316	0.2448	
Ever incarcerated entering t	-0.04506	0.2610	
Last conviction within 5 years entering t	0.23775	0.2104	
Last incarceration within 5 years entering t	-0.12757	0.2263	
Charged in $t-1$	0.04752	0.2724	
Convicted in $t-1$	0.26100	0.3419	
Incarcerated in $t-1$	-0.08968	0.2525	
Drug-related conviction in $t-1$	0.77142	0.5393	
Drug-related conviction in $t-1\times$drug felony eligibility	-0.77763	0.7740	
Any crime in $t-1\times$severe financial sanction for first offense	-0.34393	0.2196	
Enrolled in school in $t-1$	0.16989	0.0562	***
Received welfare in $t-1$	3.10300	0.0673	***
Enrolled in $t-1\times$any crime in $t-1$	-0.32084	0.2911	
Received welfare in $t-1\times$any crime in $t-1$	-0.08498	0.2383	
Enrolled in $t-1\times$drug-related conviction in $t-1$	-0.54678	0.8183	
Received welfare in $t-1\times$drug-related conviction in $t-1$	0.53274	0.7945	
Less than eight years of education entering t	0.66204	0.1814	***
Some high school entering t	0.74664	0.1488	***
High school degree entering t	0.40875	0.1472	***
GED degree entering t	0.58596	0.1551	***
Some college entering t	0.17073	0.1507	
Technical school entering t	0.02894	0.0884	
Bachelor's degree entering t	-0.92999	0.2154	***
Graduate degree entering t	-0.11192	0.1873	
Training program entering t	0.01755	0.0775	
Poor/fair health entering t	0.02222	0.0995	
Depressed entering t	0.19471	0.0734	***
Poor/fair health$\times$Depressed entering t	0.20701	0.1190	*
Poor/fair health coming into $t\times$enrolled in $t-1$	0.12928	0.1381	
Poor/fair health coming into $t\times$received welfare in $t-1$	0.22251	0.1311	*
Depressed coming into $t\times$enrolled in $t-1$	0.09458	0.1103	
Depressed coming into $t\times$received welfare in $t-1$	-0.31763	0.1142	***
Age - 18	-0.02498	0.0111	**
Age - 18 squared/100	0.03185	0.0425	
Black race	0.44131	0.0826	***
Non-white non-black	-0.01513	0.1045	
Hispanic	-0.05171	0.1004	
Married	-0.78361	0.1163	***
Black race$\times$married	0.24080	0.1321	*
Non-white non-black$\times$married	0.23812	0.1893	
Hispanic$\times$married	0.08849	0.1770	
Number of children	0.20050	0.0545	***
Number of children squared	-0.01854	0.0080	**

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 (continued): Welfare Receipt Status | Status Known

Variable name	Coeff	Std Err	
New hire rate: female, low SES *	-0.65082	0.4326	
New hire rate: female, low education *	1.69301	0.7124	**
Hiring rate as % of quarterly employment: female, low SES	0.04559	0.0383	
Hiring rate as % of quarterly employment: female, low education	-0.09612	0.0462	**
Quarterly employment: female, low SES **	0.00220	0.0013	*
Quarterly employment: female, low education **	-0.08546	0.0337	**
Average monthly earnings: female, low SES (in 000s)	-0.26593	0.1642	
Average monthly earnings: female, low education (in 000s)	0.78714	0.3490	**
Unemployment rate: female, white	0.05661	0.0453	
Unemployment rate: female, Black	0.05420	0.0131	***
Unemployment rate: female, Hispanic Black	-0.01172	0.0141	
Average public 4-year college tuition (in 000s)	0.03861	0.0428	
Average private 4-year college tuition (in 000s)	-0.03696	0.0197	*
Average public 2-year college tuition (in 000s)	-0.23675	0.0956	**
Sanction severity for first offense	-0.27180	0.0748	***
Drug felony eligibility	0.07182	0.0718	
TANF monthly benefit: three person family	-0.00154	0.0006	***
Annual lowest temperature	-0.05560	0.0104	***
Annual precipitation (in inches)	0.85236	0.3514	**
Number of non-elderly, non-disabled adults with Medicaid *	-0.29617	0.1604	*
Percent of counties HPSA designated: primary care	-0.01066	0.0030	***
Percent of counties HPSA designated: mental health care	0.00756	0.0044	*
Average cigarette price ($/pack)	-0.07302	0.0978	
State and federal cigarette taxes (% of average retail price)	-0.01462	0.0078	*
Average wine price ($/bottle)	0.06977	0.0542	
Average beer price ($/6-pack)	0.10244	0.0618	*
Violent offenses ***	0.03469	0.0182	*
Number of female prisoners **	-0.28457	0.1474	*
State and local expenditure: police protection ****	-0.07161	0.1286	
State and local expenditure: judicial and legal ****	0.45509	0.2136	**
State and local expenditure: corrections ****	0.14319	0.1241	
Time trend (1=2001)	0.01444	0.0830	
Time trend squared	-0.05743	0.0243	**
Time trend cubic	0.00426	0.0019	**
Constant	-2.49009	0.6823	***

