Transitions between the criminal and legal labour sectors

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Abstract

In this paper I study the interactions between unemployment, employment and youth crime in the context of a search model in which crime and formal jobs are income substitutes. I estimate the model using a rich panel dataset on serious juvenile offenders, the Pathways to Desistance. I find that serious offenders face search frictions in the legal labour sector, taking on average one year to receive a job offer. They also face a large destruction rate of legal jobs, which mostly determines the short job durations observed in the data. The results suggest that any improvement in the quality and access to the legal labour sector for serious offenders (i.e. reducing search frictions, reducing the exogenous layoff rate, or improving legal earnings) has the potential of reducing crime. The paper shows that policies that keep the criminals off the street, in jails or legally occupied, appear to be less costly to reduce crime relative to policies that increase the returns in the legal sector.

1 Introduction

The empirical evidence suggests that youth account for a large share of crime. Youth between the ages of 15 and 19 represented one fifth of total arrests in the United States in 2010[1]. Moreover, the literature suggests that criminal activity is highly persistent over time (Blumstein, Farrington, and Moitra 1985; Nagin and Paternoster 1991, 2000). In this context, understanding how adolescents make choices can be very useful when designing crime-reducing policies since reducing youth crime can have lasting effects as these individuals transition into adulthood.

Moreover, there has been an increased recognition in the literature that employment in the legal labour sector may be an important driver of criminal activity (Becker, 1968; Ehrlich, 1973). In particular, unemployment and low wages are likely to alter the incentives to participate in criminal activities (Raphael and Winter-Ebmer 2001; Gould, Weinberg, and Mustard 2002; Machin and Meghir 2004; Grogger 1995; Kling 2006; Nagin, Farrington, and Moffitt 1995; Lochner 2004). Given this, I study the interactions between unemployment, legal employment and crime. I explore how choices in one sector can have an impact in the other sector. I analyze these interactions in the context of a search model with a criminal and legal labour sector. Crime and jobs are income substitutes; they are modeled as part of one labour market which is subject to frictions. The search model highlights how frictions and earnings in either sector determine the transitions across crime, jobs and unemployment. Understanding the interactions across crime and legal employment has important policy implications. To the extent that these two sectors interact, this provides additional instruments for policy makers interested in reducing crime. Specifically, policies that are designed to enhance the legal labour sector conditions may have an impact on criminal behavior.

The data I employ comes from the Pathways to Desistance Study (PDS), a multi-site longitudinal study of serious adolescent offenders as they transition from adolescence into early adulthood. The Pathways to Desistance

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[1]This figure is based on data from the FBI's Uniform Crime Reports.

was designed specifically to study questions related to the evolution of criminal behavior, taking special care to also measure employment in the legal sector, educational decisions and other outcomes. As a result, the dataset contains a rich panel of information about decisions to participate in crime and the legal labour sector. This type of data is well suited for understanding the dynamics across the criminal and legal sectors. The enrolled youth were between 14 and 18 years old at the time of their committing offense and were found guilty of a serious offense. Each study participant was followed for a period of seven years past enrollment which results in a comprehensive picture of life changes in a wide array of areas over the course of this time.

This research is related to some recent work which analyzes the criminal and legal labour sector jointly. İmrohoroğlu, Merlo, and Rupert (2004) develop a dynamic equilibrium model of crime to explore potential explanations for the drop in property crime between 1980 and 1996. However, it is not their main focus to assess how policies in the legal sector affect the criminal activity. Imai and Krishna (2004) estimate a life cycle model with endogenous criminal choices, criminal skill accumulation and exogenous employment, and show that the threat of future adverse effects in the labour sector when arrested acts as a strong deterrent to crime. Emphasizing the role of human capital, Lochner (2004) constructs a two-period life-cycle model to explore the effect of labour sector conditions upon crime and educational choices. Focusing on juvenile crime, Munyo (2015) also accounts for the interaction across the two sectors in a dynamic model of behaviour with human capital accumulation; he emphasizes the role of different levels of punishment of the juvenile and adult criminal systems. Other studies model the relationship between the criminal and the formal labour sector using a search approach. Burdett, Lagos, and Wright (2003, 2004) consider an environment characterized by labour sector search and by the random interaction between criminals and formal workers. Their equilibrium search model allows them to highlight various interactions among the criminal and legal labour sector and to discuss general-equilibrium effects. My model differs from Burdett, Lagos, and Wright (2004) in two dimensions. First, criminal activity is modeled as a continuous activity as opposed to a sporadic activity. Second, crime and legal jobs are income substitutes. These distinctions are important since the implications and policy recommendations are potentially different.

Following Burdett, Lagos, and Wright (2004), Huang, Laing, and Wang (2004) incorporates the study of human capital in the context of a simple search-theoretic framework with bilateral bargaining. Less educated workers specialize in criminal activities and employed workers do not engage in crime. Finally, Engelhardt (2010) estimate an extended version of the search model of crime proposed by Burdett, Lagos, and Wright (2004). Using data from the NLSY, he focuses on how long it takes for previously incarcerated individuals to find a job.

I find that it takes roughly one year for serious offenders to receive a job offer, which is well above what is estimated in the literature for low-skilled males. The exogenous destruction rate of jobs is also larger than what is typically estimated in the literature and it mostly explains why job durations in the data are so short. Individuals also face frictions in the criminal sector. The results suggest that besides policies that target specifically the criminal sector, any improvement in the quality and access to the legal labour sector for serious offenders (i.e. reducing search frictions, reducing the exogenous layoff rate, or improving earnings) has the potential of reducing crime as well. Policies that target the legal sector achieve reductions in crime via increases in the legal employment, whereas policies targeting the criminal sector do this through increases in the population incarcerated. Finally, a back of the envelope exercise reveals that keeping the criminals off the street, in jails or legally occupied, is less costly than introducing wage subsidies to reduce crime.

This document is organized as follows. In Section 2, I describe the data used for the analysis. In Section 3, I develop the search model. Section 4 presents the empirical results from the model, as well as a number of robustness checks. In Section 5, I discuss some policy simulations. Finally, Section 6 concludes.

2 Data

I use data from the Pathways to Desistance Study (PDS) for the analysis. Participants in the PDS are adolescents who were found guilty of a serious criminal offense (almost entirely felony offenses) in the juvenile or adult court systems in Maricopa County, Arizona, or Philadelphia County, Pennsylvania between November 2000 and January 2003.[2] The study follows 1,354 individuals, who were at least 14 years old and under 18 years old at the time of their offense. Besides fulfilling the requirements of age and criminal activity, individuals had to provide consent to participate in the study. Twenty percent of the youths approached for participation declined.[3]

The initial survey occurred when individuals first entered the sample. For those in the juvenile system, the initial interview was completed within 75 days after their adjudication, and for those in the adult system within 90 days after their decertification hearing (in Philadelphia) or arraignment (in Phoenix). There were six semi-annual follow-up interviews, followed by four annual follow-up interviews. During each follow-up interview, participants completed a monthly calendar covering the period between the current and the last interview. In total, the survey follows each individual for a period of eight years. Individuals were paid $50 to participate in the initial survey, with compensation increasing for the follow-ups to minimize attrition (Monahan et al., 2009).[4]

The PDS was designed specifically to study questions related to the evolution of criminal behavior, taking special care to also measure employment in the legal sector, educational decisions and other outcomes. In other words, it follows individuals making labour and crime choices over time. As a result, this type of data is well suited for understanding the dynamics across the criminal and legal sectors. Another key feature of this dataset is that it focuses only on serious offenders. For policy makers interested in reducing overall crime rates, data on these serious offenders, who contribute significantly to aggregate crime rates, is necessary. Nevertheless, the limitation is that I cannot necessarily generalize my findings to the population at large.

The baseline survey contains basic demographic information including age, gender, ethnicity and location. In addition, the survey has detailed information regarding educational attainment, legal jobs and criminal activity for each individual. The survey also collects information on the number of legal jobs an individual holds in a given month. This includes sporadic, part-time and under-the-table jobs. For each job, the survey gathers information on the number of weeks and hours worked, the hourly wage, the type of job, among others characteristics. A unique job ID is assigned to each job to keep track of it from month to month.

The data on criminal activity comes from two different set of questions, both self-reporting. In order to encourage accurate self-reporting, individual responses are kept confidential, and participants were given a certificate of confidentiality from the U.S. Department of Justice. The survey collects information on illegal earnings. Specifically, the individual is asked whether he worked illegally in a given month. If he answers yes, then the survey also records which type of illegal work the individual was involved in (e.g. selling stolen property, selling drugs, stealing merchandise, gambling, and/or prostitution), how much money the individual earned from illegal activities and the number of weeks worked in illegal activities. The survey also collects information on 24 self-reported offenses, each of which relates to involvement in a different type of crime in a given month.[5] These questions can be used to

[2]The most serious adjudicated charges were person crimes, property crimes and drug charges for 40.4%, 25.2% and 15.5% of the participants respectively. Other charges included weapons and sex crimes. Regarding the type of disposition, 42.2% were sentenced with probation, 30.6% were sent to jail, 21.1% were adjudicated to a non incarcerated Residential Placement. Other dispositions included fines or restitution (1.6%), and dismissed charges (2.2%).

[3]The proportion of male youth found guilty of a drug charge was capped at 15% to avoid an overrepresentation of drug offenders. All female juveniles meeting the age and adjudicated crime requirements and all youths whose cases were being considered for trial in the adult system were eligible for enrollment, even if the charged crime was a drug offense.

[4]The retention rate, measured as the share of participants completing a particular interview wave, was above 90% for the first six waves and no less than 83% for the following annual interviews.

[5]For each item, the specific question in the survey is "were you engaged in this activity in month X ?". The 24 self reported offenses are: destroy property, set fire, enter a building to steal, shoplift, buy, sell or receive stolen property, use credit card illegally, steal a car

identify whether an adolescent is engaged in any criminal act within the month, covering property, violent and drug crimes, regardless of whether he made money.

Finally, I observe whether individuals were incarcerated during a given month. If incarcerated, the type of institution (e.g. jail, detention center, prison, Pennsylvania Youth Development Centers (YDC), the Arizona Department of Juvenile Corrections, among others) and the amount of days spent in the locked facility are recorded.

