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Essays on crime and search frictions

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ESSAYS ON CRIME AND SEARCH FRICTIONS

by

Bryan Engelhardt

An Abstract

Of a thesis submitted in partial fulfillment of the
requirements for the Doctor of Philosophy
degree in Economics
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The University of Iowa

May 2008

Thesis Supervisor: Professor M. Beth Ingram

ABSTRACT

In this dissertation, I investigate how government policies influence an individual's decision to search for and accept a job or crime opportunity.

Chapter 1 looks at how long it takes for released inmates to find a job, and when they find a job, how their incarceration rate changes. The purpose is to predict the effects of a successful job placement program. An on-the-job search model with crime is used to model criminal behavior, derive the estimates and analyze different types of policies. The results show the unemployed are incarcerated twice as fast as the employed and take on average four and a half months to find a job. Combining these results, it is demonstrated that reducing the average unemployment spell of criminals by two months reduces crime and recidivism by more than five percent.

Chapter 2 incorporates crime into a search and matching model of the labor market. All workers, irrespective of their labor force status, can commit crimes and the employment contract is determined optimally. The model is used to study, analytically and quantitatively, the effects of various labor market and crime policies such as unemployment insurance, hiring subsidies and the duration of jail sentences. For example, wage subsidies reduce unemployment, the crime rates of employed and unemployed workers, and improve society's welfare.

Chapter 3 investigates a market where wholesalers search for retailers and retailers search for consumers. I show how the timing, targets and types of anti-drug policies matter. For instance, supply falls if the likelihood of apprehension rises when a network is established. Alternatively, if the cost of apprehension rises for wholesale dealers when a network is searching for consumers, then revenue sharing is distorted. Such a distortion will increase retail profits and aggregate supply. As an application, the model provides an alternative explanation for why the United States cocaine market saw rising consumption and falling prices during the 1980's. Specifically, the "War on Drugs" distorted the cocaine market and increased supply.

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CERTIFICATE OF APPROVAL

PH.D. THESIS

This is to certify that the Ph.D. thesis of

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Peter Rupert

To the one who listens.

The punishment of criminals should be of use; when a man is hanged he is good for nothing.

— Voltaire

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ABSTRACT

In this dissertation, I investigate how government policies influence an individual's decision to search for and accept a job or crime opportunity.

Chapter 1 looks at how long it takes for released inmates to find a job, and when they find a job, how their incarceration rate changes. The purpose is to predict the effects of a successful job placement program. An on-the-job search model with crime is used to model criminal behavior, derive the estimates and analyze different types of policies. The results show the unemployed are incarcerated twice as fast as the employed and take on average four and a half months to find a job. Combining these results, it is demonstrated that reducing the average unemployment spell of criminals by two months reduces crime and recidivism by more than five percent.

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Chapter 3 investigates a market where wholesalers search for retailers and retailers search for consumers. I show how the timing, targets and types of anti-drug policies matter. For instance, supply falls if the likelihood of apprehension rises when a network is established. Alternatively, if the cost of apprehension rises for wholesale dealers when a network is searching for consumers, then revenue sharing is distorted. Such a distortion will increase retail profits and aggregate supply. As an application, the model provides an alternative explanation for why the United States cocaine market saw rising consumption and falling prices during the 1980's. Specifically, the "War on Drugs" distorted the cocaine market and increased supply.

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CHAPTER 1
THE EFFECT OF EMPLOYMENT FRICTIONS ON CRIME: THEORY AND ESTIMATION

1.1 Introduction

Empirical research has documented the correlation between crime, inequality and unemployment. Theory claims the unemployed and individuals earning a low wage face lower costs of committing crime and therefore perpetrate more of it. Therefore, if employment frictions contribute to unemployment and inequality, then how would a policy aimed at reducing these frictions affect unemployment, inequality and crime?

Others have asked similar questions. İmrohoroğlu et al. (2000) develop a dynamic general equilibrium model with crime in order to investigate how income redistribution policies influence crime and inequality. Engelhardt et al. (2007) use a search and matching model to see how labor market policies affect crime and unemployment.

Here I take a model that simultaneously captures crime, inequality and unemployment and integrate heterogeneous crime opportunities, agents and firms. After constructing a hybrid model from the related literature, I develop a procedure that estimates the model's parameters. Constructing and estimating the model serves several purposes. First, it confirms the empirical link between crime and unemployment demonstrated by Gould et al. (2002) and others. Furthermore, estimation highlights how heterogeneighty is necessary to simultaneously capture crime, inequality and unemployment. Finally, the structural model with the estimated parameters is used to demonstrate how policies aimed at reducing employment frictions, in particular a successful job placement program, would reduce both unemployment and crime.[1]

In constructing an empirically relevant model, I merge several ideas found in the related literature. In particular, the model I develop builds upon the on-the-job search model of crime proposed by Burdett et al. (2004) by integrating heterogeneous types of agents and firms as found in Burdett and Mortensen (1998). I add heterogeneous crime opportunities following Engelhardt et al. (2007). The resulting characteristics of the hybrid model are as follows. First, it takes time for agents to find a job due to labor market frictions and from these frictions unemployment and wage inequality occur. Adding heterogeneous firms enables the model to characterize the observed wage distribution accurately. Adding heterogeneous agents allows the model to explain why some individuals do not engage in crime, a result dependent on how much an individual values his leisure. Finally, incorporating a distribution of crime opportunities captures the fact individuals commit crime at different rates depending on their employment status and earnings.

After constructing a model, I implement an estimation procedure and test whether crime decisions are influenced by employment frictions. The likelihood function is derived from the model and is able to identify employment frictions and incarceration rates using data taken from the National Longitudinal Survey of Youth (NLSY). The main result is that individuals who are unemployed are caught committing crime and imprisoned two times faster than low wage workers and four times

[1] I do not explicitly explain how employment frictions can be reduced except for a small example in Section 3.5. However, several studies have analyzed job placement programs for former inmates including Chung et al. (1991) and Visher et al. (2005).

faster than high wage workers. Moreover, individuals released from jail take an average of four and a half months to find a job.

Next, I turn to policy analysis. Consider, for example, a program capable of cutting the average time it takes for criminals to find a job from four months to two months. What I find is this program could reduce the equilibrium crime rate by more than five percent. Also, the same policy can reduce the recidivism rate by roughly the same amount. As an alternative tool for fighting crime, I find the elasticity of crime with respect to the duration of incarceration to be -0.33. This is consistent with Levitt (2004) who finds the elasticity to be between -0.1 and -0.4 depending upon the type of crime.

In evaluating how much employment frictions affect crime, I discover several other interesting results. Specifically, I find further support that the labor market of those previously incarcerated is roughly equal to their peers, a finding in line with Grogger (1995). However, the expected wage offer of the unemployed who have previously been incarcerated is 35% less than those never convicted and incarcerated for a crime. In relation to the literature, I reinforce the claims that demographics are associated with criminal participation, specifically age, race, education and location of residence (urban/rural). Finally, the estimation I propose provides a new approach in testing whether a relationship exists between an individual's criminal participation, employment status and wage.[2] For instance, I find those paid the minimum wage are

[2]All previous studies to my knowledge rely on multi-stage regression models including Grogger (1998), Gould et al. (2002) and Machin and Meghir (2004).

incarcerated 25% less than those who are unemployed, while those paid at the upper end of the wage distribution are imprisoned 75% less. The results are based on the way I assign the upper and lower end of the wage distribution.