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	
Ever charged entering t	0.20483	0.0910	**
Ever convicted entering t	-0.02413	0.1791	
Ever incarcerated entering t	0.08443	0.1889	
Last conviction within 5 years entering t	-0.12576	0.1629	
Last incarceration within 5 years entering t	-0.00261	0.1780	
Charged in $t-1$	0.31133	0.2297	
Convicted in $t-1$	-0.34544	0.2904	
Incarcerated in $t-1$	0.09754	0.2190	
Drug-related conviction in $t-1$	-0.30704	0.6449	
Drug-related conviction in $t-1\times$drug felony eligibility	0.84083	0.6038	
Any crime in $t-1\times$severe financial sanction for first offense	-0.18675	0.2032	
Enrolled in school in $t-1$	2.33837	0.1548	***
Received welfare in $t-1$	0.14814	0.0522	***
Enrolled in $t-1\times$any crime in $t-1$	-0.93283	0.2541	***
Received welfare in $t-1\times$any crime in $t-1$	0.17330	0.2213	
Enrolled in $t-1\times$drug-related conviction in $t-1$	0.91829	0.7501	
Received welfare in $t-1\times$drug-related conviction in $t-1$	-0.04356	0.6349	
Less than eight years of education entering t	-0.61946	0.1630	***
Some high school entering t	0.01399	0.1068	
High school degree entering t	0.16981	0.1088	
GED degree entering t	0.40099	0.1159	***
Some college entering t	0.64556	0.1115	***
Technical school entering t	0.45589	0.0620	***
Bachelor's degree entering t	0.66616	0.1289	***
Graduate degree entering t	0.73489	0.1364	***
Training program entering t	0.49441	0.0546	***
Poor/fair health entering t	0.00461	0.0888	
Depressed entering t	0.17664	0.0647	***
Poor/fair health$\times$Depressed entering t	-0.20078	0.1090	*
Poor/fair health coming into $t\times$enrolled in $t-1$	0.07808	0.1031	
Poor/fair health coming into $t\times$received welfare in $t-1$	0.16072	0.1249	
Depressed coming into $t\times$enrolled in $t-1$	-0.24996	0.0832	***
Depressed coming into $t\times$received welfare in $t-1$	0.08900	0.0921	
Age - 18	-0.14332	0.0187	***
Age - 18 squared/100	0.72784	0.1451	***
Age - 18 cubic/1000	-0.14010	0.0339	***
Black race	0.32440	0.0542	***
Non-white non-black	0.07211	0.0717	
Hispanic	-0.14512	0.0693	**
Married	-0.29508	0.0720	***
Black race$\times$married	0.27110	0.0887	***
Non-white non-black$\times$married	0.08396	0.1237	
Hispanic$\times$married	0.21959	0.1145	*
Number of children	-0.10666	0.0646	*
Number of children squared	0.01110	0.0092	

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 (continued): School Enrollment Status

Variable name	Coeff	Std Err	
Violent offenses ***	0.00290	0.0147	
Number of female prisoners **	-0.12377	0.1102	
State and local expenditure: police protection ****	-0.19831	0.1015	*
State and local expenditure: judicial and legal ****	0.45605	0.1605	***
State and local expenditure: corrections ****	-0.08572	0.0894	
New hire rate: female, low SES *	-0.53291	0.3114	*
New hire rate: female, low education *	0.71890	0.5436	
Hiring rate as % of quarterly employment: female, low SES	0.05218	0.0302	*
Hiring rate as % of quarterly employment: female, low education	-0.04410	0.0373	
Quarterly employment: female, low SES **	0.00108	0.0009	
Quarterly employment: female, low education **	-0.02139	0.0250	
Average monthly earnings: female, low SES (in 000s)	-0.05479	0.1244	
Average monthly earnings: female, low education (in 000s)	-0.17992	0.2767	
Unemployment rate: female, white	-0.04101	0.0332	
Unemployment rate: female, Black	0.01900	0.0103	*
Unemployment rate: female, Hispanic Black	-0.01603	0.0095	*
Average public 4-year college tuition (in 000s)	-0.02630	0.0300	
Average private 4-year college tuition (in 000s)	-0.01685	0.0145	
Average public 2-year college tuition (in 000s)	0.16760	0.0710	**
Sanction severity for first offense	0.00121	0.0551	
Drug felony eligibility	-0.02753	0.0539	
TANF monthly benefit: three person family	0.00051	0.0004	
Annual lowest temperature	0.01178	0.0073	
Annual precipitation (in inches)	-0.35846	0.2609	
Number of non-elderly, non-disabled adults with Medicaid *	-0.00050	0.1217	
Percent of counties HPSA designated: primary care	-0.00079	0.0020	
Percent of counties HPSA designated: mental health care	0.00449	0.0031	
Average cigarette price ($/pack)	0.05313	0.0706	
State and federal cigarette taxes (% of average retail price)	-0.00678	0.0052	
Average wine price ($/bottle)	0.01817	0.0441	
Average beer price ($/6-pack)	0.00730	0.0522	
Time trend (1=2001)	0.22787	0.0729	***
Time trend squared	-0.02665	0.0214	
Time trend cubic	0.00026	0.0016	
Constant	-2.18558	0.6997	***