2.1 Sample selection

In this study, I focus on individuals who do not pursue further schooling beyond age 19, once they have transitioned out of school. I can then focus on a sample of individuals who are only deciding between legal jobs, crime and unemployment without having to look at schooling choices.[6] The age threshold is chosen to concentrate on a sample of individuals who did not go to college and that presumably face a similar labour market. Individuals older than 19 who only obtain schooling if they are incarcerated are not excluded from the sample. The intuition is that schooling obtained in jail should not significantly boost the chances of getting a job or any other labour market outcome relative to school dropouts (Cameron and Heckman 1993).

A job is defined as an employment relationship including part-time and under-the-table jobs that engages at least 20 hours per week. Most individuals hold exactly one job at a point in time (98.1%). However, to deal with overlapping jobs, those jobs which are completely covered by another job are dropped. For the jobs that partly overlap, the starting date of the later job is replaced by the stopping date of the older job. For the jobs that completely overlap, the job with the higher wage is used. The job is right censored if it is still ongoing at the last completed interview. Average monthly earnings within a job are used. Earnings in the data are trimmed based on the 1st and 99th percentile from the Current Population Survey Data for High School Dropouts between 18 and 25 years old.

An income crime is defined as an illegal activity aimed at earning money. It includes selling stolen property, selling drugs, stealing merchandise, gambling and prostitution.[7] I make a distinction between participating in income crimes and participating in non-violent crimes without making money; I refer to the latter as other crimes. I choose to model other crimes explicitly since they are found to be relevant in determining transitions to income crimes relative to fully unemployed individuals (Mancino, 2016). Since the engagement in other crimes happens mostly right before engaging in income crimes, those other crimes that happen immediately after reporting an income crime are re-categorized as income crimes.[8] This means that, by definition, a month of income crime cannot be immediately followed by a month of other crimes. Analogous to the legal sector, average monthly criminal earnings are used for the income crime spells and they are trimmed 1% at the top and bottom of the distribution.

Monthly labour market histories are constructed according to the following rules. Based on the major activity occurring during a particular month, an individual could be in one of the following states: incarcerated, unemployed, employed in the legal sector, engaged in income crimes, engaged in other crimes, or both legally employed and engaged in income crimes.[9] If an individual spent more than 15 days in jail, detention or prison, he is classified as

or motorcycle, sell marijuana or other illegal drugs, carjack someone, drive drunk or high, pay for sex, force sex upon another person, kill someone, shoot someone, rob someone with a weapon, beat up someone, engage in a fight, carry a gun, eater a car to steal, and go joyriding.

[6]In the selected sample, most of the individuals stop attending school at age 18 (42.25%); 34.3% and 23.4% quit at ages 19 and 17 respectively. Note that the individuals in the sample initially got into the survey at different ages. Consequently the residual time, defined as the time to complete the eight years of the survey, also differs.

[7]More than 80% of the income criminal activities in a given month involve selling drugs as one of those activities. In 65% of the cases, selling drugs is the only criminal activity.

[8]The reduced form analysis revealed that having a period of zero income crime immediately after reporting positive crimes has no significant effect on future transitions. Moreover, only 10.4% of the income crime spells include at least a month of engagement in other crimes exclusively.

[9]I do not distinguish between fully employed individuals who participate in other crimes and those who do not, since this distinction does not seem relevant in determining transitions. Moreover, in only 5.9% of the months, fully employed individuals engage in other

incarcerated in that month.[10] If he was free or incarcerated for less than 15 days in a given month, he is classified as employed, engaged in income crimes, engaged in other crimes, or employed/criminal based on the definitions given above. He is classified as unemployed if he is not engaged in crime, working legally or incarcerated in a given month.

The monthly transitions are determined based on the unemployment, jail, employment and crime states. An individual makes an unemployment-to-job transition if he is unemployed in the current month and legally employed in the next month. Similarly, he makes an unemployment-to-income crime transition if he is unemployed in the current month and engaged in income-crimes in the next month. An employed worker makes a job-to-job transition if he changes jobs between months. He makes an employment-to-income crime transition if he has a legal job in the current month and switches to income criminal activities in the next month. An employed worker makes an employment to crime/ employment transition if he has a legal job in the current month and engages in crime in the following month, while keeping his current job.[11] An employed worker makes an employment-to-unemployment transition if he has a job in the current month but does not hold the job in the following month, nor engages in criminal activities.[12] A criminal makes an income crime-to-employment transition if he is involved in income crime activities in the current month and is legally employed in the next month. He makes a crime-to-crime/employment transition if he is currently engaged in income crimes and continues to engage in crime plus he is legally employed in the following month. A criminal makes an income crime-to-jail transition if he engages in income criminal activities in the current month and is incarcerated in the following month. Transitions for criminal/ employed individuals are defined analogously. Note that both unemployment to jail transitions and employment to jail transitions are possible since there may be a gap between engagement in crime and incarceration, or an individual may be participating in other criminal activities which are not explicitly modeled and which led him to jail. Finally, an individual makes a jail-to-unemployment transition if he is incarcerated in the current month and free (and not holding a legal job or engaging in crime) in the next month.[13]

The final sample consists of 568 individuals.[14] The retention rate, defined as the share of individuals that stay in the sample, is on average 64% for the first five years. Table 1 reports descriptive statistics for the sample. About 10.9% of the sample is female. There is a large percentage of minorities, with blacks and Hispanics representing 36.8% and 36.6% respectively. Around 26.6% of the individuals have a High School degree while 33.6% have completed a GED. With respect to location, 46.6% of the individuals initially live in Philadelphia. The average age at labour market entry is 19 years old.

Tables 2, 3 and 4 report descriptive statistics on earnings, durations and transitions. The monthly crime rate

crimes.

[10] Only in 7.4% of the observations in which the individual reports to be in jail in a given month he stays less than 15 days incarcerated. Five different institutions are considered as locked institutions which have incarceration as the main goal: jail, prison, detention centers, Pennsylvania Youth Development Centers (YDC), and the Arizona Department of Juvenile Corrections (ADJC).

[11] Note that the job duration is presumably longer than the employment duration as defined here, since the job may not change when an individual transitions from employment to crime/employment. The same statement holds for overall crime duration.

[12] All the employment to unemployment transitions are treated as exogenous. Even if 54.0% of these transitions are voluntary (e.g. the individual quits), the unemployment durations following voluntary and involuntary separations are not statistically different. Moreover, the reason for leaving the job does not predict future transitions (i.e. voluntary transitions are not more likely to end in crime after a period of unemployment). Thus, it seems like a harmless assumption.

[13] One potential concern when using monthly transitions is that an individual may be categorized as a criminal/employed on a given month when he is really transitioning either from employment to crime, or viceversa. For example, individual A is participating in the criminal sector in month 1, he is participating in the legal and criminal sectors in month 2, and he is only participating in the legal sector in month 3. It is likely that the individual is not really participating simultaneously in the two sectors in month 2; but it is instead a consequence of data aggregation. To avoid this missclassification, the transitions from employment to crime/employment to crime, where the middle state holds for exactly one month and the individual works less than two weeks in the legal sector in that month, are recategorized as employment to crime transitions directly. Crime to employment/crime to employment transitions are recategorized analogously.

[14] The original sample of monthly data starts with 1,265 individuals that complete the first follow-up survey after the baseline survey. Of this total, 39.5% makes the transition out of school after age 19, and 15.5% has missing data.

in the sample is 7.7%. This might seem low; however, this aggregates to an annual crime rate of 18.3%. Average reported criminal earnings are $3,415 per month. This is almost two times higher than the mean reported legal earnings ($1,226 per month). A comparison of the median rates also reflects the premium in the criminal sector ($1,439 and $1,185 per month in the criminal and legal sector respectively). Average legal earnings in the sample are similar to average legal earnings for black male High School Graduates in the NLSY (Bowlus, Kiefer, and Neumann, 2001).

Unemployment spells lasts on average 5.6 months. This is relatively high compared to the average unemployment duration in the NLSY, even for low-skilled individuals. Bowlus (1998) finds that unemployment duration is 3.6 months for low-skilled individuals from the NLSY. Moreover, the duration of legal jobs is short. In particular, legal jobs last on average 6.7 months which is below averages in the NLSY. Bowlus, Kiefer, and Neumann (2001) reports that job duration is roughly 19 months for black High School Graduates in the NLSY, while Engelhardt (2010) finds similar duration when focusing on individuals who have criminal records. Furthermore, income crime spells last on average 4.6 months, slightly smaller than the duration of legal jobs. Average time spent in jail is 9.6 months.

The results above suggest that frictions may play a relevant role in the interactions across crime and jobs. On the one hand, search frictions may explain why individuals stay unemployed for long periods of time and why they choose to participate in criminal activities. On the other hand, one possible explanation for the short duration of legal jobs can be the large destruction rates. Another reason could be that individuals voluntarily transition out of jobs and into crimes once they have a good opportunity. The model in the next section aims at disentangling what drives the interactions across these two labour sectors.

3 Model

The model is built in the spirit of the standard search model (Mortensen, 1986). However, it departs from it by allowing for two different labour sectors in which individuals can participate simultaneously. Following a large fraction of the empirical search literature, I adopt a partial equilibrium framework.

The economy is populated by a continuum of homogeneous, risk-neutral, and infinitely-lived workers, who maximize the discounted stream of expected lifetime utility. Time is continuous and individuals discount the future with interest rate r. At each point in time individuals can be unemployed, wage-employed, devoted to income crimes, employed in both sectors, devoted to other crimes or incarcerated. Let the value functions of each state be represented by V^u, $V^e(w)$, $V^c(y)$, $V^{ec}(w,y)$, V^z and J respectively. The state variables upon which workers make decisions include the employment state, monthly legal earnings w, and monthly criminal earnings y. I introduce the intensive margin of labour supply by assuming that legal employment and criminal activity are full-time activities when the individual is fully devoted to either sector. Individuals can also choose to participate in both sectors simultaneously; in such a case the legal job and the criminal activity are full-time and part-time activities respectively.[15] Hours worked in the criminal and legal sector are denoted as h_c and h_e, and $l \in (0,1)$ stands for leisure, where $l = 1 - h_e - h_c$. Hours worked in a given sector are equal to $\frac{2}{3}$ and $\frac{1}{3}$ when the activity is full-time and part-time respectively.[16]

The individuals face monthly earnings offer distributions $F(w)$ and $M(y)$ in the legal and criminal sector respectively. Earnings in either sector remain constant for the duration of the spell. The arrival rate of job offers (λ), income crime opportunities (η), other crime opportunities (ν), arrests (π), exogenous separations from crime (τ), exogenous separations from legal employment (δ), and releases from prison (κ) are Poison processes that vary depending on the state. The superscripts indicate the state.