Section 3.2 introduces the models environment and characterizes the resulting equilibrium. Section 1.3 outlines the estimation procedure, discusses the estimated parameters including demographic effects, and analyses the accuracy of the model. Finally, Section 3.5 discusses the models policy implications.

1.2 Model

In this section, I present the environment of the model and outline the equilibrium. The derivation of the wage distribution, incarceration rate and unemployment rate is completed in the Appendix.

1.2.1 Environment

The hybrid model is composed of assumptions taken from Burdett and Mortensen (1998), Burdett et al. (2004) and Engelhardt et al. (2007). To begin, there exists a continuum of risk neutral heterogeneous agents and firms who discount the future at rate r. There are two types of firms and two types of agents.

Agents differ by their utility flow when unemployed, which is b_k where $k \in \{c, nc\}$, $b_c < b_{nc}$, and ϕ is the proportion of type c agents. Unemployed agents receive job offers at rate λ_0, observe a wage offer drawn randomly from a wage offer distribution $F(w)$, and if accepted, become employed instantaneously and are paid the wage over the tenure of the job.

The agent's utility flow when employed is equal to the wage. Agents lose jobs at rate δ and receive new job offers at rate λ_1 with a wage drawn randomly from $F(w)$. Given acceptance of a new wage offer, the agent will change jobs instantaneously.

Employed and unemployed agents receive crime opportunities at rate μ.[3] The value of a crime opportunity is drawn from a discrete distribution $\Gamma(g)$ with the set of values g_j where $g_j < g_{j+1}$ on the support $\mathcal{G}$. The timing of the crime opportunities is instantaneous where agents receive a crime opportunity, realize its payoff, and decide whether to take the opportunity. The utility flow of a crime is instantaneous with value g_j.

Agents committing crime are instantaneously caught with probability π, consume z while in jail, and are released with probability ρ.

Firms have a linear production function and differ by their marginal (= average) revenue product p_i, where $i \in \{L, H\}$, $p_L < p_H$, and φ is the proportion of low productivity firms. Firms post and commit to pay two types of wages, $\{w_c, w_{nc}\}$, depending upon the agent's criminal history.[4]

There are several reasons for incorporating heterogenous types of agents, crime opportunities and firms into the environment. First, two types of agents allows for

[3]Even though the arrival rate of crime is independent of an agents labor force status, the employed individuals could commit less crime due to the fact unemployed agents accept crime opportunities that the employed reject. The potential for such a decision comes from adding heterogeneous crime opportunities. Also, allowing for a state dependent μ will not change the estimation results as discussed below.

[4]I assume firms observe an agent's criminal history because the alternative is less realistic. For example, 96% of Human Resource professionals report their companies do background checks according to the Society for Human Resource Management Workplace Violence Survey.

the possibility that some individuals may never commit crime and risk imprisonment because of their high value of leisure (or figuratively freedom). A distribution of crime opportunities is included to enable the model to predict different crime rates conditional on agents employment status and wage. In other words, agents commit crime at different rates because some accept lower value opportunities as their costs of being caught are lower. Finally, a distribution of firm productivities enables the model to fit the wage distribution as demonstrated below.[5]

1.2.2 Characterization of equilibrium

I will characterize the model's equilibrium in the steady state. To begin, an equilibrium contains a distribution of wage offers made by the firms, $F(w)$. On the supply side, agents maximize utility by following a set of reservation rules. In particular, they follow a reservation wage strategy for taking a job. In other words, an agent of type k accepts any wage above R_k where the reservation wage is determined at the point where agents are indifferent between unemployment and being employed with a wage R_k. The other type of reservation strategy is the reservation crime value. Following the same logic, the crime reservation value is identified at the point where the agent is indifferent between accepting or declining a crime opportunity.

[5]I include only two types of firms because of the limited number of observations. The alternative specification given the limited number of observations would be to assume a parametric form for firm productivity such as in Bontemps et al. (1999). I take the non-parametric approach because it is simple, easily interpreted and I argue sufficient within the context of discussing crime. Bowlus et al. (1995) take a similar approach and estimate the optimal number of firm types to be five. Given the model I propose and estimate, I demonstrate two is adequate. The sample size imposes a constraint because of the link between firm productivity and crime opportunities, which I explain in detail following Proposition 1.2.

For example, the unemployed accept opportunities $g_j > g_u$ where g_u is the crime reservation value of the unemployed and g_j is located on the support $\mathcal{G}$. Finally, an equilibrium contains a mass of individuals incarcerated, unemployed and employed.

Before defining an equilibrium, I provide and discuss several propositions that point out several important features.

To begin, agents with a criminal history can be thought of as operating in an independent labor market. The idea is straight forward. Firms cannot decrease profits by using the information about an agent's criminal history. Therefore, due to the additively separable property of the profit function, the wage offer distribution the criminal agents face, $F_c(w)$, can be considered and solved independently of the distribution the non-criminal agents face, $F_{nc}(w)$. The fact implicitly implies firms observe an agent's criminal history, assume he will commit crime again, and therefore pay him accordingly.

Proposition 1.1 describes why an agent's value of leisure/freedom is important in determining his decision to commit crime.

Proposition 1.1. *If $\lambda_1 < \lambda_0$, p_L is sufficiently large, and b_k is greater than a threshold value $\overline{b}$, then type k agents never engage in crime.*

The proof is in the appendix. Intuitively, agents who place a high value on their leisure find the cost of imprisonment to be too high and do not commit crime.

Proposition 1.1 is an appealing result for multiple reasons. First, it simplifies the model's solution. Second, the assumption that agents differ according to the value of leisure, b, has been used in the literature such as Eckstein and Wolpin (1995) to enable the model to fit the observed wage distribution and duration of unemployment simultaneously. Third, it enables the model to accurately capture the observed recidivism and crime rates simultaneously.[6] Finally, the result can provide a intuitive explanation for why some individuals may never engage in crime; they value their freedom.

Given Proposition 1.1, I assume a fraction of agents never commit crime or $b_c < \bar{b} < b_{nc}$. The assumption is reasonable for two reasons. First, the model cannot match crime rates and recidivism rates simultaneously with homogeneous agents. Second, I observe a large number of individuals who are never incarcerated.

From the assumption $b_c < \bar{b} < b_{nc}$, the wage offer distributions $F_c(w)$ and $F_{nc}(w)$ can be solved using only one type of agent. Although characterizing the "criminal labor market" with homogeneous agents is simplistic, it is appealing because it allows for a more transparent discussion about the effects of employment frictions

[6]With homogeneous b, the estimated model either overestimates the crime rate or underestimates the recidivism rate. For example, take the best case scenario by assuming the lower bound on the amount of crime committed. If the model's crime rate is positive then the unemployed must be committing crime. Now, observe a few features of the data. First, the aggregate number of unemployed individuals is approximately 5%. Second, the opportunities an unemployed individual takes to commit crime is approximately 1 per month. Piehl and DiIulio (1995) contain a detailed discussion of multiple microeconomic data sources for the number of opportunities, all of them quoting roughly 12 per year. Alternatively, the number of crimes a criminal commits per month can be backed out from the recidivism rate given the probability of being caught. In either case, the minimum amount of crime in the model is $(1)(.05) = 5\%$ per month. However, the monthly property crime rate given by the FBI is roughly .03% per month. Hence, the model with homogeneous agents produces more than fifteen times too much crime. From proposition 1.1, we see only a fraction of the population commit crime in the heterogeneous case. Thus, the model can produce an appropriate amount of crime given the mass of criminal agents is relatively small. Note, I estimate similar values for the number of crimes committed by an individual as found in Piehl and DiIulio (1995) given π is roughly 2.5%.