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 Not Known

Variable name	Coeff	Std Err	
Ever charged entering t	0.15168	0.2089	
Ever convicted entering t	-0.01309	0.3458	
Ever incarcerated entering t	-0.80359	0.3953	**
Last conviction within 5 years entering t	0.39267	0.3211	
Last incarceration within 5 years entering t	-0.25583	0.4051	
Charged in $t-1$	0.55980	0.3738	
Convicted in $t-1$	4.16215	0.4522	***
Incarcerated in $t-1$	2.18206	0.3916	***
Employed in t	-0.39759	0.1378	***
Enrolled in t	-0.12384	0.1014	
Received welfare in t	0.13279	0.1290	
Poor/fair health entering t×employed in t	-0.03326	0.2466	
Depressed entering t×employed in t	0.25812	0.1821	
Poor/fair health entering t×enrolled in t	-0.25708	0.2396	
Depressed entering t×enrolled in t	0.16803	0.1923	
Poor/fair health entering t×received welfare in t	-0.31509	0.2525	
Depressed entering t×received welfare in t	0.27494	0.1988	
Less than eight years of education entering t	-0.06708	0.2361	
Some high school entering t	0.05831	0.1727	
High school degree entering t	0.14148	0.1647	
GED degree entering t	0.02235	0.1928	
Some college entering t	-0.08360	0.1671	
Technical school entering t	0.05521	0.1201	
Bachelor's degree entering t	-0.38209	0.2087	*
Training program entering t	-0.15485	0.1293	
Poor/fair health entering t	-0.15196	0.1869	
Depressed entering t	-0.29098	0.1499	*
Poor/fair health×Depressed entering t	0.50531	0.2560	**
Age - 18	0.04452	0.0203	**
Age - 18 squared/100	-0.21727	0.0752	***
Black race	-0.20249	0.0989	**
Non-white non-black	0.03467	0.1338	
Hispanic	0.15012	0.1270	
Married	-0.12768	0.1509	
Black race×married	0.11668	0.1922	
Non-white non-black×married	-0.09599	0.2700	
Hispanic×married	-0.29146	0.2358	
Number of children	-0.12881	0.0937	
Number of children squared	0.02080	0.0141	
Last interviewed in wave 1 entering t	-0.03653	0.1535	
Last interviewed in wave 2 entering t	0.39327	0.2440	
Last interviewed in wave 3 entering t	3.65816	0.3543	***
Last interviewed in wave 4 entering t	7.98152	0.4831	***
Violent offenses ***	-0.04410	0.0173	**
Number of female prisoners **	-0.17590	0.0955	*
State and local expenditure: police protection ****	0.41410	0.1183	***
State and local expenditure: judicial and legal ****	-0.34478	0.1789	*
State and local expenditure: corrections ****	-0.61028	0.1470	***
Time trend (1=2001)	0.18688	0.0925	**
Time trend squared	-0.35918	0.0249	***
Time trend cubic	0.02347	0.0022	***
Constant	-3.88817	0.4202	***

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 Charge Status | Status Known

Variable name	Coeff	Std Err	
Ever charged entering t	2.17882	0.2369	***
Ever convicted entering t	0.53128	0.3224	*
Ever incarcerated entering t	-0.82933	0.3326	**
Last conviction within 5 years entering t	-0.84733	0.3413	**
Last incarceration within 5 years entering t	0.21457	0.3785	
Charged in $t-1$	-2.26124	1.0194	**
Convicted in $t-1$	5.58062	1.0692	***
Incarcerated in $t-1$	0.44594	0.3296	
Employed in t	-0.16163	0.1583	
Enrolled in t	-0.18671	0.1587	
Received welfare in t	0.31058	0.1429	**
Poor/fair health entering $t\times$employed in t	0.61182	0.2920	**
Depressed entering $t\times$employed in t	-0.24848	0.2181	
Poor/fair health entering $t\times$enrolled in t	0.55832	0.3287	*
Depressed entering $t\times$enrolled in t	0.05971	0.2661	
Poor/fair health entering $t\times$received welfare in t	0.09787	0.2829	
Depressed entering $t\times$received welfare in t	0.03939	0.2393	
Less than eight years of education entering t	0.73055	0.3724	**
Some high school entering t	0.59102	0.2590	**
High school degree entering t	0.37377	0.2462	
GED degree entering t	0.34902	0.2685	
Some college entering t	0.28924	0.2499	
Technical school entering t	0.04015	0.1999	
Bachelor's degree entering t	0.00726	0.3222	
Training program entering t	-0.09200	0.1944	
Poor/fair health entering t	0.07507	0.2526	
Depressed entering t	0.64696	0.1794	***
Poor/fair health$\times$Depressed entering t	-0.49496	0.2957	*
Age - 18	0.08400	0.0284	***
Age - 18 squared/100	-0.33141	0.1043	***
Black race	-0.12678	0.1502	
Non-white non-black	-0.18791	0.2186	
Hispanic	-0.41954	0.2108	**
Married	-0.41528	0.2021	**
Black race$\times$married	0.39482	0.2762	
Non-white non-black$\times$married	0.33030	0.3978	
Hispanic$\times$married	0.07201	0.3506	
Number of children	-0.04868	0.1117	
Number of children squared	0.00909	0.0161	
Violent offenses ***	0.06005	0.0230	***
Number of female prisoners **	0.19874	0.1340	
State and local expenditure: police protection ****	-0.27307	0.1869	
State and local expenditure: judicial and legal ****	0.50730	0.2350	**
State and local expenditure: corrections ****	-0.04305	0.2289	
Time trend (1=2001)	0.29225	0.0629	***
Time trend squared	-0.09403	0.0200	***
Time trend cubic	0.00788	0.0016	***
Constant	-7.11069	0.6796	***