[15] This is consistent with the facts observed in the data used for the empirical analysis. See Mancino (2016) for further details.
[16] This notation is consistent with Zhao (2015) who built a search model for multiple job holding.

The value of unemployment equals the flow utility of leisure (α_l), plus the expected value of changing labour market status. In particular, the individual is subject to job offers drawn from $F(w)$ at rate λ^u, income crime opportunities drawn from $M(y)$ at rate η^u, other crime opportunities at rate ν^u, and arrests at rate π^u. The flow Bellman equation for an unemployed worker is,

$$\begin{aligned}(r+\eta^u+\lambda^u+\nu^u+\pi^u)V^u &= \alpha_l \\ &+ \lambda^u \int \max\left[V^e(x), V^u\right] dF(x) \\ &+ \eta^u \int \max\left[V^c(x), V^u\right] dM(x) \\ &+ \nu^u \max\left[V^z, V^u\right] \\ &+ \pi^u J\end{aligned} \tag{1}$$

The value of wage-employment equals the corresponding flow utility of leisure (α_l) and legal earnings (w) plus the expected value of an exogenous termination at rate δ^e, plus the expected value of receiving a new job offer at rate λ^e, plus the expected value of receiving an income or other crime opportunity at rates η^e and ν^e respectively, plus the expected value of getting arrested at rate π^e. Analogous to unemployed individuals, workers choose to accept or reject offers.[17] However, upon accepting an income crime opportunity, they must also decide whether to participate only in the criminal sector or to split their time between the criminal and legal labour sectors. The flow Bellman equation for a wage-employed worker who works at a firm offering monthly legal earnings w is,

$$\begin{aligned}(r+\delta^e+\lambda^e+\eta^e+\nu^e+\pi^e)V^e(w) &= (1-h_e)\alpha_l + h_e w + \delta^e V^u \\ &+ \lambda^e \int \max\left[V^e(x), V^e(w)\right] dF(x) \\ &+ \eta^e \int \max\left[V^c(x), V^{ec}(w,x), V^e(w)\right] dM(x) \\ &+ \nu^e \max\left[V^z, V^e(w)\right] \\ &+ \pi^e J\end{aligned} \tag{2}$$

The value of participating in other crimes equals the corresponding flow utility of leisure (α_l) and non-pecuniary benefits from other crimes (α_z), plus the expected value of receiving a job offer or an income-crime opportunity at rates λ^z and η^z respectively, plus the expected value of getting arrested at rate π^z, and the expected value of an exogenous termination of the criminal activity at rate τ^z. The flow Bellman equation for participation in other crimes is,

$$\begin{aligned}(r+\eta^z+\lambda^z+\tau^z+\pi^z)V^z &= (1-h_c)\alpha_l + h_c\alpha_z \\ &+ \lambda^z \int \max\left[V^e(x), V^z\right] dF(x) \\ &+ \eta^z \int \max\left[V^c(x), V^z\right] dM(x) \\ &+ \tau^z V^u \\ &+ \pi^z J\end{aligned} \tag{3}$$

The value of income-crime activity equals the corresponding flow utility of leisure (α_l), plus pecuniary (criminal earnings) and non-pecuniary benefits from crime ($y+\alpha_c$), plus the expected value of changing labour market status. In particular, the individual is subject to job offers with monthly earnings w drawn from $F(w)$ at rate λ^c, exogenous terminations at rate τ^c and arrests at rate π^c. Upon facing job offers, individuals choose to accept or reject legal job offers as well as deciding whether to participate only in the criminal sector or to split the time between the criminal and legal labour sectors. The flow Bellman equation for a worker who is devoted to income-crime activities

[17] Note that the model is such that either every unemployed individual or none at all engages in other crimes.

with monthly earnings y is,

$$\begin{aligned}(r+\pi^c+\lambda^c+\tau^c)V^c(y) &= (1-h_c)\alpha_l + h_c(y+\alpha_c) \\ &+ \lambda^c \int \max\left[V^e(x), V^{ec}(x,y), V^c(y)\right] dF(x) \\ &+ \tau^c V^u + \pi^c J\end{aligned} \tag{4}$$

The value of participating simultaneously in legal and income criminal activities equals the flow utility of legal earnings (w), plus pecuniary and non-pecuniary benefits from crime ($y+\alpha_c$), plus the expected value of receiving a job offer with monthly earnings w drawn from $F(w)$ at rate λ^{ec}, plus the expected value of an exogenous termination from criminal and legal activities at rates τ^{ec} and δ^{ec} respectively, plus the expected value of getting arrested at rate π^{ec}. Analogous to income criminals, individuals choose whether to accept job offers and if they participate simultaneously in the criminal and legal labour sectors. The flow Bellman equation for an individual participating in both income sectors with legal earnings w and criminal earnings y is,

$$\begin{aligned}(r+\delta^{ec}+\pi^{ec}+\lambda^{ec}+\tau^{ec})V^{ec}(w,y) &= h_e w + h_c(y+\alpha_c) \\ &+ \lambda^{ec} \int \max\left[V^{ec}(x,y), V^e(x), V^{ec}(w,y)\right] dF(x) \\ &+ \delta^{ec} \max(V^c(y), V^u) \\ &+ \tau^{ec} \max(V^e(w), V^u) \\ &+ \pi^{ec} J\end{aligned} \tag{5}$$

Finally, the value of jail equals the flow utility of incarceration (α_j) plus the expected value of being released at rate κ and facing an immediate job offer or income crime opportunity with probabilities ρ_e and ρ_c respectively. The Bellman's equation for an incarcerated individual is,

$$(r+\kappa)J = \alpha_j + \kappa\left[(1-\rho_c-\rho_e)V^u + \rho_c \int \max(V^c(x), V^u) dM(x) + \rho_e \int \max(V^e(x), V^u) dF(x)\right] \tag{6}$$

3.1 Analysis of model properties

Individuals need to decide whether to accept a job and participate in criminal activities. They maximize future expected utility by following a set of reservation rules. In this section I define such reservation rules. In what follows I assume that the value of engaging in other crimes is larger than the value of unemployment (i.e. $V^z > V^u$). Note that if this is not the case, the model predicts that no one ever engages in other crimes.

Since $V^e(w)$ and $V^c(y)$ are continuous and increasing functions in their arguments, an unemployed agent only accepts offers in the legal and criminal sector that are at least as good as the reservation values denoted by w^* and y^* and determined by $V^e(w^*) = V^u$ and $V^c(y^*) = V^u$ respectively. For an individual participating in other crimes, the reservation values for accepting job offers and income crime opportunities are denoted as $\breve{w}$ and $\breve{y}$ and are defined analogously.

For a wage employed worker, the reservation legal value at which he is indifferent between accepting a new job offer and staying with the current job is the current legal earnings. Regarding income crime opportunities, a wage employed worker only accepts offers that are at least as good as the reservation criminal value denoted by $\bar{y}(w)$ and determined by $\max\{V^{ec}(w,\bar{y}), V^c(\bar{y})\} = V^e(w)$. The set of crime opportunities can be further decomposed to deal with the two possibilities faced by the worker once he accepts the income crime opportunity. Conditional on accepting the crime offer y, the worker chooses to participate in both sectors if his current legal earnings are at least as good as the reservation legal value denoted by $\breve{w}(y)$ and determined by $V^{ec}(\breve{w}, y) = V^c(y)$. Otherwise, he quits his legal job. The probability of accepting an income crime opportunity is consequently decreasing in current legal earnings and conditional on accepting the crime opportunity, the individual does not necessarily quit his legal job. Finally, a worker chooses to participate in other crimes if his current legal earnings are below $\breve{w}$.

An individual participating in income crimes only accepts job offers that are at least as good as the reservation legal value denoted by $\bar{w}(y)$ and determined by $\max\{V^{ec}(\bar{w},y),\, V^{e}(\bar{w})\} = V^{c}(y)$. The set of job offers can be further decomposed to account for the two possibilities faced by the criminals. In particular, conditional on accepting the job offer the criminal chooses to participate in both sectors if his current criminal earnings are at least as good as the reservation value denoted by $\breve{y}(w)$ and determined by $V^{ec}(w,\breve{y}) = V^{e}(w)$. Alternatively, he accepts the criminal opportunity and desists from crime. Thus, the probability of accepting a job offer is decreasing in current criminal earnings. However, the individual does not necessarily quits crime upon accepting the job. Note that accepting a legal job necessarily implies fewer hours devoted to the criminal sector since the job is full-time by assumption. If the individual chooses to take the legal job, he can still participate in crime on a part-time basis. In this case he not only gives up criminal earnings and non-pecuniary benefits from crime, but also leisure hours.

Similarly, an individual participating in the legal and criminal sector only accepts job offers that are at least as good as the reservation legal value denoted by $\bar{w}(w,y)$ and determined by $\max\{V^{ec}(\bar{w},y),\, V^{e}(\bar{w})\} = V^{ec}(w,y)$. Note that the lowest legal earnings accepted are given by the current legal earnings. Analogous to the previous cases, facing a new job offer may lead to three possible outcomes. Furthermore, if an employed/criminal is exogenously separated from one sector, he chooses to stay in the alternative sector as long as his legal or criminal earnings are larger than the reservation values of unemployed individuals (i.e. w^* or y^*).

Finally, an individual released from jail who immediately receives either a job or crime offer chooses to accept or reject the offers based on the unemployment reservation values.

3.2 Estimation

The set of parameters to estimate (θ) includes the mobility parameters, the utility parameters and the earnings distribution parameters,

$$\theta = \begin{cases} \lambda^u, \lambda^z, \lambda^e, \lambda^c, \lambda^{ec}, \\ \eta^u, \eta^z, \eta^e, \nu^u, \nu^e, \\ \delta^e, \delta^{ec}, \tau^z, \tau^c, \tau^{ec}, \\ \pi^u, \pi^z, \pi^e, \pi^c, \pi^{ec}, \\ \gamma^{ec}, \kappa, \rho_e, \rho_c, \mu_w, \mu_y, \\ \sigma_w, \sigma_y, \alpha_l, \alpha_c, \alpha_j, \alpha_z \end{cases}$$

The parameters are estimated via indirect inference (Gourieroux, Monfort, and Renault, 1993). The idea behind this method is to find a set of structural parameters that minimize the distance between a set of moments from the real data and the simulated data. The moments used for the estimation should help to identify the parameters and should capture the main features of the model.