on crime as the results are not conditional on an agents type. The next simplification to the model's equilibrium and addition I make to the theory is

Proposition 1.2. *In equilibrium, if firms of the same type are offering wages above and below the threshold to deter the agent from a crime, then the equilibrium is not Pareto efficient.*

To outline the idea, assume one agent is working and accepts any crime opportunity worth g_j or more. Also, another agent is making a higher wage that deters him from accepting an opportunity worth g_j. Assuming both agents work for the same type of firm, the firm with the worker who takes the g_j opportunity is indifferent in switching to a wage that deters her worker from taking it (otherwise the other firm would deviate since both firms are identical). Therefore, firms are indifferent from deterring a crime opportunity worth g_j, while the criminal agents and their victims are strictly better off. Hence, it is not Pareto efficient if firms of the same type are offering wages above and below the threshold to deter them from g_j.

Given Proposition 1.2, I simplify the equilibrium by assuming that identical type firms deter their workers from the same type of crimes. In words, firms of the same type lose workers at the same rate even though they pay different wages. Individuals paid different wages can commit the same amounts of crime because $\Gamma(g)$ is discrete. Although the assumption might seem restrictive, it can be empirically tested. In addition, it can be relaxed by adding additional firms. From a game theoretic perspective, the assumption can be viewed as allowing only symmetric equilibria.

This leads me to the final simplifying result. Agents do not flow from high productivity firms to low productivity firms, or

Proposition 1.3. *High productivity firms pay higher wages than lower productivity firms.*

The proof is given in the Appendix.

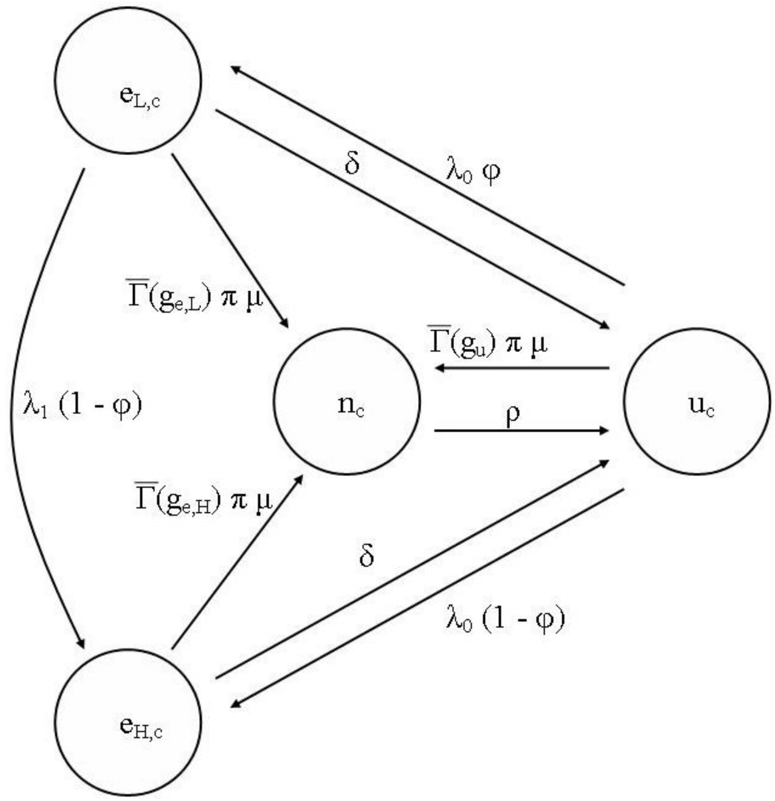
Figure 2.1 demonstrates the flows for an agent choosing to commit crime. At any point in time there is a fraction of agents, $e_{i,k}$, of type k who are employed at type i firms. In addition, there is a fraction of unemployed agents u_k of type k, and a fraction of agents in jail, n_k. To reiterate, agents do not flow from $e_{H,k}$ to $e_{L,k}$ due to Proposition 1.3. Also, as described in Proposition 1.2, individuals employed by the same type of firm are deterred from the same type of crimes. Therefore, employed individuals commit crime at a rate $\mu\overline{\Gamma}(g_{e,i})$, where $\overline{\Gamma}(g_j) = 1 - \Gamma(g_j)$ and $g_{e,i}$ is the highest crime value an agent will choose not to take given he is employed by firm $i \in \{L, H\}$. Finally, the unemployed criminal types commit crime at the same rate, $\mu\overline{\Gamma}(g_u)$, where g_u is the highest crime value the unemployed agent will decline.

At this point, it is important to highlight the reason I incorporate a distribution of crime opportunities into the model. The reason is to allow for different criminal participation rates for those unemployed and employed, or for those paid at the lower or higher end of the wage distribution. Analytically this means, $\overline{\Gamma}(g_{e,H}) \leq \overline{\Gamma}(g_{e,L}) \leq \overline{\Gamma}(g_u)$, because higher productivity firms pay higher wages and the cost of being caught is lower when unemployed than when employed.

An equilibrium of the model is given as

Definition 1.1. *A steady-state equilibrium is defined by*

Figure 1.1: Worker Flows



(i) *a set of reservation wages,* R_k*, for* $k \in \{c, nc\}$ *that maximizes agents' expected utility*

(ii) *crime reservation values conditional on unemployment,* g_u*, employment at low productivity firms,* $g_{e,L}$*, and employment at high productivity firms,* $g_{e,H}$*, which maximize agents' expected utility*

(iii) *a fraction of agents unemployed,* u_k*, employed,* $e_{i,k}$*, and incarcerated,* n_k *for* $k \in \{c, nc\}$ *and* $i \in \{L, H\}$ *that equate the flows in and out of each state*

(iv) *a crime rate*

$$\mu\overline{\Gamma}(g_u)u_c + \mu\overline{\Gamma}(g_{e,L})e_{L,c} + \mu\overline{\Gamma}(g_{e,H})e_{H,c}, \text{ and}$$

(v) a wage offer distribution, $F(w)$, that is based on firms maximizing steady-state profits.

Given the above definition and assumptions, the model has the potential for multiple equilibria as first shown by Burdett et al. (2003). The resulting equilibria can be summarized by the way employment and/or higher wages deter agents from committing crime. The number of potential equilibria could be large depending upon the support of $\mathcal{G}$, but I summarize them as

Characterization of Equilibria[7]

1. $\overline{\Gamma}(g_{e,H}) = \overline{\Gamma}(g_{e,L}) < \overline{\Gamma}(g_u)$,

2. $\overline{\Gamma}(g_{e,H}) < \overline{\Gamma}(g_{e,L}) \leq \overline{\Gamma}(g_u)$, and

3. $\overline{\Gamma}(g_{e,H}) = \overline{\Gamma}(g_{e,L}) = \overline{\Gamma}(g_u)$.