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: Criminal Conviction Status | Charged

Variable name	Coeff	Std Err	
Ever charged entering t	-0.58849	0.6476	
Ever convicted entering t	-4.17894	1.3808	***
Ever incarcerated entering t	0.64936	1.2741	
Last conviction within 5 years entering t	1.23568	1.0246	
Last incarceration within 5 years entering t	-1.47216	1.4092	
Convicted in $t-1$	6.10198	1.3599	***
Incarcerated in $t-1$	2.51601	1.4233	*
Employed in t	-0.60034	0.3162	*
Enrolled in t	-0.54187	0.2984	*
Received welfare in t	-0.06732	0.2718	
Less than eight years of education entering t	1.51520	1.0280	
Some high school entering t	0.28968	0.6472	
High school degree entering t	0.98875	0.6291	
GED degree entering t	0.23438	0.7533	
Some college entering t	-0.19553	0.6540	
Technical school entering t	0.35402	0.4822	
Bachelor's degree entering t	-0.20388	0.9402	
Training program entering t	0.36664	0.5200	
Poor/fair health entering t	0.45747	0.4357	
Depressed entering t	-0.27259	0.3045	
Poor/fair health×Depressed entering t	0.37339	0.6563	
Age - 18	0.08594	0.0702	
Age - 18 squared/100	-0.30602	0.2754	
Black race	-0.79984	0.3885	**
Non-white non-black	-0.65285	0.6136	
Hispanic	0.01740	0.5251	
Married	-0.62333	0.5666	
Black race×married	1.01429	0.7011	
Non-white non-black×married	-0.36082	1.0028	
Hispanic×married	-0.61764	0.9290	
Number of children	-0.01927	0.2524	
Number of children squared	0.00541	0.0375	
Violent offenses ***	-0.00203	0.0525	
Number of female prisoners **	-0.01564	0.3435	
State and local expenditure: police protection ****	-0.30476	0.5706	
State and local expenditure: judicial and legal ****	1.27686	0.6201	**
State and local expenditure: corrections ****	-0.57926	0.5107	
Time trend (1=2001)	0.62777	0.1296	***
Time trend squared	-0.04791	0.0502	
Time trend cubic	-0.00363	0.0046	
Constant	-4.63674	1.7319	***

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: General Health Status in $t+1$

Variable name	Coeff	Std Err	
Ever charged entering $t+1$	-0.00089	0.0036	
Ever convicted entering $t+1$	-0.02278	0.0073	***
Ever incarcerated entering $t+1$	0.02265	0.0080	***
Last conviction within 5 years entering $t+1$	0.00807	0.0086	
Last incarceration within 5 years entering $t+1$	-0.01050	0.0089	
Charged in t	0.01132	0.0043	***
Convicted in t	-0.01663	0.0106	
Incarcerated in t	0.00273	0.0079	
Drug-related conviction in t	-0.04019	0.0249	
Poor/fair health entering t	-1.01159	0.0041	***
Depressed entering t	-0.00620	0.0026	**
Poor/fair health×Depressed entering t	-0.00048	0.0051	
Employed in t	0.00224	0.0015	
Enrolled in t	-0.00352	0.0016	**
Received welfare in t	-0.00088	0.0016	
Poor/fair health entering t×employed in t	0.00713	0.0041	*
Poor/fair health entering t×enrolled in t	0.00557	0.0058	
Poor/fair health entering t×received welfare in t	-0.00062	0.0049	
Depressed entering t×employed in t	0.00315	0.0027	
Depressed entering t×enrolled in t	0.00045	0.0036	
Depressed entering t×received welfare in t	0.00364	0.0037	
Less than eight years of education entering t	0.00918	0.0047	**
Some high school entering t	0.00564	0.0039	
High school degree entering t	0.00598	0.0038	
GED degree entering t	0.00355	0.0041	
Some college entering t	0.00498	0.0039	
Technical school entering t	-0.00320	0.0027	
Bachelor's degree entering t	0.00543	0.0041	
Graduate degree entering t	0.00404	0.0044	
Training program entering t	-0.00660	0.0022	***
Age - 18	-0.00011	0.0001	
Black race	-0.00622	0.0018	***
Non-white non-black	-0.00414	0.0023	*
Hispanic	-0.00224	0.0021	
Married	-0.00016	0.0019	
Black race×married	0.00238	0.0024	
Non-white non-black×married	0.00146	0.0030	
Hispanic×married	-0.00002	0.0028	
Number of children	0.00659	0.0006	***
Number of children squared	-0.00060	0.0001	***
Annual lowest temperature	-0.00021	0.0001	**
Annual precipitation (in inches)	0.00709	0.0071	
Number of non-elderly, non-disabled adults with Medicaid *	-0.00377	0.0049	
Percent of counties HPSA designated: primary care	0.00000	0.0000	
Percent of counties HPSA designated: mental health care	-0.00000	0.0000	
Average cigarette price ($/pack)	0.00961	0.0019	***
State and federal cigarette taxes (% of average retail price)	-0.00046	0.0001	***
Average wine price ($/bottle)	0.00006	0.0008	
Average beer price ($/6-pack)	-0.00204	0.0009	**
Time trend (1=2001)	-0.01157	0.0011	***
Time trend squared	0.00203	0.0004	***
Time trend cubic	-0.00011	0.0000	***
Constant	3.99460	0.0130	***