I assume that the legal and criminal earnings distributions are log normal. The parameters of the earnings distribution $F(w)$ are then identified from the accepted legal earnings information. Similarly, the parameters of the criminal earnings distributions $M(y)$ are identified from data on accepted criminal earnings. Hence, I use the first and second moment of accepted earnings in each sector for the estimation. The superefficient estimators $w^* = \min(w)$ and $y^* = \min(y)$ are used (Flinn and Heckman, 1982). These estimators yield estimates for α_l and α_c respectively.[18]

[18] As it is standard in search models, I assume that individuals are not willing to accept negative earnings to participate in either

From the search literature I know that the mobility parameters are identified by durations and transition information. As a consequence, I include moments concerning the state durations as well as conditional transitions by state to identify mobility parameters. There are eight sets of mobility parameters in the model which are allowed to vary by state: arrival rate of job offers, arrival rate of income crime opportunities, arrival rate of other criminal opportunities, arrival rate of an exogenous separation from legal employment, or crime, arrest rate, jail release rate and probabilities of immediate offers after jail. The model dictates that the transition probability between any two states is equal to the corresponding arrival rate times the probability that the individual chooses to make the transition. Flinn and Heckman (1982) show that transition information is enough to identify the mobility parameters as long as the wage offer distribution is assumed to be recoverable. Intuitively, once we know the distribution of wages and the minimum wage accepted by individuals, the transition probabilities can be used to identify arrival rates. In this sense, the transitions from unemployment to full time employment identify the arrival rate of formal jobs for the unemployed. Similarly, the transitions from unemployment to income crime identify the arrival rate of income crime opportunities for the unemployed. For individuals employed in the legal sector, the transitions from employment to unemployment identify the termination rate. Job-to-job transitions identify the arrival rate of job offers for employed individuals. Job-to-crime and job-to-crime/employment identify the arrival rate of income crime opportunities. Finally, job-to-other crimes and job-to-jail transitions identify the arrival rate of other crimes and arrests respectively. For individuals solely participating in income crimes, the transitions from income crime to unemployment identify termination rates in the criminal sector. Crime-to-employment and crime-to-crime/employment transitions identify the arrival rate of job offers for criminals. The arrival rate of arrests for income criminals is identified by crime-to-jail transitions. The arrival rates for criminals engaged in other crimes and individuals participating simultaneously in crime and legal employment are identified analogously. Finally, the transitions out of jail identify the release rate, and the probabilities of jumping into legal employment or income crime directly after jail identify the probabilities of getting immediate offers in either sector.

The utility parameters α_z and α_j are identified using six additional moments. First, I use the share of months that individuals participate in any criminal activity, as well as the share of months that individuals participate in other crimes only. The intuition is that larger values of α_j should make any criminal activity more attractive, whereas larger values of α_z should make other crimes more attractive relative to any other criminal activity. I also regress legal earnings against an indicator on whether the individual comes from unemployment or other crimes, which should help to identify α_z; as well as regressing accepted legal earnings for income-criminals transitioning into the legal sector against an indicator on whether the individual is currently engaged in income-criminal activities or not. The intuition for these moments is similar to that of the superefficient estimators. The full list of moments can be seen in Table 5.

The estimation procedure works as follows. First, I calculate the selected moments in the original sample. I then start the procedure by guessing parameter values for the arrival rates of job offers (λ^u, λ^z, λ^e, λ^c, λ^{ec}), income crime opportunities (η^u, η^z, η^e), other crime opportunities (ν^u, ν^e), separation rates from jobs (δ^e, δ^{ec}), destruction rates of crimes (τ^z, τ^c, τ^{ec}), arrest rates (π^u, π^z, π^e, π^c, π^{ec}), release rate (κ), immediate probabilities of jobs and crimes for inmates (ρ_e,ρ_c), the flow utility parameters (α_j, α_z), and the parameters from the earnings distributions (μ_w , μ_y , σ_w , and σ_y). For a given guess of parameters, I estimate the flow utility of leisure and income crimes (α_l and α_c) as described above. Next, I simulate data based on these parameters. For the simulation, I mimic the sampling scheme of the original data. In particular, I draw a vector of pseudo-random draws that determine the initial state and initial survey (e.g. 1 to 10). I also draw a vector of pseudo-random draws that determine the probability of attrition conditional on the survey (initial and posterior surveys).[19] From this simulated data, I

sector. If this assumption does not hold for this population, I am imposing an upper bound on α_l and α_c.

[19] Individuals drop out of the sample for two main reasons. First, they are not interviewed again after completing the 10th survey.

calculate the set of selected moments. The indirect inference estimate of the structural parameters minimizes the difference between the simulated and sample moments. Let m represent the vector of moments in the data and let $m(\theta)$ represent the vector of simulated moments given the parameter values θ. The criterion function is then,

$$\Phi(\theta) = (m - m(\theta))' W^{-1}(m - m(\theta))$$

where W is a weighting matrix. I use a diagonal weighting matrix during estimation, where each diagonal element is the variance of the corresponding moment. I calculate the matrix W by bootstrapping 500 samples from the original sample of data and calculating the sample moments for each bootstrapped sample. I minimize the objective function using Simulated Annealing.

4 Results

I now present the results from my baseline specification. In Subsection 4.2, I consider alternative specifications to evaluate the robustness of the results. In particular, I use different trimming percentages for the criminal earnings. In subsection 4.3, I present the estimation results using different subsamples based on location and gender.

Before discussing the parameter estimates, I judge the fit of the model by looking at the moments I explicitly target in the estimation procedure. The sample and estimated moments are reported in Table 6. The search model does a very good job in fitting the first and second moments of the accepted earnings distributions in the criminal and legal labour sectors. The model also fits well durations and conditional transitions with the exception of those involving simultaneous participation in the legal and income-criminal sector. I also obtain a good fit for the share of months spent in any criminal activity. I do not fit well the coefficients on the regression relating legal earnings and transitions from unemployment and other crimes into the legal sector. Overall, I cannot reject the null-hypothesis of the Sargan-Hansen Test of over identifying restrictions, suggesting that the model is correctly specified.

The parameter estimates for the estimated baseline model are presented in Table 7. The results suggest that average earnings offered in the legal sector are larger than average earnings offered in the criminal sector; the variation is larger for criminal earnings though. Regarding the arrival rates of job offers, the results imply that on average, it takes 12.7 months for unemployed individuals to receive a job offer. This estimate is 2.4 times larger than that estimated by Bowlus (1998) for low skilled males in the United States and 2 times larger than the arrival rate of job offers estimated for individuals with criminal records from the NLSY (Engelhardt, 2010). This suggests that search frictions are present, and may be more binding for serious offenders relative to the rest of the population. Moreover, the model predicts that the chance of finding a job is at least two times smaller for individuals who are currently engaged in criminal activities relative to unemployed individuals, which may reflect the fact that these individuals simply have less time or less incentives to keep searching for jobs. It may also be that these individuals are the ones with a more serious offense history, which at the same time damages their likelihood of finding a job.

Different from what the standard search literature finds, the arrival rate of job offers for legally employed individuals is larger than the arrival rate for unemployed individuals. One reason may be that for serious offenders, having a legal job is a good signal to get further offers. The results also suggest that the job separation rate is more than double in this sample in comparison to low-skilled males from NLSY (Bowlus, 1998). The job separation rate for individuals who are simultaneously participating in the criminal and legal labour sector is not significantly different from unemployed individuals.

Income criminal opportunities are also subject to frictions. In fact, the arrival rate of income crime opportunities is considerably smaller than the arrival rate of job offers for unemployed individuals. As expected, criminal oppor-

Second, they can voluntarily drop out (i.e. attrition). In the simulated data individuals are not interviewed beyond the 10th survey and they face a probability of attrition at any point in time.

tunities arrive four times faster than in unemployment for individuals engaged in other crimes, but still at a smaller rate than job offers. One explanation for this is that given the low reservation crime value, which determines that individuals accept almost any income-crime offer, the arrival rate has to be low in order to explain the transitions to the income criminal sector observed in the data. Otherwise, we would see more transitions to the income criminal sector.

With regards to the utility flows, the results imply that the non-pecuniary benefits from crime are large. In particular, the non-monetary value of income crime is around 1,830 dollars for income criminals whereas the non-monetary benefits from other crimes are almost half of this. One reason for the large non-pecuniary benefits from income crime is that this parameter is identified based on the crime earnings distribution and the reservation crime value. Since the model does not allow for any growth in earnings within the criminal sector (i.e. no crime to crime transitions) the model puts a lot of weight on the non-pecuniary benefits from crime in order to explain the low reservation crime value observed in the data. Allowing for some source of variation within the criminal sector would help to improve this feature. Regarding the flow utility in jail, the model estimates it to be around 412 dollars relative to 1,099 dollars for the flow utility of unemployment.

Finally, inmates face a 18.3% probability of having a job offer immediately after being released. Similarly, there is an 11.3% probability of getting an immediate income criminal opportunity after jail. Training programs while in jail may potentially explain the transition to the legal sector. Another potential explanation is that inmates may be allowed to return to their previous jobs although this is hardly observed in the data.

Based on these estimates, I now perform a simple exercise in order to understand how frictions contribute to the durations observed in the data. I first focus on the average unemployment duration. In the previous section I found that average unemployment duration for serious offenders is larger than what is typically observed in other datasets. The estimates found here suggest that search frictions in the legal and criminal sector partly explain this. One question is by how much would the unemployment duration change if there were no crime opportunities. In Table 8, I present the average unemployment duration based on a simulation using the baseline parameter estimates, and compare it to the average unemployment duration based on a simulation in which there are no crime opportunities (i.e. $\nu^u = 0$, $\nu^e = 0$, $\eta^u = 0$, $\eta^e = 0$, $\eta^z = 0$). The results in the second column show that the unemployment duration would be 1.5 months longer in a scenario with no crime.