Interpretation of the equilibria is critical in understanding the results. Equilibrium 1 is where employment deters agents from committing crime. In other words, all firms pay wages high enough that when an individual finds a job then he commits less crime. Equilibrium 2 is where high productivity firms, by paying higher wages,

[7]As noted above, if an agent commits crime at all then they commit crime when unemployed. It is seen by realizing the costs of crime when unemployed are not more than when employed.

deter their workers from committing as much crime as when they are unemployed or even employed at a lower paying, lower productivity firm. Finally, Equilibrium 3 is where everyone commits the same amount of crime independent of his wage or labor force status. It is critical to realize that if I am unable to reject Equilibrium 3 then I am unable to claim employment or higher wages deter crime and therefore the justification of a job placement program is lost.

1.3 Estimation

Maximum likelihood Estimation (MLE) is used to estimate the parameters. Given the estimates, I assess the effect employment frictions have on crime.

1.3.1 Data

For estimation of the model I use data from the NLSY, a panel data set initiated within the United States (U.S.) in 1979. Starting in 1989 and ending in 1993, the NLSY contains weekly data on whether or not an individual is incarcerated, while it contains data on an individual's labor force status for the entire panel. The duration of individuals in each state, whether employed, unemployed or incarcerated, along with their wages when employed, are sufficient to identify the relevant parameters of the model. Therefore, the model is estimated using data starting in 1989.

From Proposition 1.1 and assumption $b_c < \overline{b} < b_{nc}$, I break the sample into two subgroups, criminals and non-criminals, or $\{b_c, b_{nc}\}$. I identify an individual as a criminal if I observe him to be incarcerated during the sample period. If I never observe an individual to be incarcerated, I partition him into the non-criminal sub-sample.[8] In order to minimize the effects of business cycles, I reduce the flow sampling to those entering the unemployed state between 1989 and 1991. In assuming observations are missing at random, I exclude them. In addition, anyone exiting the labor market is excluded as it is likely the behavior of such and individual, at least in a certain period, deviates substantially from the behavior as described in the model.

The descriptive statistics are found in Table 1.1. For the non-criminal subgroup, the data begins with a duration of unemployment, t_1. Unemployment is interrupted by an agent becoming employed, $d_{1,e}$. Once employed the wage is observed, $\tilde{w}$. The length of time an agent is employed at his first job is recorded as t_2. At the end of the employment period, the labor force status the agent transitions to is recorded. The agent transitions to unemployment, $d_{2,u} = 1$, or become employed with another firm, $d_{2,e}$.

For the criminal subgroup, the data also begins with a period of unemployment, t_1. However, prior to this period an individual could have been incarcerated and the time they spent incarcerated is t_0, which is potentially left censored. For the criminal sub-group, unemployment is interrupted and observed by either an agent going to jail, $d_{1,n} = 1$, or becoming employed, $d_{1,e} = 1$. If employed, the wage is observed, $\tilde{w}$. If the agent is incarcerated then the construction of the individual's panel is complete. However, if the agent becomes employed then the duration of employ-

[8] This type of partitioning creates latent variable bias when estimating the parameters of the non-criminal group due to the fact criminal types could be in the non-criminal sample. However, I argue the bias is small due to previous evidence that these groups have similar employment opportunities.

ment is recorded as t_2. At the end of the employment period, the reason for exiting employment is recorded. The reasons include incarceration, $d_{2,n} = 1$, unemployment, $d_{2,u} = 1$, or employment, $d_{2,e} = 1$.

In interpreting an individual's work history, we see the average wage of the criminal type is smaller than non-criminals. Also, we find the average duration of unemployment is smaller. However, a smaller duration does not imply the criminal types find jobs faster but rather they find a job *or* are caught committing crime and imprisoned faster than non-criminals find a job. The same interpretation is true for the duration of employment.

It is important to note an attempt to estimate the model with an increased number of firm types is unreasonable as I observe less than fifty individuals incarcerated while employed. Specifically, a limited number of firms are used because each firm requires the estimation of an additional parameter, $\overline{\Gamma}(g_{e,i})$, and identification of each parameter requires the sample to be bisected for every additional firm. Therefore, I limit the number of firm types, or parameters $\overline{\Gamma}(g_{e,i})$, to two.

1.3.2 Likelihood function

I will break down how the parameters are estimated using MLE. The model implies a particular distribution for all dependent variables. I do not have complete information on all observations due to missing data and censoring (in particular prior convictions). I build the likelihood on the assumption that the data is missing randomly and censoring, with respect to former criminal activity or job

Table 1.1: Work History Sample Means

Variable	Criminals	Non-Criminals	Full Sample
$d_{1,n}$	0.1		0.02
$d_{1,e}$	0.88	0.99	0.97
$d_{2,e}$	0.11	0.19	0.17
$d_{2,u}$	0.4	0.49	0.47
$d_{2,n}$	0.19		0.03
t_0	13.54		2.48
	(10.21)		(6.82)
t_1	3.9	4.64	4.51
	(6.7)	(6.21)	(6.31)
t_2	20.53	26.1	25.08
	(26.18)	(19.44)	(20.81)
$\tilde{w}$	1034.48	1111.45	1097.34
	(560.66)	(705.8)	(684.19)
N	209	931	1140

Note: Standard deviations are in parentheses. Duration and wage statistics are monthly. Unemployment is defined by individuals that claim at least some time is spent searching for work. Employment is defined by those working at least 30 hours per week. The transition probabilities do not sum to one at each stage because the data is right censored.

history, is uninformative. In addition, I assume in the model and estimation that an individual does not transition between criminal and non-criminal states or vice-versa. Assuming individuals exit the criminal state would increase the estimated incarceration rates. The likelihood of the sample is obtained by multiplication of each individual's contribution. To simplify the composition, I outline the criminal likelihood function as the non-criminal likelihood can be deduced by constraining $\mu\pi\overline{\Gamma}(g_u) = \mu\pi\overline{\Gamma}(g_{e,L}) = \mu\pi\overline{\Gamma}(g_{e,H}) = 0$.

In the data I observe criminals exiting jail into unemployment, and from the model the arrival rate of exiting is a Poisson process, therefore the duration of incarceration is exponential. Hence ρ is estimated by

$$P(t_0) = \rho e^{-\rho t_0}.$$

t_0 is the only period that is potentially left censored due to the choice of using flow sampling at the point individuals enter unemployment. Therefore, the likelihood contribution of an individual who is left censored while incarcerated is $P(t_0) = e^{-\rho t_0}$ instead of $P(t_0) = \rho e^{-\rho t_0}$. Going forward, right censoring of the data occurs and is accounted for in estimation but is suppressed until the complete likelihood is composed in Equation 1.1.

At the beginning of the sampling period, individuals are in the unemployed state. They transition out of unemployment according to a Poisson process; therefore the duration of unemployment is exponential, or $P(t_1)$. The likelihood functions is

$$P(t_1) = (\mu\pi\overline{\Gamma}(g_u) + \lambda_0)e^{-(\mu\pi\overline{\Gamma}(g_u)+\lambda_0)t_1}.$$

The likelihood of transitioning to jail or employment after being unemployed, $P(n_{t_1})$ and $P(e_{t_1})$ respectively, is

$$P(n_{t_1}) = \frac{\mu\pi\overline{\Gamma}(g_u)}{\mu\pi\overline{\Gamma}(g_u) + \lambda_0},\ and$$
$$P(e_{t_1}) = \frac{\lambda_0}{\mu\pi\overline{\Gamma}(g_u) + \lambda_0}.$$

Obviously, for the non-criminal sub-group the probability of transitioning to jail is zero. If a criminal type transitions to jail then I end the individual's contribution to the likelihood function. Otherwise, an individual transitions to employment and receives a wage offer from the distribution $f_C(w)$, which is the density function of $F_C(w)$ derived in Equation A.6 in the Appendix.