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: Depression Status in $t+1$

Variable name	Coeff	Std Err	
Ever charged entering $t+1$	0.23439	0.1318	*
Ever convicted entering $t+1$	-0.10216	0.2743	
Ever incarcerated entering $t+1$	0.06725	0.2809	
Last conviction within 5 years entering $t+1$	0.07443	0.2758	
Last incarceration within 5 years entering $t+1$	-0.15073	0.2960	
Charged in t	0.39827	0.2414	*
Convicted in t	0.44390	0.4469	
Incarcerated in t	-0.39727	0.3370	
Drug-related conviction in t	-0.66476	0.4719	
Poor/fair health entering t	0.40365	0.1193	***
Depressed entering t	4.93735	0.0758	***
Poor/fair health×Depressed entering t	-1.24534	0.1172	***
Employed in t	-0.93671	0.0954	***
Enrolled in t	0.42444	0.0790	***
Received welfare in t	0.36595	0.0852	***
Poor/fair health entering t×employed in t	-0.08666	0.1690	
Poor/fair health entering t×enrolled in t	0.19716	0.1403	
Poor/fair health entering t×received welfare in t	0.09873	0.1363	
Depressed entering t×employed in t	2.34658	0.1260	***
Depressed entering t×enrolled in t	-0.90126	0.0977	***
Depressed entering t×received welfare in t	-0.48730	0.1124	***
Less than eight years of education entering t	0.39802	0.2069	*
Some high school entering t	0.44336	0.1688	***
High school degree entering t	0.28925	0.1683	*
GED degree entering t	0.47774	0.1793	***
Some college entering t	0.39705	0.1674	**
Technical school entering t	0.29703	0.1040	***
Bachelor's degree entering t	-0.05543	0.1986	
Graduate degree entering t	0.20291	0.2009	
Training program entering t	0.03833	0.0898	
Age - 18	0.02876	0.0180	
Age - 18 squared/100	-0.29690	0.1586	*
Age - 18 cubic/1000	0.07167	0.0391	*
Black race	-0.07390	0.0759	
Non-white non-black	-0.05885	0.0987	
Hispanic	-0.15076	0.0945	
Married	0.19192	0.1027	*
Black race×married	-0.11769	0.1299	
Non-white non-black×married	0.02400	0.1679	
Hispanic×married	-0.15425	0.1582	
Number of children	-0.02217	0.0434	
Number of children squared	0.00310	0.0067	
Annual lowest temperature	0.01003	0.0069	
Annual precipitation (in inches)	-1.04923	0.3443	***
Number of non-elderly, non-disabled adults with Medicaid *	-0.00590	0.2104	
Percent of counties HPSA designated: primary care	-0.00053	0.0017	
Percent of counties HPSA designated: mental health care	-0.00420	0.0035	
Average cigarette price ($/pack)	0.21308	0.1032	**
State and federal cigarette taxes (% of average retail price)	-0.00420	0.0065	
Average wine price ($/bottle)	0.01414	0.0458	
Average beer price ($/6-pack)	0.12754	0.0560	**
Time trend (1=2001)	-0.01877	0.0564	
Time trend squared	-0.03985	0.0192	**
Time trend cubic	0.00422	0.0015	***
Constant	-4.72344	0.6057	***