Another observation from the descriptive statistics was that job durations are short and similar in length to income crime spells. I next try to disentangle the role of the large exogenous separation rate found here and the endogenous transitions into crime in explaining the average job duration. In the second row of Table 8, I show the average job duration under three different scenarios. I first restrict the model to have no crime opportunities (i.e. $\nu^u = 0$, $\nu^e = 0$, $\eta^u = 0$, $\eta^e = 0$, $\eta^z = 0$). In the second simulation I let the job destruction rate be zero (i.e. $\delta^e = 0$ and $\delta^{ec} = 0$). Finally I do not allow for either crime opportunities or exogenous separations from formal jobs. I find that by banning the arrival rate of criminal opportunities and exogenous separations from legal jobs, the average job duration is 6 months longer than in the baseline specification. If instead I only ban criminal opportunities, the average job duration increases by less than 1 month. This suggests that the large separation rate mostly explains the short duration of formal jobs while there is a small role for endogenous transitions into crime. Moreover, this large destruction rate may play a relevant role in recidivism. In other words, exogenously separating individuals from formal jobs increases the crime rate since criminal activities are more attractive to individuals that are unemployed relative to individuals that have a formal job. Subsection 4.3 sheds light on these type of interactions.

4.1 Sensitivity Analysis

In this Section I present the results using different trimming percentages for earnings in the criminal sector.

The trimming percentage plays a key role in the estimation. First, it affects the average and standard deviation of the accepted criminal earnings in the data. Second, it alters minimum earnings. Given that minimum earnings are explicitly used in the estimation procedure, and since there is no theoretical justification for the trimming percentage used in the baseline model, this section aims at understanding how sensitive the results are to this assumption.

The baseline model uses a trimming percentage of 1% in the bottom and top of the distribution. Table 9 presents the parameter estimates for the model using different combination of trimming percentages in the top and the bottom of the criminal earnings distribution (e.g. 1% and 5%). Minimum criminal earnings double when the trimming percentage is 5% relative to 1% in the bottom of the distribution, jumping from $81 to $207 monthly. As expected, the parameters of the criminal earnings distribution change with the trimming percentages. Overall, the mobility parameters are very similar to the baseline parameters, except for the arrival rates of criminal opportunities whose identification relies on the criminal earnings distribution as well as minimum criminal earnings observed in the data (i.e. η^u,η^e and η^{ec}). Moreover, the arrival rates in the criminal sector are somewhat affected by the changes in the trimming percentages. Finally, the utility parameters are quite sensitive to the trimming percentage used in the estimation. However, these parameters are very noisy both in the baseline and alternative specifications.

4.2 Observed Heterogeneity

The literature has found large differences in crime rates based on gender, race and location. Using the Pathways to Desistance Data, Mancino, Navarro, and Rivers (2016) find that individual heterogeneity is strongly related to criminal behavior. Moreover, other research has found large differences in employment frictions based on gender and race (Bowlus, Kiefer, and Neumann, 2001; Bowlus, 1997). In order to determine the importance of allowing for heterogeneity in the model, Table 10 shows the results of my model for different samples. In column 1, I focus on a sample of males only. Columns 2 and 3 explore potential differences by location. In this exercise I am implicitly assuming that people face different labour markets based on gender and location, and consequently the model can be estimated separately for each group (Van den Berg and Ridder, 1998).

Given that females make up only 10% of the whole sample, the results are very similar when I focus only on males. However, offers in the criminal sector are on average larger for this population. Moreover, they seem to face less frictions in the legal sector as reflected by the larger arrival rates of job offers. The results also suggest that the consumption value of jail is lower than for the whole population, although this estimate has large confidence bands.

Before discussing the parameter estimates by location, it should be noted that the differences by location also capture racial differences since 85% of the black population in the sample is located in Philadelphia and 83% of the Hispanic population comes from Maricopa. The estimates suggest that arrests happen more often in Maricopa than in Philadelphia. Nevertheless, individuals stay on average two more months in jail in the latter. Earnings in the legal sector are on average larger in Maricopa, however Philadelphia has larger criminal earnings on average. Furthermore, serious offenders seem to face less frictions in the legal sector in Maricopa. In particular, jobs arrive at a faster rate and they are destructed at a slower rate. There are no consistent differences regarding the arrival rate of criminal opportunities. Finally, the consumption value of jail is larger in Arizona than in Pennsylvania although these estimates are very noisy. Job opportunities after being released are also more likely in Arizona. At the same time, the flow utility of unemployment in Arizona doubles the one in Pennsylvania.

4.3 Illustrating the results

In this section I attempt to emphasize how the criminal and legal labour sectors interact with each other. Specifically, I focus on the role of legal employment frictions, the quality of legal jobs, unemployment benefits, arrest rate and release rate in determining transitions across sectors. Understanding the role of each of these factors is crucial since their implications both in the criminal and the legal labour sector are potentially different. For this purpose I present three sets of simulations. First, I isolate the importance of the characteristics of the legal sector in determining transitions across crime and jobs. In particular, I illustrate the effect of the lack of access to jobs and their low quality by simulating separately an increase in the arrival rate of job offers, an increase in the average legal earnings offers, and a reduction in the destruction rate. Second, I focus on the characteristics of the criminal sector by simulating a change in the apprehension rate and the average sentence length. I then analyze how unemployment contributes to crime and employment by simulating a change in unemployment benefits.

The results are presented in Table 11. The first column shows the predicted outcomes of the model using the baseline parameter estimates; particularly the distribution of the population across different states, average earnings and average durations. The next columns show the same predicted outcomes under alternative values of the parameters. In what follows, I refer to overall unemployment as the state that encompasses unemployment plus any crime state that does not entail activity in the legal sector.

In Columns 2 to 4, I show that due to the interactions between sectors, crime can be reduced by changing the characteristics of the legal labour sector. I begin by simulating a 100% increase in the arrival rate of job offers (λ^u, λ^e, λ^c, λ^{ec}, λ^z), which is equivalent to reducing by half the average time elapsed until the first job offer. The results in Column 2 show that making it easier for serious offenders to access to legal jobs reduces the monthly crime rate by 19% on average (1.5 percentage points). Given that job offers arrive more often, people spend less time unemployed and the employment rate goes up by 39.6%. Note that the average job duration also goes down due to the larger arrival rate while on the job.

Second, I simulate a 50% increase in the average legal earnings offered to serious offenders. Shifting the distribution of legal offers makes the legal sector more attractive relative to the criminal sector, yielding a 1.2 percentage point reduction in the monthly crime rate. Not only do the average accepted legal earnings increase, but also the average criminal earnings accepted go up since individuals require higher earnings in the criminal sector in order to choose it relative to the legal sector. Different from the previous simulation, the unemployment rate and unemployment duration stay relatively flat. This arises because the search frictions remain unchanged and jobs still get exogenously destroyed at a high rate.

Finally, I simulate a 50% decrease in the destruction rate of legal jobs (δ^e, δ^{ec}) that yields a reduction in the monthly crime rate of 14.6% (1.2 percentage point). The effect on the unemployment rate is similar to doubling the arrival rates of job offers. However, the unemployment duration does not change since search frictions are still present. Moreover, crime goes down because people are sent back to unemployment at a smaller rate, increasing the average length of legal jobs.

Next, I show that crime can also go down by making changes specifically in the criminal sector (columns 5 and 6). First, I simulate a 50% decrease in the release rate (ρ), which is equivalent to an increase in the average sentence length of approximately 6 months. The 20.9% reduction in crime is accompanied by a 28.9% increase in the share of people incarcerated, while unemployment and employment go down. The elasticity of crime with respect to the average sentence length is -0.496. This elasticity is slightly larger than what is typically found in the literature (Levitt, 2004). Using a search framework, Engelhardt (2010) finds that the elasticity of crime with respect to the average time spent incarcerated is between -0.18 and -0.38. However, his estimates only capture the effect of keeping the criminals off the street (incapacitation effect) whereas my estimate comprises both the incapacitation and deterrence effect. Of the total effect on crime, 46.7% comes from incapacitation in my model.

Second, I simulate a 50% increase in the arrest rate (π^u, π^e, π^c, π^{ec}, π^z), which reduces crime by 27%. The model yields an estimate of the elasticity of crime with respect to the arrest rate of -0.67. The reduction in crime as a result of an increase in the arrest rate can be further decomposed to account for the incapacitation effect and the deterrence effect. I find that most of the total effect comes through deterrence (68%). Note that increasing the arrest rate directly raises the destruction rate of unemployment and employment spells. Consequently, both unemployment and employment go down while the incarcerated population increases.

Lastly, I simulate a 50% increase in unemployment benefits. For this exercise I assume that α_l is composed of 50% unemployment benefits and that the rest is the utility of leisure. This means that unemployment benefits are estimated to be 550 dollars monthly.[20] I then simulate a 50% increase in unemployment benefits. The results are presented in column 7. Since non wage-employed individuals who are engaged in crime are also entitled to unemployment benefits, an increase in unemployment benefits creates an incentive to engage in crime, yielding a small increase in the monthly crime rate of 2.8%. In other words, the increase in unemployment benefits raises the value of both full unemployment and crime relative to the legal sector. This result was already pointed out by Burdett, Lagos, and Wright (2004).

Overall, the results stress that any policy improving the quality and access to the legal labour sector for serious offenders has the potential to reduce crime. The effects on crime are sizable and comparable to changes obtained by shifting the arrest rate or the average sentence length. Policies targeting the legal sector achieve reductions in crime via increases in the legal employment, whereas the main effects of policies targeting the criminal sector come through increases in the population incarcerated. Finally, the results also highlight that increasing unemployment benefits may have unintended consequences on crime.

5 Policy Analysis

In Section 4.1. I found that sizable reductions in crime can be achieved either by targeting the criminal or the legal sector. In this section, I simulate the effect of two policies which have been discussed in the literature for the purpose of reducing crime. The two policies are designed to achieve the same goal in terms of average reduction in the monthly crime rate within a specific period. The first target is to reduce the monthly crime rate by 1 percentage point over the first year after the policy was implemented. Second, I target the same average reduction in the fifth year after the policy was implemented. The idea behind these different targets is to understand the short term and long term effects of each policy.