Depending upon the equilibrium, agents transition out of employment with different probabilities. The differences in transition probabilities arise because employed agents might be employed at low or high productivity firms. On the other hand, Proposition 1.2 argues that those employed by the same type of firm take the same crime opportunities. In other words, agents employed by low productivity firms transition out of employment at the same rate, and those employed at a high productivity firms transition out of employment at the same rate.

From the model, agents employed by type i firms find their average time of employment to be distributed exponentially. Hence, the duration of employment is

$$P(t_2|\tilde{w}) = (\mu\pi\overline{\Gamma}(g_{e,i}) + \lambda_1(1 - F(\tilde{w})) + \delta)e^{-(\mu\pi\overline{\Gamma}(g_{e,i})+\lambda_1(1-F(\tilde{w}))+\delta)t_2}$$

for $i \in \{L, H\}$ depending on if $\tilde{w} \in [\underline{w}_{L,c}, \overline{w}_{L,c}]$ or $\tilde{w} \in [\underline{w}_{H,c}, \overline{w}_{H,c}]$.[9]

The likelihood of transitioning to a job, jail, or unemployment after being employed, $P(e_{t_2})$, $P(n_{t_2})$, and $P(u_{t_2})$, respectively, is

$$\begin{aligned}
P(e_{t_2}|\tilde{w}) &= \frac{\lambda_1(1 - F(\tilde{w}))}{\mu\pi\overline{\Gamma}(g_{e,i}) + \lambda_1(1 - F(\tilde{w})) + \delta}, \\
P(n_{t_2}|\tilde{w}) &= \frac{\mu\pi\overline{\Gamma}(g_{e,i})}{\mu\pi\overline{\Gamma}(g_{e,i}) + \lambda_1(1 - F(\tilde{w})) + \delta}, \ \textit{and} \\
P(u_{t_2}|\tilde{w}) &= \frac{\delta}{\mu\pi\overline{\Gamma}(g_{e,i}) + \lambda_1(1 - F(\tilde{w})) + \delta}.
\end{aligned}$$

In summary, the likelihood function is constructed from

- Wage offers:

$$\tilde{w} \quad = \quad \text{wage received by unemployed} \quad \sim f_C(w)^{10}$$

- Duration times:

[9] As described in the Appendix, $\underline{w}_{i,c}$ and $\overline{w}_{i,c}$ is the lowest and highest wage paid by firms of type i.

[10] The wage offer distribution is

$$f_C(w) = \begin{cases} \frac{\varphi(1+\kappa_1)}{2\kappa_1} \frac{1}{\sqrt{(p_1 - w_{L,c})(p_1 - \underline{w}_{L,c})}} & \text{if} \quad \underline{w}_{L,c} \leq w \leq \overline{w}_{L,c} \\ \frac{(1-\varphi)(1+\kappa_2)}{2\kappa_2} \frac{1}{\sqrt{(p_2 - w_{H,c})(p_2 - \underline{w}_{H,c})}} & \text{if} \quad \underline{w}_{H,c} \leq w \leq \overline{w}_{H,c}, \end{cases}$$

where $\kappa_1 = \frac{\lambda_1\varphi}{\delta + \mu\pi\overline{\Gamma}(g_{e,L}) + \lambda_1(1-\varphi)}$ and $\kappa_2 = \frac{\lambda_1(1-\varphi)}{\mu\pi\overline{\Gamma}(g_{e,H}) + \delta}$. The wage distribution is derived in the appendix including the closed form solutions for $\overline{w}_{L,c}$ and $\overline{w}_{H,c}$.

$$\begin{array}{lcll} t_0 & = & \text{duration of jail} & \sim P(t_0) \\ t_1 & = & \text{duration of unemployment} & \sim P(t_1) \\ t_2|\tilde{w} & = & \text{duration of job, conditional on } \tilde{w} & \sim P(t_2|\tilde{w}) \end{array}$$

- Transition indicators:

$$\begin{array}{lcl} d_{1,e} & = & 1 \text{ if unemployment-to-job transition, otherwise} = 0 \\ d_{1,n} & = & 1 \text{ if unemployment-to-jail transition, otherwise} = 0 \\ d_{2,e} & = & 1 \text{ if job-to-job transition, otherwise} = 0 \\ d_{2,n} & = & 1 \text{ if job-to-jail transition, otherwise} = 0 \\ d_{2,u} & = & 1 \text{ if job-to-unemployment transition, otherwise} = 0 \end{array}$$

- Transition Probabilities:

$$\begin{array}{ll} \text{unemployment-to-job transition} & \sim P(e_{t_1}) \\ \text{unemployment-to-jail transition} & \sim P(n_{t_1}) \\ \text{job-to-job transition, conditional on } \tilde{w} & \sim P(e_{t_2}|\tilde{w}) \\ \text{job-to-jail transition, conditional on } \tilde{w} & \sim P(n_{t_2}|\tilde{w}) \\ \text{job-to-unemployment, conditional on } \tilde{w} & \sim P(u_{t_2}|\tilde{w}) \end{array}$$

The resulting likelihood function given by the model dependent on the observed data (durations and transitions) is

$$l(\theta) = P(t_0)P(t_1)P(n_{t_1})^{d_{1,n}}[P(e_{t_1})f_C(w)P(t_2)\prod_{i=e,u,n} P(i_{t_2})^{d_{2,i}}]^{d_{1,e}}, \tag{1.1}$$

where $\theta = (\rho, \lambda_0, \lambda_1, \delta, \varphi, \mu\pi\overline{\Gamma}(g_u), \mu\pi\overline{\Gamma}(g_{e,L}), \mu\pi\overline{\Gamma}(g_{e,H}), \underline{w}_{L,c}, \underline{w}_{H,c}, \overline{w}_{L,c}, \overline{w}_{H,c})$.[11]

I propose super-efficient estimators

$$\underline{w}_{L,c} = \min\{\tilde{w}\}, \quad \overline{w}_{L,c} = \tilde{w}_{\varphi}, \quad \underline{w}_{H,c} = \tilde{w}_{1-\varphi}, \quad \text{and} \quad \overline{w}_{H,c} = \max\{\tilde{w}\}$$

where the estimators have been shown to be super-efficient; the theory of local cuts (Christensen and Kiefer (1994)) justifies conditioning on these estimates.[12] The notation $\tilde{w}_{\varphi}$ represents the φ percentile of the observed wage distribution, or in other words, φ defines the point between low and high wage workers. Also, φ identifies the rate at which agents are deterred from crime given their wage, or $\mu\pi\overline{\Gamma}(g_{e,L})$ and $\mu\pi\overline{\Gamma}(g_{e,H})$.

The parameters that are not estimated are $(b_c, b_{nc}, z, \mu, \pi, \Gamma(g))$. These estimates are unobtainable due to the inability to measure the value of each crime opportunity, the number of crimes opportunities and the probability of being caught. In effect, the model is estimated from the decisions made by the firms, offered wages and in turn the incarceration rates, while many of the parameters known by the agents

[11]Although suppressed in the text, the likelihood function accounts for both left and right censoring of durations. The simplified form is

$$\begin{aligned} l(\theta) \quad = \quad & \rho^{d_0^n} e^{-\rho t_0} e^{-(\mu\pi\overline{\Gamma}(g_u)+\lambda_0)t_2} (\mu\pi\overline{\Gamma}(g_u))^{d_{1,n}} \\ & [\lambda_0 f_C(w) e^{-(\mu\pi\overline{\Gamma}(g_{e,i})+\lambda_1(1-F(\tilde{w}))+\delta)t_2} (\mu\pi\overline{\Gamma}(g_{e,i}))^{d_{2,n}} (\lambda_1(1-F(\tilde{w})))^{d_{2,e}} \delta^{d_{2,u}}]^{d_{1,e}}, \end{aligned}$$

where $d_0^n = 1$ if the duration of incarceration is not left censored.