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: Attrition at the end of t

Variable name	Coeff	Std Err	
Charged in t	-0.18159	0.4523	
Convicted in t	-0.93006	0.5586	*
Incarcerated in t	0.30539	0.3756	
Drug-related conviction in t	0.36221	0.7234	
Employed in t	-0.17280	0.1350	
Enrolled in t	0.02837	0.1118	
Received welfare in t	-0.35665	0.1153	***
Less than eight years of education in t	0.91412	0.2920	***
Some high school in t	0.56614	0.2523	**
High school degree in t	0.26912	0.2501	
GED degree in t	0.26282	0.2674	
Some college in t	0.18921	0.2498	
Technical school in t	-0.08693	0.1366	
Bachelor's degree in t	0.06914	0.2808	
Graduate degree in t	0.22671	0.2835	
Training program in t	-0.22136	0.1271	*
Poor/fair health in t	-0.26168	0.1572	*
Depressed in t	-0.10210	0.1046	
Age - 18	0.01334	0.0071	*
Black race	-0.22653	0.1354	*
Non-white non-black	-0.05375	0.1592	
Hispanic	0.19049	0.1626	
Married	-0.31923	0.1614	**
Black race×married	0.13375	0.2027	
Non-white non-black×married	0.35958	0.2392	
Hispanic×married	-0.21848	0.2342	
Number of children	-0.11606	0.0816	
Number of children squared	0.01313	0.0117	
Time trend (1=2001)	-1.99059	0.6171	***
Time trend squared	0.78827	0.2074	***
Time trend cubic	-0.08267	0.0214	***
Constant	-0.97557	0.7526	

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 - Ever Charged, Convicted, or Incarcerated

Variable name	Coeff	Std Err	
Age - 18	0.06446	0.0147	***
Black race	-0.48239	0.2707	*
Non-white non-black	0.05812	0.3428	
Hispanic	-1.21885	0.3631	***
Married	-0.99360	0.3857	***
Black race×married	0.35073	0.5542	
Non-white non-black×married	-1.18268	0.9058	
Hispanic×married	0.65198	0.6968	
Number of children	-0.83471	0.5793	
Number of children squared	0.17519	0.1153	
Respondent's mother highest grade completed	0.01209	0.0499	
Respondent's father highest grade completed	-0.07229	0.0535	
Respondent's mother deceased	-0.09825	0.3917	
Respondent's father deceased	0.12589	0.3239	
Violent offenses ***	-0.17456	0.0453	***
Number of female prisoners **	0.83741	0.2608	***
State and local expenditure: police protection ****	0.39613	0.4518	
State and local expenditure: judicial and legal ****	0.57147	0.5439	
State and local expenditure: corrections ****	-1.01089	0.5203	*
Constant	-6.52008	0.8407	***

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 - General Health

Variable name	Coeff	Std Err	
Age - 18	0.00360	0.0024	
Black race	-0.06116	0.0421	
Non-white non-black	-0.09367	0.0588	
Hispanic	-0.05656	0.0572	
Married	0.09408	0.0470	**
Black race×married	-0.06107	0.0660	
Non-white non-black×married	-0.05349	0.0873	
Hispanic×married	-0.14203	0.0817	*
Number of children	-0.14390	0.0738	*
Number of children squared	0.03900	0.0173	**
Respondent's mother highest grade completed	0.01915	0.0058	***
Respondent's father highest grade completed	0.00736	0.0060	
Respondent's mother deceased	-0.05223	0.0605	
Respondent's father deceased	-0.07598	0.0441	*
Annual lowest temperature	-0.00254	0.0027	
Annual precipitation (in inches)	0.07427	0.2899	
Percent of counties HPSA designated: primary care	0.00234	0.0016	
Percent of counties HPSA designated: mental health care	0.00107	0.0041	
Average cigarette price ($/pack)	-0.10000	0.0361	***
State and federal cigarette taxes (% of average retail price)	0.00298	0.0032	
Average wine price ($/bottle)	0.02920	0.0320	
Average beer price ($/6-pack)	-0.02259	0.0367	
Constant	3.93432	0.2067	***

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: Initial Condition - Depression Status

Variable name	Coeff	Std Err	
Age - 18	-0.00819	0.0089	
Black race	-0.09170	0.1448	
Non-white non-black	-0.16948	0.1993	
Hispanic	-0.03181	0.1932	
Married	-0.22951	0.2045	
Black race×married	0.14622	0.2626	
Non-white non-black×married	0.52599	0.3050	*
Hispanic×married	-0.47618	0.2949	
Number of children	0.14586	0.2570	
Number of children squared	-0.01641	0.0542	
Respondent's mother highest grade completed	0.03063	0.0206	
Respondent's father highest grade completed	-0.05597	0.0223	**
Respondent's mother deceased	-0.10414	0.2026	
Respondent's father deceased	0.04001	0.1502	
Annual lowest temperature	-0.01404	0.0096	
Annual precipitation (in inches)	0.01189	1.0222	
Percent of counties HPSA designated: primary care	0.00234	0.0053	
Percent of counties HPSA designated: mental health care	-0.02542	0.0148	*
Average cigarette price ($/pack)	0.00397	0.1245	
State and federal cigarette taxes (% of average retail price)	0.00820	0.0115	
Average wine price ($/bottle)	-0.01055	0.1130	
Average beer price ($/6-pack)	0.02333	0.1362	
Constant	-1.61981	0.7018	**