In each case I assess the cost of the policy. The full cost of a policy includes the change in unemployment benefits paid to unemployed individuals, plus the change in prison expenditures, plus the change in income taxes collected from legal workers, plus any extra cost specific to each policy (e.g. cost of a subsidy). Analogous to the previous section, I assume that unemployment benefits are 550 dollars per month.[21] In order to determine the prison expenditures, I use the average annual cost per inmate in Arizona and Pennsylvania which is estimated at $27,810 per inmate per year (of Justice, 2004). Regarding the taxes on income, I use a tax rate of 13.8% which is approximately the sum of the federal tax rate for low earnings plus the average state tax rate on income in Arizona and Pennsylvania. For each policy, the average monthly crime rate using the appropriate values of the parameters is compared against the monthly crime rate using the baseline parameter estimates over the targeted period. The results are presented in Table 12.

I start by simulating a policy that increases the average sentence length. The literature has found strong linkages between increased punishment and lower crime rates (Levitt, 2004). The implications of a reduction in the release rate in the model were carefully discussed in the previous section. The results are shown in the first column of Table

[20]The laws in Pennsylvania and Arizona determine that unemployment benefits are on average 130 dollars weekly for a person who worked at a minimum wage job for 6 months in a given year.

[21] The underlying assumption is that α_l is composed of 50% unemployment benefits and that the rest is the utility of leisure.

12. In order to achieve a 13% average reduction in the monthly crime rate over the first year after the policy is implemented, the release rate has to be 36% smaller, which implies that inmates spend on average 7.4 more months in jail. If instead the objective was to achieve a 13% average reduction five years after the policy takes place, the release rate has to go down by 22% -approximately 3.7 more months in jail on average. These number reflects the dynamics behind the model. In particular, since the incapacitation effect takes a larger share of the reduction in crime as time goes by (because of the increasing prison population), the reduction in the release rate needed to achieve the goal over a longer period is consequently smaller.

Next, I simulate the introduction of a wage subsidy for serious offenders. The government pays a monthly wage subsidy to each worker who participates in the legal sector in a given month. Wage subsidies have been proposed in the literature as a means of reducing criminal activity for low-skilled workers (Hoon and Phelps, 2003). Within the model, the introduction of a wage subsidy is practically similar to a shift in the distribution of legal earnings. By boosting legal earnings, people are less willing to take income crime opportunities when they are fully unemployed or wage-employed. The results in Column 2 of Table 12 show that the government needs to pay a $770 subsidy monthly to achieve the crime reduction in the first year. If instead the goal is to achieve an average crime reduction of 13% five years after the implementation, then the monthly wage subsidy amounts to $610. In the short run, this policy mostly affects individuals who are already employed since the arrival rates are not allowed to change as a consequence of the policy (i.e. search effort does not respond to the introduction of the policy). In the long run, the employment rate increases at a faster pace since it incorporates the fact that more people are transitioning into jobs and fewer people are doing voluntary job-to-crime transitions, thus the subsidy need not be as big as when I target the reduction in the short run.

In terms of the cost, the policy targeting the criminal sector appears to be more effective than wage subsidies, even if we account for the lost tax revenue coming from legal workers. Wage subsidies are costly since jobs still get exogenously destroyed at a high rate and search frictions dictate that legal jobs are not immediately available. Consequently, incapacitating the criminals via incarceration is less costly.

In order to further emphasize the role of search frictions in reducing crime, I next simulate the introduction of a one-time job placement program for inmates. Under this program, the inmates who are currently incarcerated are offered a legal job once they are released, which immediately reduces the search frictions otherwise faced by them. Policies of this kind have been largely examined in the criminology literature and had been implemented in the past (Wilson et al., 1999; Visher, Winterfield, and Coggeshall, 2005; Uggen, 2000). For instance, the National Supported Work Demonstration program, which was introduced in nine cities in the United States in the 1980s, assigned individuals who had been recently incarcerated to a minimum wage job. Within my model, such a policy has no long run effects but it can achieve a reduction in crime in the short run.[22] In particular, if the job placement program gave a minimum wage job to current inmates who are released ($1,100 monthly earnings), the average crime reduction in the first year would be 8.2%. The results in Table 13 show that achieving the same goal through wage subsidies or by reducing the release rate is more expensive.

Overall, the results suggest that policies that reduce the time individuals spend on the streets are more effective in reducing crime than policies that increase the returns in the legal sector. Incapacitation may come either through incarceration or formal jobs. The implications on employment are obviously different under the two policies with the latter stimulating formal employment.

6 Conclusion

In this paper, I present a search model with a criminal and a legal labour sector in which the two sectors are

[22] Uggen (2000) finds no long run effects of similar policies on youth crime.

income substitutes. The search model highlights how frictions and earnings in either sector determine interactions across crime, jobs and unemployment.

I estimate the model using a unique dataset on serious offenders from Pennsylvania and Arizona. I find that serious offenders receive job offers at a rate twice as slow than the population as a whole. Moreover, jobs are destroyed twice as fast as what is typically estimated, which determines the short job durations observed in the data. Given the interactions between sectors, I find that reducing search frictions, reducing the exogenous destruction rate, or improving legal earnings has the potential to reduce crime. The policy simulations suggest that keeping the criminals off the street, in jails or legally occupied, can achieve crime reductions at a smaller cost than introducing wage subsidies.

One limitation of the model proposed here is that it does not account for unobserved heterogeneity. There are potentially permanent differences in some of the main parameters of the model that I am ignoring which alter the interactions across sectors. For instance, there are presumably permanent differences in the utility flows of crime, which determines that some individuals are more likely to return to crime. These permanent differences may also determine that some individuals face less frictions in the criminal sector or the legal sector and they can consequently transition into this sector more easily. Another limitation is that the model is not rich enough to fully explain the transitions into income crime. The non-pecuniary benefits from crime have to be very large in order to explain the transitions into a criminal sector that offers no income growth, but still individuals accept very low earnings. Adding a source of income variation within the income criminal sector can potentially reduce the role of non-pecuniary benefits.

Finally, it is important to emphasize that I focus on youth serious offenders. While this is a relevant group for policy purposes, my findings cannot be generalized to the population at large. In other words, the factors driving the interactions between the legal and criminal sector may not be the same for individuals who are sporadically engaged in crime. More importantly, what helps to reduce serious crime may not be as useful to reduce petty crimes such as shoplifting. I feel that the model proposed by Burdett, Lagos, and Wright (2003) would be more accurate to explain the behaviour of less serious criminals.

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Table 1: Pathways to Desistance
Descriptive Statistics:
Mean and Standard Deviation

Variable	Mean	Std. Dev.
Female	0.109	*0.312*
Black	0.368	*0.483*
Hispanic	0.366	*0.482*
White	0.231	*0.422*
Philadelphia	0.467	*0.499*
Age at Labour Market Entry	18.981	*1.548*
High School Degree	0.266	*0.442*
GED	0.336	*0.473*
Individuals	568	

Notes:
1. Summary statistics for these variables are calculated using only the survey at the time they enter the selected sample.

Table 2: Pathways to Desistance - States and Earnings

Variable	Mean	Std. Dev.
Monthly crime rate	0.077	*0.267*
Monthly employment rate	0.347	*0.476*
Monthly legal earnings	1,226.9	*492.7*
Monthly criminal earnings	3,415.0	*5,082.1*
Number of observations	24,661	

Notes:
1. Each observation is an individual-month pair.
1. The monthly crime rate is calculated as the number of individuals engaged in crime in a given month, over the number of individuals. The employment rate is
2. Legal earnings and criminal earnings are monthly and are expressed in 2001

Table 3: Pathways to Desistance Descriptive Statistics: Durations

Variable	Mean	Censoring Rate
Unemployment	5.576	0.191
Employment	6.693	0.143
Income Crime	4.553	0.094
Employment/Crime	3.153	0.059
Other crimes	1.958	0.042
Jail	9.647	0.269
Number of spells	3,527	

Notes:
1. Durations are in months and include censored spells.

Table 4: Pathways to Desistance Descriptive Statistics:
Conditional Transitions

Variable	Mean	Std. Dev.
Fraction of completed unemployment spells ending in:		
Job	0.548	*0.498*
Income crime	0.095	*0.294*
Jail	0.229	*0.421*
Other crime	0.127	*0.333*
Fraction of completed job spells ending in:		
Unemployment	0.475	*0.500*
Job	0.332	*0.471*
Income crime	0.035	*0.185*
Jail	0.070	*0.255*
Job/ crime	0.057	*0.232*
Other crime	0.031	*0.175*
Fraction of completed income crime spells ending in:		
Unemployment	0.339	*0.474*
Job	0.060	*0.238*
Jail	0.532	*0.500*
Job/ crime	0.069	*0.253*
Fraction of completed job/crime spells ending in:		
Unemployment	0.024	*0.153*
Job	0.548	*0.501*
Income crime	0.262	*0.442*
Jail	0.119	*0.326*
Job/ crime	0.048	*0.214*
Fraction of completed other crime spells ending in:		
Unemployment	0.520	*0.501*
Job	0.170	*0.377*
Income crime	0.150	*0.358*
Jail	0.160	*0.368*
Fraction of completed jail spells ending in:		
Unemployment	0.696	*0.460*
Job	0.177	*0.382*
Income crime	0.127	*0.333*
Number of spells	3,527	

Notes:

1. The transition probabilities sum to one since I only consider completed spells for the calculation.

2. Job-to-job/crime transitions imply no change in the legal job. Job/crime-to-job transitions may or may not imply a change in job. Job/crime to job/crime transitions necessarily imply a change in the legal job.

Table 5: List of Moments Used in the Estimation Procedure

- Earnings
  - Average legal earnings
  - Standard deviation legal earnings
  - Average criminal earnings
  - Standard deviation criminal earnings
- Adjusted durations
  - Unemployment duration
  - Job duration
  - Income crime duration
  - Job/Crime duration
  - Other crimes duration
  - Jail duration
- Conditional transitions
  - Unemployment to
    - Job
    - Other crime
    - Jail
  - Job to
    - Unemployment
    - Job
    - Income crime
    - Job/ crime
    - Jail
  - Income crime to
    - Unemployment
    - Jail
    - Job/ crime
  - Job/ crime to
    - Unemployment
    - Same job
    - Income crime
    - Jail
    - Employment/ crime
  - Other crimes to
    - Unemployment
    - Job
    - Jail to
  - Jail to
    - Unemployment
    - Job
- Additional moments
  - Share of months income crime
  - Share of months other crime
  - b0 : w(t) = b0+b1*other crimes(t-1)
  - b1 : w(t) = b0+b1*other crimes(t-1)
  - b0: w(t) = b0 +b1*employed/criminal(t)
  - b1: w(t) = b0 +b1*employed/criminal(t)

Notes:

1. Adjusted durations are calculated as the sum of durations of censored and uncensored spells over the number of uncensored spells.