[12]These sample extremes serve as estimators of the unknown productivities and reservation wages as discussed in Bowlus et al. (1995). Asymptotically to order $N^{1/2}$ and ignoring the variability in estimates of the reservation wages and productivities, Kiefer and Neumann (1991) show that the bias from these estimates is ignorable for sample sizes over 200.

are not observed and in turn not estimated. However, if data on the total value of crime committed, the aggregate number of crimes committed and the value of the crime when an individual is caught were attainable then the remaining parameters could be estimated. Derivation of the likelihood in such a situation is given in the Appendix as well as an explanation of how the currently estimated parameters and standard errors are left unchanged with the additional data.

1.3.3 Findings

The estimated parameter values are represented in Table 1.2.

The parameter estimates for the labor market frictions provide adequate reason to estimate the criminal market as they are significantly different than what Burdett et al. (2004) use to evaluate a similar model. For instance, the job arrival rate implies on average an individual, either previously incarcerated or not, waits roughly 18 weeks for employment. The estimate is nearly three times greater than values found in related studies including Burdett et al. (2004), or Bowlus et al. (1995) who use the same data set but earlier in the panel. Also, the job separation rate is at least two times faster (higher) than estimates from similar models (van den Berg and Ridder (1998),Bontemps et al. (2000)). On the other hand, on-the-job arrival rates of new jobs are close to related studies.

It is key to note the resulting unemployment rates are consistent with the data. The unemployment rate for non-criminals is 8.5% while the unemployment rate for criminals is 12.5%. The difference arises from the fact that criminals are separated

Table 1.2: Parameters Estimates by b_c, b_{nc}, and the Full Sample

Parameters	Criminals	Non-Criminals	Full Sample
$\hat{\delta}$	0.022	0.02	0.02
	[0.017, 0.028]	[0.018, 0.021]	[0.018, 0.022]
$\hat{\lambda}_0$	0.226	0.213	0.215
	[0.19, 0.277]	[0.2, 0.231]	[0.202, 0.232]
$\hat{\lambda}_1$	0.013	0.011	0.011
	[0.008, 0.018]	[0.01, 0.014]	[0.01, 0.014]
$\hat{\varphi}$	0.794	0.88	0.88
	[0.761, 0.908]	[0.785, 0.897]	[0.783, 0.897]
$\hat{\rho}$	0.051		0.051
	[0.045, 0.057]		[0.045, 0.057]
$\widehat{\mu\pi\overline{\Gamma}(g_u)}$	0.026		0.026
	[0.02, 0.033]		[0.02, 0.033]
$\widehat{\mu\pi\overline{\Gamma}(g_{e,L})}$	0.01		0.012
	[0.007, 0.015]		[0.007, 0.015]
$\widehat{\mu\pi\overline{\Gamma}(g_{e,H})}$	0.011		0.006
	[0.003, 0.02]		[0.003, 0.019]

Note: Arrival rates are monthly. In brackets are the 95% confidence interval from bootstrapping with 500 draws.

from their jobs due to incarceration, and when released, enter unemployment. In support of my results, I note the multi-stage regression approach taken by Grogger (1995) who finds the same results that those previously incarcerated face only a slightly tougher job market.

The key finding from the estimation comes from the parameters $\mu\pi\overline{\Gamma}(g_u)$, $\mu\pi\overline{\Gamma}(g_{e,L})$, and $\mu\pi\overline{\Gamma}(g_{e,H})$. The reason is these estimates allow me to evaluate the equilibrium described in Section 1.2.2.

As shown in Table 1.2, the estimate for $\mu\pi\overline{\Gamma}(g_u)$ is significantly greater than $\mu\pi\overline{\Gamma}(g_{e,L})$ and $\mu\pi\overline{\Gamma}(g_{e,H})$. Therefore, I can reject Equilibrium 3 with confidence. Also, for the full sample I find evidence that agents are deterred from crime when paid a higher wage, or $\mu\pi\overline{\Gamma}(g_{e,H}) < \mu\pi\overline{\Gamma}(g_{e,L})$. Hence, I find evidence that employment and higher wages deter individuals from crime. In other words, economic incentives reduces criminal participation, or $\mu\pi\overline{\Gamma}(g_{e,H}) < \mu\pi\overline{\Gamma}(g_{e,L}) < \mu\pi\overline{\Gamma}(g_u)$.

The reason estimates for the criminal sub-sample are unable to reject Equilibrium 1 arises from how φ is estimated. Estimates for $\mu\pi\overline{\Gamma}(g_{e,L})$ and $\mu\pi\overline{\Gamma}(g_{e,H})$ rely critically on the estimate of φ. On the other hand, φ is estimated through the wage dispersion. As claimed in the introduction, having heterogeneous firms allows me to estimate more adequately wage inequality as shown in Figure 1.2. Alternatively, it might not seem very reasonable to hinge estimates for criminal participation on considerations of the shape of the wage distribution. Therefore, I plot $\mu\pi\overline{\Gamma}(g_{e,L})$ and $\mu\pi\overline{\Gamma}(g_{e,H})$ for $\varphi \in [.05, .95]$ where the end points are excluded due to an inadequate number of observations.

Figure 1.2: Wage Distribution

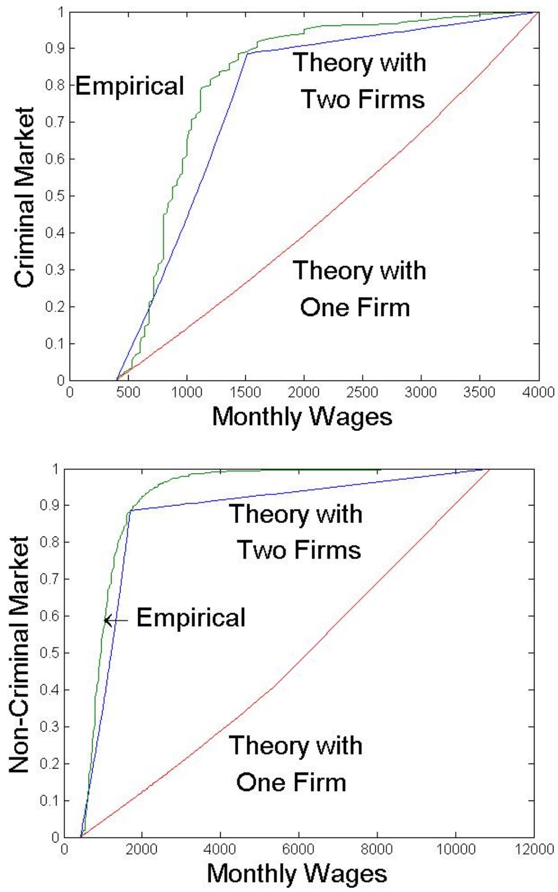
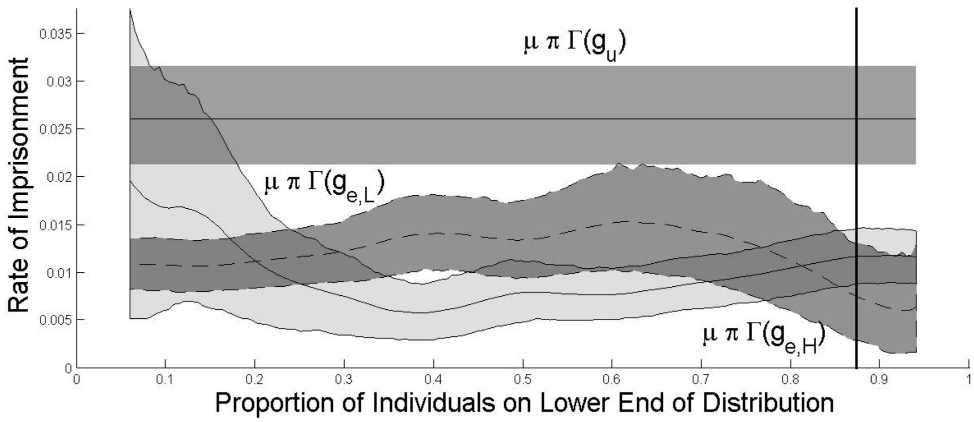