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 A16: Estimation Results: Correlated Unobserved Heterogeneity

	Employment status unknown at t			Nonemployment at t $\mid$ known status			Welfare status unknown at t			Welfare Receipt at t $\mid$ known status			Enrolled at t			Prob. Weight	
Mass point	Coeff	Std Err		Coeff	Std Err		Coeff	Std Err		Coeff	Std Err		Coeff	Std Err			
Permanent																	
2	-0.178	0.232		0.045	0.114		0.193	0.135		0.170	0.179		-0.249	0.111	**	0.072	**
3	3.082	0.256	***	-1.986	0.199	***	-0.286	0.135	**	-0.590	0.176	***	-0.100	0.104		0.078	**
4	4.033	0.211	***	-3.167	0.242	***	-0.390	0.116	***	-1.039	0.154	***	0.142	0.084	*	0.201	***
5	0.208	0.196		0.120	0.100		-0.132	0.119		-0.051	0.166		-0.225	0.095	**	0.128	**
6	3.486	0.225	***	-2.461	0.213	***	-0.360	0.118	***	-1.002	0.161	***	0.148	0.088	*	0.207	***
7	-2.675	0.555	***	1.101	0.161	***	-0.249	0.244		0.016	0.417		-0.797	0.211	***	0.043	***
8	1.835	0.161	***	-0.863	0.109	***	-0.027	0.126		-0.475	0.195	**	0.044	0.118		0.167	***
Time-varying																	
2	-0.225	0.308		0.493	0.175	***	-0.247	0.223		0.401	0.144	***	0.180	0.358		0.037	***
3	-0.210	0.209		0.263	0.162		-0.360	0.146	**	0.292	0.121	**	0.094	0.307		0.284	
4	-0.068	0.211		0.530	0.185	***	-0.478	0.157	***	0.373	0.129	***	0.154	0.246		0.137	***
5	0.338	0.456		0.720	0.283	**	-0.756	0.377	**	0.310	0.252		0.394	0.411		0.006	***
6	-0.135	0.222		0.304	0.173	*	-0.386	0.161	**	0.465	0.132	***	0.218	0.315		0.081	***
7	-0.526	0.297	*	0.531	0.312	*	-1.195	0.181	***	0.423	0.364		-0.126	0.430		0.156	***
8	-1.244	2.268		1.785	1.315		-0.593	1.221		1.343	0.517	***	2.851	3.133		0.030	***

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 0.105 and 0.269, respectively.

Table A17: Estimation Results: Correlated Unobserved Heterogeneity

	Charge status unknown at t			Charged at t | known status			Conviction at t | charged at t			Health in $t+1$			Depression in $t+1$			Prob. Weight	
Mass point	Coeff	Std Err		Coeff	Std Err		Coeff	Std Err		Coeff	Std Err		Coeff	Std Err			
Permanent																	
2	1.160	0.305	***	1.422	0.431	***	2.592	0.876	***	-1.001	0.004	***	0.720	0.128	***	0.072	**
3	1.122	0.297	***	1.100	0.436	**	2.842	0.876	***	-1.002	0.004	***	0.320	0.141	**	0.078	**
4	0.992	0.290	***	0.923	0.425	**	2.503	0.979	**	-0.001	0.003		-0.130	0.125		0.201	***
5	1.207	0.292	***	1.145	0.420	***	3.606	1.077	***	0.996	0.003	***	-0.498	0.126	***	0.128	**
6	1.104	0.286	***	1.227	0.411	***	2.587	0.927	***	0.995	0.003	***	-0.562	0.135	***	0.207	***
7	1.336	0.368	***	1.618	0.446	***	3.985	1.078	***	0.004	0.006		-0.039	0.189		0.043	***
8	1.234	0.304	***	1.632	0.422	***	3.525	0.933	***	-0.002	0.004		-0.061	0.145		0.167	***
Time-varying																	
2	-0.914	0.220	***	0.165	0.292		0.772	0.668		-1.982	0.003	***	0.723	0.132	***	0.037	***
3	-0.755	0.112	***	0.090	0.229		0.237	0.424		-1.000	0.001	***	0.274	0.093	***	0.284	
4	-1.513	0.162	***	0.146	0.294		1.184	0.629	*	-0.494	0.001	***	0.247	0.112	**	0.137	***
5	-0.655	0.472		-0.122	0.647		0.310	1.079		1.963	0.011	***	-0.641	0.255	**	0.006	***
6	-0.903	0.164	***	-0.157	0.307		1.345	0.462	***	0.877	0.004	***	-0.091	0.117		0.081	***
7	-18.439	0.000	***	-0.290	0.413		0.810	0.755		0.003	0.001	***	-0.063	0.154		0.156	***
8	-0.120	0.319		-0.145	0.474		0.893	1.200		-0.001	0.002		-0.060	0.272		0.030	***

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 0.105 and 0.269, respectively.