Table 6: Baseline Model - Data and Estimated Moments

	Data		Model	
	Moment	Standard Error of Moment	Moment	Standard Error of Moment
Earnings				
Average legal earnings	7.422	*0.016*	7.429	*0.003*
Standard deviation legal earnings	0.435	*0.010*	0.436	*0.002*
Average criminal earnings	7.915	*0.098*	7.879	*0.018*
Standard deviation criminal earnings	1.281	*0.057*	1.298	*0.013*
Adjusted durations				
Unemployment duration	6.890	*0.313*	6.958	*0.054*
Job duration	7.810	*0.311*	7.867	*0.060*
Income crime duration	5.023	*0.349*	5.265	*0.080*
Jail duration	13.204	*0.939*	13.691	*0.163*
Job/Crime duration	3.350	*0.389*	3.517	*0.096*
Other crimes duration	2.044	*0.171*	2.140	*0.038*
Conditional transitions				
Unemployment to				
Job	0.548	*0.021*	0.544	*0.003*
Income crime	0.095	*0.011*	0.103	*0.002*
Jail	0.229	*0.015*	0.227	*0.003*
Other crime	0.127	*0.013*	0.126	*0.002*
Job to				
Unemployment	0.475	*0.020*	0.469	*0.003*
Job	0.332	*0.018*	0.340	*0.003*
Income crime	0.035	*0.006*	0.038	*0.001*
Job/crime	0.057	*0.012*	0.049	*0.002*
Jail	0.070	*0.010*	0.072	*0.002*
Other crime	0.031	*0.006*	0.031	*0.001*
Income crime to				
Unemployment	0.339	*0.032*	0.355	*0.007*
Job	0.060	*0.016*	0.019	*0.002*
Jail	0.532	*0.035*	0.544	*0.007*
Employment/crime	0.069	*0.016*	0.083	*0.004*
Job / crime to				
Unemployment	0.024	*0.017*	0.023	*0.004*
Same job	0.500	*0.076*	0.548	*0.012*
New job	0.048	*0.025*	0.001	*0.001*
Income crime	0.262	*0.057*	0.247	*0.011*
Jail	0.119	*0.038*	0.140	*0.009*
Job/ crime	0.048	*0.027*	0.041	*0.005*
Other crimes to				
Unemployment	0.520	*0.042*	0.527	*0.008*
Job	0.170	*0.027*	0.173	*0.006*
Income crime	0.150	*0.025*	0.129	*0.006*
Jail	0.160	*0.027*	0.171	*0.006*
Jail to				
Unemployment	0.696	*0.024*	0.704	*0.005*
Job	0.177	*0.020*	0.182	*0.004*
Income crime	0.127	*0.017*	0.115	*0.003*
Additional moments				
Share of months income crime	0.096	*0.009*	0.094	*0.001*
Share of months other crime	0.027	*0.003*	0.023	*0.000*
b0 : w(t) = b0+b1*other crimes(t-1)	7.341	*0.020*	7.325	*0.004*
b1 : w(t) = b0+b1*other crimes(t-1)	0.046	*0.090*	0.086	*0.018*
b0: w(t) = b0 +b1*job/criminal(t)	7.191	*0.123*	7.289	*0.037*
b1: w(t) = b0 +b1*job/criminal(t)	0.267	*0.171*	0.264	*0.040*
Minimum earnings				
Legal earnings		332.67		
Criminal earnings		81.11		

Notes:

1. Adjusted durations are in months and are calculated as the sum of durations of censored and uncensored spells over the number of uncensored spells.

2. Minimum earnings are monthly.

Table 7: Baseline Model - Parameter Estimates

Parameter	Estimate	Standard Error
mu_w	7.3131	0.0548
var_w	0.1989	0.0352
mu_y	7.6269	0.1209
var_y	1.8901	0.1454
kappa	0.0757	0.0065
lambda_u	0.0786	0.0091
eta_u	0.0152	0.0040
nu_u	0.0185	0.0020
pi_u	0.0333	0.0027
lambda_e	0.1188	0.0115
eta_e	0.0132	0.0035
delta_e	0.0608	0.0033
nu_e	0.0040	0.0033
pi_e	0.0090	0.0032
lambda_c	0.0425	0.0330
tau_c	0.0675	0.0090
pi_c	0.1059	0.0098
lambda_ec	0.0396	0.0498
tau_ec	0.1529	0.1247
pi_ec	0.0355	0.0297
delta_ec	0.0628	0.0258
lambda_cz	0.0922	0.0185
eta_cz	0.0679	0.0350
tau_cz	0.2544	0.0324
pi_cz	0.0783	0.0150
rho_e	0.1828	0.0255
rho_c	0.1127	0.0354
alpha_j	410.26	1,625.61
alpha_z	1,365.07	2,756.88
alpha_l *	1,101.22	[-353.9 ; 2,439.4]
alpha_c *	2,749.58	[-1,640.4 ; 8,112.4]

Notes:

1. Arrival rates are monthly.

* In the brackets are the 95% confidence intervals from bootstrapping with 500 draws.

Table 8: The effect of criminal opportunities and job destruction rates on average durations

	(1) Baseline	(2) No criminal opportunities	(3) No exogenous separation from jobs	(4) No criminal opportunities and no exogenous separations from jobs
Average unemployment duration	6.42	7.91	7.34	7.88
Average job duration	7.06	7.77	12.09	13.08

Notes:

1. Durations are in months.

2. The first column shows the predicted outcomes of the model using the baseline parameter estimates. In Column 2, I simulate a scenario in which there are no criminal opportunities (i.e. η=0 and v=0). In the third column I simulate a scenario in which jobs are not exogenously destroyed (δ=0). In the last column I simulate a scenario without criminal opportunities and exogenous destruction of jobs. In each case, the rest of the parameters are set equal the baseline.

Table 9: Parameter Estimates - Sensitivity Analysis

Parameter	(1) 5% at bottom, 1% at top		(2) 1% at bottom, 5% at top		(3) 5% at bottom, 5% at top	
	Estimate	**Standard Deviation**	**Estimate**	**Standard Deviation**	**Estimate**	**Standard Deviation**
mu_w	7.3161	*0.0552*	7.3153	*0.0246*	7.3158	*0.0365*
var_w	0.1978	*0.0724*	0.1974	*0.0138*	0.1959	*0.0316*
mu_y	7.6254	*0.2478*	7.5685	*0.1398*	7.7359	*0.2325*
var_y	1.8882	*0.3588*	1.6471	*0.0516*	1.3765	*0.3332*
kappa	0.0757	*0.0056*	0.0757	*0.0055*	0.0757	*0.0061*
lambda_u	0.0791	*0.0131*	0.0792	*0.0052*	0.0793	*0.0057*
eta_u	0.0159	*0.0049*	0.0138	*0.0033*	0.0137	*0.0038*
nu_u	0.0185	*0.0027*	0.0185	*0.0019*	0.0185	*0.0018*
pi_u	0.0333	*0.0042*	0.0333	*0.0033*	0.0333	*0.0026*
lambda_e	0.1172	*0.0361*	0.1143	*0.0136*	0.1172	*0.0107*
eta_e	0.0133	*0.0025*	0.0136	*0.0038*	0.0123	*0.0024*
delta_e	0.0608	*0.0043*	0.0608	*0.0037*	0.0608	*0.0038*
nu_e	0.0040	*0.0033*	0.0040	*0.0033*	0.0040	*0.0033*
pi_e	0.0090	*0.0015*	0.0090	*0.0013*	0.0090	*0.0011*
lambda_c	0.0345	*0.0202*	0.0403	*0.0321*	0.0338	*0.0176*
tau_c	0.0675	*0.0089*	0.0675	*0.0157*	0.0675	*0.0122*
pi_c	0.1059	*0.0089*	0.1059	*0.0106*	0.1059	*0.0169*
lambda_ec	0.0441	*0.0252*	0.0389	*0.0356*	0.0469	*0.0380*
tau_ec	0.1551	*0.0315*	0.1544	*0.0373*	0.1548	*0.0336*
pi_ec	0.0355	*0.0192*	0.0355	*0.0250*	0.0355	*0.0122*
delta_ec	0.0585	*0.0486*	0.0608	*0.0578*	0.0554	*0.0116*
lambda_cz	0.0887	*0.0231*	0.0912	*0.0202*	0.0841	*0.0180*
eta_cz	0.0738	*0.0577*	0.0762	*0.0248*	0.0701	*0.0341*
tau_cz	0.2544	*0.0312*	0.2544	*0.0269*	0.2544	*0.0337*
pi_cz	0.0783	*0.0190*	0.0783	*0.0160*	0.0783	*0.0170*
rho_e	0.1820	*0.0270*	0.1824	*0.0242*	0.1804	*0.0240*
rho_c	0.1349	*0.0405*	0.1280	*0.04*	0.1353	*0.0562*
alpha_j	129.39	*1,950.66*	686.46	*896.08*	10.36	*1,100.52*
alpha_z	1,344.06	*2,506.31*	981.46	*1,158.18*	1,481.89	*2,262.65*
alpha_l *	1,201.59	*[-1,531.4 ; 3,222.1]*	962.10	*[149.8 ; 1,725.7]*	1,288.56	*[-194.1 ; 2,367.2]*
alpha_c *	3,078.66	*[-4,073.9 ; 7,679.3]*	2,127.08	*[-290.1 ; 4,849.9]*	3,247.29	*[-1,465.4 ; 6,758.7]*
Minimum Legal Earnings	332.67		332.67		332.67	
Minimum Criminal Earnings	207.39		81.11		207.39	

Notes:

1. Arrival rates and minimum earnings are monthly.

2. In Column 1, I estimate the model using a trimming percentage of 5 % at the bottom and 1% at the top of the criminal earnings distribution. In Column 2, I use a trimming percentage of 1% in the bottom and 5% in the top for the criminal earnings distribution. Finally, column 3 uses a 5% trimming percentage in the top and the bottom of the criminal earnings distribution.