Figure 1.3 demonstrates how wages affect criminal participation. The x-axis is labeled "Proportion of Low Wage Workers" because of the interpretation of how the model is estimated. The interpretation is low productivity firms, or firms who pay lower wages, are differentiated at the point φ. Therefore, φ captures both the fraction of low productivity firms, as well as what is referred to as "the lower end of the wage distribution." Hence, the model is estimated with φ from low to high and the corresponding crime rates are plotted.

Figure 1.3: Criminal Participation with Full Sample



Note: The 15^{th} and 85^{th} percentiles are plotted as confidence bands.

It is interesting to see how wages affect criminal participation differently depending upon how φ is determined. Only at the upper and lower end of the distribution do I find evidence higher wages deter crime, although the confidence interval is too wide at the lower end to provide any significant evidence.

1.3.4 Demographic effects

In previous research it has been found that employment frictions are dependent upon occupation, age, and/or education. In addition, crime is consistently found to be significantly related to race, gender, and an individual's location of residence. I use the same approach as van den Berg and Ridder (1998) to analyze how these variables are related to employment frictions and crime. Specifically, I introduce "heterogeneity by assuming that there are separate labor markets(or segments of the labor market, or sub-markets) for different types of individuals." For example, there exist separate markets for those with different education levels. An alternative argument could be urban/rural areas tend to have thicker/thinner labor markets. The result is the model can be estimated separately by demographic.

The issue with this approach is the large number of observations needed in each category. For instance, I observe very few females or college graduates committing crime. Also, the sample ages range from 24 to 32. Therefore, I am forced to limit the results based on demographic variables in two ways. First, I look at demographics which can be split into two sub-groups, i.e. {Black,White}. Second, I restrict attention to demographics that when split both groups retain at least 25% of the criminal observations. Table 1.3 contains the demographic break down of the sample.

Table 1.5 contains the estimation results from the demographic categories that fall under the restrictions mentioned above. The results show almost universally that the unemployed are caught committing crime at a faster rate. Also, the results demonstrate the rural, those without an education, and black individuals find jobs at slower rate and lose their jobs faster. In addition, the individuals facing a tougher job market tend to commit more crime when unemployed with the exception of high school graduates. The findings align themselves with other empirical studies. For instance, Grogger (1998) and many others find race is correlated with criminal participation. Also, Uggen (2000) finds older criminals have a lower likelihood of criminal participation when employed which is what I find for those employed at the upper end of

Table 1.3: Demographic Sample Means

Variable	Criminals	Non-Criminals	Full Sample
Male	0.92	0.54	0.61
Married	0.13	0.33	0.29
Black	0.53	0.33	0.37
White	0.39	0.61	0.57
Urban	0.74	0.76	0.76
Rural	0.26	0.24	0.24
High School Diploma	0.51	0.74	0.7
Older than 28	0.43	0.44	0.44

the wage distribution. Surprisingly, I find those living in a rural area have a slightly higher incarceration rate which runs contrary to many findings. However, the results on criminal participation have large confidence bands due to the limited number of observations and should be interpreted with caution.

1.3.5 Model evaluation

I have provided evidence that economic incentives play a role in criminal behavior. At this point, I evaluate how well the model predicts recidivism rates as well as the elasticity between crime, incarceration and the likelihood of apprehension.

Policy makers and researchers alike concern themselves with recidivism rates.

Table 1.4: Parameters Estimates by Demographic

	Race		Residence	
	Black	White	Urban	Rural
$\hat{\delta}$	0.026	0.017	0.02	0.02
	[0.023, 0.029]	[0.015, 0.019]	[0.018, 0.022]	[0.017, 0.024]
$\hat{\lambda}_0$	0.171	0.254	0.221	0.201
	[0.151, 0.191]	[0.234, 0.279]	[0.205, 0.24]	[0.175, 0.227]
$\hat{\lambda}_1$	0.015	0.011	0.014	0.009
	[0.011, 0.018]	[0.009, 0.013]	[0.01, 0.015]	[0.008, 0.016]
$\hat{\varphi}$	0.868	0.857	0.793	0.918
	[0.797, 0.923]	[0.766, 0.896]	[0.785, 0.904]	[0.735, 0.918]
$\hat{\rho}$	0.042	0.067	0.048	0.058
	[0.035, 0.051]	[0.055, 0.08]	[0.041, 0.056]	[0.046, 0.074]
$\mu\pi\hat{\overline{\Gamma}}(g_u)$	0.033	0.015	0.024	0.035
	[0.024, 0.045]	[0.011, 0.021]	[0.019, 0.032]	[0.021, 0.06]
$\mu\pi\hat{\overline{\Gamma}}(g_{e,L})$	0.011	0.011	0.011	0.012
	[0.006, 0.017]	[0.005, 0.017]	[0.007, 0.016]	[0.004, 0.02]
$\mu\pi\hat{\overline{\Gamma}}(g_{e,H})$	0.015	0.002	0.009	0.007
	[0.005, 0.043]	[0, 0.016]	[0.002, 0.018]	[0, 0.074]

Note: Arrival rates are monthly. In brackets are the 95% confidence interval from bootstrapping with 500 draws.