Table A18: Estimation Results: Correlated Unobserved Heterogeneity

	Attrition			Criminal Record at $t=1$			Health at $t=1$			Depression at $t=1$			Prob. Weight	
Mass point	Coeff	Std Err		Coeff	Std Err		Coeff	Std Err		Coeff	Std Err			
Permanent														
2	0.183	0.309		4.043	0.347	***	-0.681	0.103	***	1.013	0.241	***	0.072	**
3	-0.154	0.334		4.434	0.310	***	-0.565	0.096	***	0.725	0.246	***	0.078	**
4	-0.148	0.295		3.223	0.343	***	0.002	0.078		0.022	0.224		0.201	***
5	0.387	0.272		3.811	0.290	***	0.618	0.083	***	-0.741	0.266	***	0.128	**
6	0.353	0.295		3.488	0.278	***	0.702	0.079	***	-1.210	0.265	***	0.207	***
7	0.275	0.444		3.778	0.453	***	-0.151	0.148		-0.023	0.424		0.043	***
8	0.220	0.356		4.499	0.284	***	-0.064	0.117		0.258	0.266		0.167	***
Time-varying														
2	1.325	0.394	***										0.037	***
3	0.678	0.358	*										0.284	
4	-4.753	0.006	***										0.137	***
5	0.678	0.746											0.006	***
6	0.685	0.389	*										0.081	***
7	1.288	0.587	**										0.156	***
8	-0.985	2.124											0.030	***

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 0.105 and 0.269, 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

$$H_{t+1} = \beta_0 + \beta_{c1} CR_t + \epsilon_t^H \ . \tag{10}$$

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

$$\begin{aligned} e_t &= \alpha_0 + \alpha_{c2} CR_t + \epsilon_t^E & (11) \\ H_{t+1} &= \beta_0 + \beta_{c3} CR_t + \beta_{e3} e_t + \epsilon_t^H \ . & (12) \end{aligned}$$

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

$$\begin{aligned} e_t &= \alpha_0 + \alpha_{c4} CR_t + \alpha_{r4} r_t + \alpha_{cr4} CR_t r_t + \epsilon_t^E & (13) \\ H_{t+1} &= \beta_0 + \beta_{c5} CR_t + \beta_{e5} e_t + \beta_{r5} r_t + \beta_{cr5} CR_t r_t + \epsilon_t^H \ . & (14) \end{aligned}$$

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

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.

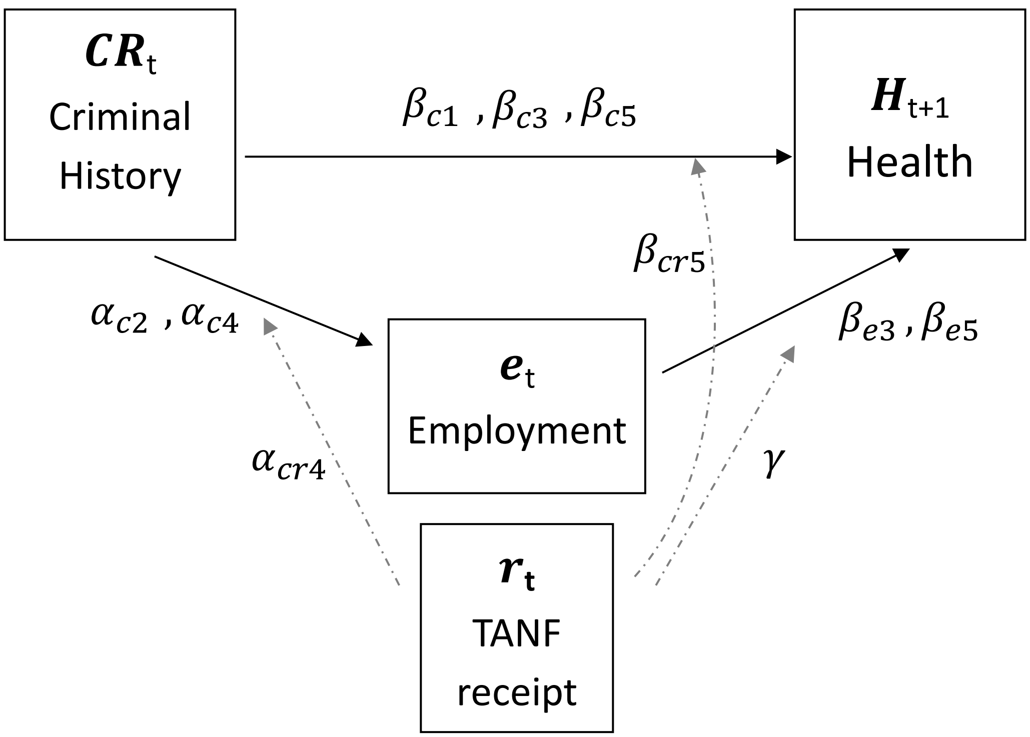

Figure B1: A Model of the Relationships

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 3 & RE		
	Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev		Coeff	Std Dev	
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).