* In the brackets are the 95% confidence intervals from bootstrapping with 500 draws.

Table 10: Parameter Estimates - Observed Heterogeneity

	(1) Males Only		(2) Arizona		(3) Pennsylvania	
	Estimate	Standard Deviation	Estimate	Standard Deviation	Estimate	Standard Deviation
mu_w	7.3238	*0.0592*	7.3437	*0.0303*	7.2506	*0.1912*
var_w	0.2024	*0.0300*	0.1787	*0.0160*	0.2318	*0.1278*
mu_y	7.6790	*0.1502*	6.7792	*0.1941*	8.2375	*0.2637*
var_y	1.7166	*0.1421*	2.5468	*0.1110*	1.4476	*0.3116*
kappa	0.0731	*0.0078*	0.0810	*0.0091*	0.0698	*0.0131*
lambda_u	0.0829	*0.0098*	0.0893	*0.0093*	0.0687	*0.0118*
eta_u	0.0160	*0.0050*	0.0110	*0.0054*	0.0190	*0.0048*
nu_u	0.0198	*0.0031*	0.0227	*0.0034*	0.0139	*0.0031*
pi_u	0.0380	*0.0032*	0.0366	*0.0045*	0.0295	*0.0084*
lambda_e	0.1232	*0.0131*	0.1364	*0.0154*	0.0848	*0.0182*
eta_e	0.0149	*0.0024*	0.0213	*0.0069*	0.0129	*0.0024*
delta_e	0.0596	*0.0043*	0.0506	*0.0045*	0.0840	*0.0086*
nu_e	0.0044	*0.0040*	0.0041	*0.0034*	0.0038	*0.0045*
pi_e	0.0102	*0.0028*	0.0092	*0.0014*	0.0085	*0.0024*
lambda_c	0.0463	*0.0179*	0.0642	*0.0189*	0.0703	*0.0352*
tau_c	0.0653	*0.0132*	0.0766	*0.0126*	0.0604	*0.0109*
pi_c	0.1080	*0.0231*	0.1149	*0.0157*	0.0991	*0.0158*
lambda_ec	0.0431	*0.0419*	0.0559	*0.0878*	0.0413	*0.1277*
tau_ec	0.1476	*0.1155*	0.1729	*0.0662*	0.1064	*0.0970*
pi_ec	0.0368	*0.0253*	0.0254	*0.0259*	0.0601	*0.0278*
delta_ec	0.0631	*0.0512*	0.0819	*0.0309*	0.0718	*0.0966*
lambda_cz	0.0860	*0.0839*	0.0919	*0.0183*	0.0762	*0.0969*
eta_cz	0.0673	*0.0401*	0.0896	*0.0792*	0.1108	*0.0846*
tau_cz	0.2469	*0.0411*	0.2577	*0.0620*	0.2485	*0.2030*
pi_cz	0.0832	*0.0674*	0.0808	*0.0167*	0.0739	*0.0774*
rho_e	0.1901	*0.0263*	0.2368	*0.0314*	0.0822	*0.0215*
rho_c	0.1229	*0.0357*	0.1661	*0.0820*	0.1305	*0.0599*
alpha_j	221.59	*2,458.67*	841.37	*868.45*	39.30	*2,377.92*
alpha_z	1,471.96	*4,659.92*	1,078.00	*1,604.94*	-176.59	*4,024.11*
alpha_l *	1,341.93	*[-1,343.3 ; 4,472.1]*	1,251.29	*[166.6 ; 2,119.1]*	716.31	*[-5746.1 ; 1,831.2]*
alpha_c *	3,307.44	*[-295.8 ; 10,394.2]*	2,193.24	*[-1,165.1 ; 5,240.5]*	2,590.13	*[-8,781.5; 10,215.5]*
Number of spells	3,210		2,097		1,430	

Notes:

1. Arrival rates and minimum earnings are monthly.

2. In column 1, I estimate the model on a sample of males only. In Columns 2 and 3 I estimate the model using individuals originally located in Arizona and Pennsylvania respectively.

* In the brackets are the 95% confidence intervals from bootstrapping with 500 draws.

Table 11: Illustration of Results - Simulations

	(1) Baseline	(2) Increase in the Arrival Rate of Job Offers (100%)	(3) Increase in Average Legal Earnings Offered (50%)	(4) Reduction in the Destruction Rate of Legal Jobs (50%)	(5) Reduction in the Sentence Length (50%)	(6) Increase in the Arrest Rate (50%)	(7) Increase in Unemployment Benefits (+ $500 per month)
Monthly distribution across states							
Fraction Unemployed (U)	29.90	21.59	30.42	22.89	26.86	27.37	36.03
Fraction Employed (E)	35.58	49.67	37.56	47.24	32.56	33.04	26.94
Fraction Criminal (C+Z+EC)	7.83	6.32	6.61	6.68	6.19	5.71	8.05
Fraction Incarcerated (J)	26.69	22.43	25.40	23.19	34.40	33.88	28.99
Monthly Earnings (dollars)							
Average accepted legal earnings	1,399.1	1,475.4	2,079.4	1,508.5	1,391.8	1,379.7	1,558.5
Average accepted criminal learnings	3,912.8	4,466.5	4,804.5	4,507.8	4,517.7	4,179.7	4,033.3
Durations (in months)							
Average unemployment duration	6.42	4.40	6.50	6.45	6.49	5.87	7.67
Average job duration	7.06	6.01	7.16	8.94	7.11	6.89	7.70

Notes:

1. The first column shows the predicted outcomes of the model using the baseline parameter estimates. In Column 2 I increase each arrival rate of job offers by 100%. In Column 3 I increase the mean of the legal earnings distribution by 5.5% which is equivalent to a 50% in crease in legal earnings offered. In Column 4, the destruction rates of legal jobs decrease by 50%. In columns 5 and 6, the arrest rate and the release rate increase and decrease by 50% respectively. In the last column I simulate an increase in unemployment benefits by adding $500 to the value of unemployment, other crimes, and income crimes. In each case, the rest of the parameters remain unchanged.

Table 12: Achieving a 1 percentage point reduction in the monthly crime rate

Target Period	(1) Increase in Average Sentence Length			(2) Wage Subsidy		
	Extra Time Incarcerated (months)	Annual Direct Cost per Youth Offender (dollars)	Annual Full Cost per Youth Offender (dollars)	Monthly wage subsidy (dollars)	Annual Direct Cost per Youth Offender (dollars)	Annual Full Cost per Youth Offender (dollars)
One year after implementation	7.4	882.0	726.9	770.0	3,481.6	3,345.5
Five years after implementation	3.7	1,013.6	884.5	610.0	2,805.5	2,495.5

Notes:

1. In Column 1 , I calculate the necessary increase in the average sentence length in order to achieve a 1%-point average reduction in the monthly crime rate for the two different periods targeted. The annual direct cost of the increase in the average sentence length accounts for the extra cost incured as a consequence of having additional people incarcerated. I use the average annual cost per inmate in Pennsylvania and Arizona (Bureau of Justice Statistics, State Prison Expenditures 2001, DOJ). The full cost includes the direct cost plus the change in unemployment benefits paid due to a potential change in the number of people unemployed, plus the change in income taxes collected due to a possible change in the number of wage-employed workers. I assume that unemployment benefits are 550 dollars per month and the tax rate on income is 13.8%. In column 2, I do a similar exercise but the policy instrument is now a subsidy wage paid to each serious offender. The annual direct cost accounts for the amount paid to each serious offender working in the legal sector. The full cost includes the direct cost plus the change in prison expenditures due to a possible change in the prison population, plus the change in unemployment benefits paid due to a potential change in the number of people unemployed, plus the change in income taxes collected due to a possible change in the number of wage-employed workers.
2. The cost per youth offender is calculated as the total cost over the number of individuals simulated.

Table 13: Policy Simulations: A one-time job placement program, a wage subsisdy, and a reduction in the release rate.

Target Period	(1) One-time Job Placement after Jail: Monthly Wage Offered (dollars)	(1) Annual Direct Cost per Youth Offender (dollars)	(1) Annual Full Cost per Youth Offender (dollars)	(2) Increase in Average Sentence Length: Extra Time Incarcerated (months)	(2) Annual Direct Cost per Youth Offender (dollars)	(2) Annual Full Cost per Youth Offender (dollars)	(3) Wage Subsidy: Monthly Wage Subsidy (dollars)	(3) Annual Direct Cost per Youth Offender (dollars)	(3) Annual Full Cost per Youth Offender (dollars)
One year after implementation	1,100.0	761.8	247.8	4.2	569.8	467.9	560.0	2,478.0	2,365.7

Notes:

1. In Column 1 , I simulate a one time job placement program that offers current inmates a minimum wage job once they are released. The annual direct cost accounts for the cost of the wage paid to each released inmate for the duration of that job. The full cost includes the direct cost plus the change in unemployment benefits paid due to a potential change in the number of people unemployed, plus the change in income taxes collected due to a possible change in the number of wage-employed workers. I use the average annual cost per inmate in Pennsylvania and Arizona (Bureau of Justice Statistics, State Prison Expenditures 2001, DOJ). I also assume that unemployment benefits are 550 dollars per month and the tax rate on income is 13.8%. In Columns 2 and 3 I calculate the necessary increase in the average sentence length and the amount of a wage subsidy in order to achieve the same crime reduction obtained by the job placement program in the first year of implementation. The annual direct cost of the increase in the average sentence length accounts for the extra cost incured as a consequence of having additional people incarcerated. The full cost includes the direct cost plus the change in unemployment benefits paid due to a potential change in the number of people unemployed, plus the change in income taxes collected due to a possible change in the number of wage-employed workers. The annual direct cost of the wage subsidy accounts for the amount paid to each serious offender working in the legal sector. The full cost includes the direct cost plus the change in prison expenditures due to a possible change in the prison population, plus the change in unemployment benefits paid due to a potential change in the number of people unemployed, plus the change in income taxes collected due to a possible change in the number of wage-employed workers.

2. The cost per youth offender is calculated as the total cost over the number of individuals simulated.