Table 1.5: Parameters Estimates by Demographic (continued)

	High School Diploma		Age	
	No	Yes	Under 28	Over 28
$\hat{\delta}$	0.023	0.019	0.02	0.02
	[0.02, 0.027]	[0.017, 0.021]	[0.018, 0.022]	[0.017, 0.022]
$\hat{\lambda}_0$	0.183	0.233	0.223	0.206
	[0.164, 0.205]	[0.216, 0.254]	[0.205, 0.247]	[0.186, 0.227]
$\hat{\lambda}_1$	0.012	0.011	0.013	0.011
	[0.01, 0.016]	[0.01, 0.014]	[0.01, 0.015]	[0.009, 0.015]
$\hat{\varphi}$	0.848	0.87	0.808	0.875
	[0.772, 0.88]	[0.793, 0.902]	[0.76, 0.923]	[0.775, 0.9]
$\hat{\rho}$	0.051	0.05	0.057	0.044
	[0.042, 0.06]	[0.043, 0.059]	[0.048, 0.066]	[0.036, 0.052]
$\widehat{\mu\pi\overline{\Gamma}(g_u)}$	0.021	0.031	0.032	0.018
	[0.014, 0.03]	[0.022, 0.044]	[0.025, 0.042]	[0.009, 0.03]
$\widehat{\mu\pi\overline{\Gamma}(g_{e,L})}$	0.011	0.01	0.008	0.016
	[0.006, 0.019]	[0.005, 0.016]	[0.005, 0.014]	[0.008, 0.025]
$\widehat{\mu\pi\overline{\Gamma}(g_{e,H})}$	0.022	0.002	0.011	0.005
	[0.006, 0.057]	[0, 0.01]	[0.002, 0.025]	[0.001, 0.026]

Note: Arrival rates are monthly. In brackets are the 95% confidence interval from bootstrapping with 500 draws.

Although not previously discussed, the model is set up to evaluate recidivism.[13] The prediction of the recidivism rates for 6, 12, 24, and 36 months are in Table 1.6 using the estimated parameters from the full sample. I am unable to make an exact comparison between the model and the data because the two contain different measures of recidivism. Thus, I include several different measures found in the data. What I see is the estimated model, which captures those returned to prison for new and old offenses, generally lies between the U.S. recidivism rates of those reconvicted and those returned to prison for a new offense.

Besides recidivism, the model is capable of predicting the elasticity of crime with respect to the average time spent incarcerated ($\frac{1}{\rho}$), and the number incarcerated (n_c) from a change in ρ. The elasticities can be calculated from Table 1.7.[14] In general, changes in ρ can have two effects on deterring crime. This exercise captures the incapacitation effect (keeping criminals off the streets), and not the crime deterrence effect. The reason I do not evaluate the deterrence effect is because not all the parame-

[13]The definition of recidivism is given a convicted criminal just left jail, what is the probability he will return within "t" periods. The calculation can be considered as a function of the Markov transition matrix between $(u_c, e_{L,c}, e_{H,c})$ where

$$P = \begin{pmatrix} (1-\lambda_0) & \lambda_0\varphi & \lambda_0(1-\varphi) \\ \delta & (1-\delta)(1-\lambda_1) + (1-\delta)\lambda_1\varphi & (1-\delta)\lambda_1(1-\varphi) \\ \delta & 0 & (1-\delta) \end{pmatrix}.$$

In words, the probability of going to jail in the t^{th} period, $\Phi(t)$, is dependent on if he gets caught, π, the opportunity to commit a crime, μ, if he takes it dependent on his employment state, $(\overline{\Gamma}(g_u)P^t_{1,1} + \overline{\Gamma}(g_{e,L})P^t_{1,2} + \overline{\Gamma}(g_{e,H})P^t_{1,3})$, and he did not go to jail in the previous periods. Analytically it is $\Phi(t) = \pi\mu(\overline{\Gamma}(g_u)P^t_{1,1} + \overline{\Gamma}(g_{e,L})P^t_{1,2} + \overline{\Gamma}(g_{e,H})P^t_{1,3})(1 - Rec_t)$ where the recidivism rate, Rec_t, is he goes to jail before the t^{th} period, or $Rec_t = \sum_{i=1}^{t}\Phi(i)$.

[14]Estimates for the recidivism rate and wage distribution are excluded because they are not a function of ρ.

Table 1.6: Prediction of Recidivism Rates

	Model with Full Sample	U.S. Data Rearrested	Reconvicted	Returned to prison for new offense
Rec_6 (%)	11.5	29.9	10.6	5.1
Rec_{12} (%)	18.7	44.1	21.5	10.6
Rec_{24} (%)	30.2	59.2	36.4	19.2
Rec_{36} (%)	39.9	67.4	46.2	25.8

Note: U.S. data are reported by the Bureau of Justice Statistics for the time period 1994-1997.

ters are identified in the estimation procedure. On the other hand, a sufficiently small change in ρ only alters the incapacitation effect and not the equilibrium/deterrence effect because $\Gamma(g)$ is discrete.

I find the elasticity of crime with respect to the average time spent incarcerated, $\frac{1}{\rho}$, to be -0.18. My findings are an improvement from previous models such as Burdett et al. (2004) as my results align themselves with several other empirically based studies outlined in Levitt (2004) who argues "Typical estimates of elasticities of crime with respect to expected punishment range from -0.1 and -0.4 (depending upon the crime)."

Alternatively, the elasticity of crime with respect to the prison population

Table 1.7: Changes in the Duration of Incaceration (ρ)

	ρ		
	0.031	0.051	0.071
Unemployed Criminals (%)	8.9	10	10.6
Incarcerated Criminals (%)	29.2	20.1	15.3
Employed Criminals (%)	61.9	69.9	74.1
Crime Index	88.54	100	105.99

Note: Crime is indexed because π is not uniquely identified.

has been debated. The question's relevance is rooted in the costs prisons impose on state and federal budgets. My estimate of the elasticity of crime with respect to the population incarcerated due to a rise in ρ is -0.25 and is in line with Levitt (1996) who states "elasticities(of crime) with respect to prison populations range from -0.147 to -0.703 (depending upon the crime)."

The final comparison I make is how crime rates change with respect to the probability of being caught. I find the elasticity of crime with respect to the probability of apprehension to be -0.19 as seen in Table 1.8. How the estimate compares to the literature is not completely clear as it is hard to measure. However, Levitt (1997) finds the elasticity of crime with respect to the number of police to be between -0.05 and -1.98. Therefore, if the apprehension technology is linear in the quantity of police then my estimate is within the range of the crime literature albeit the range is large.

Finally, it is important to point out that an increase in π destroys jobs. Table 1.8 shows an increase in the probability of being caught reduces the amount of employed criminals.

Table 1.8: Changes in the Likelihood of Apprehension (π)

	Likelihood of Apprehension Index		
	50	100	150
Unemployed Criminals (%)	9.4	10	10.4
Incarcerated Criminals (%)	10.9	20.1	27.8
Employed Criminals (%)	79.6	69.9	61.8
Crime Index	109.01	100	92.26
Rec_{12}	9.79	18.7	26.81
Rec_{36}	22.42	39.93	53.58
Average Wage of Criminals	1306.33	1202.67	1123.46

Note: Crime and the likelihood of apprehension are indexed because π is not uniquely identified.

To reiterate, the model shows it is able to accurately predict the appropriate elasticities of crime with respect to time incarcerated, the size of the prison population and the likelihood of apprehension. In addition, the model is in the range of U.S. recidivism rates while accurately capturing crime, inequality, and unemployment. The results are innovative within the crime literature because the predictions are based on estimates from a structural model.

1.4 Policy discussion

The main result highlighted in the introduction is that reductions in labor market frictions can reduce crime. Although the model does not explain how frictions are reduced, Wilson et al. (1999), Visher et al. (2005) and others analyze the effectiveness of specific job placement programs. Alternatively, I calculate in Table 1.9 the effects of a *successful* program. Specifically, how does crime change given a placement program that works. I find the elasticity of crime with respect to the average time unemployed ($\frac{1}{\lambda_0}$) to be 0.11. Also, recidivism falls as it becomes easier to find a job. The reason is individuals commit less crime when employed, half as much. Therefore, if released inmates find jobs faster then they commit fewer crimes and do not return as quickly. In effect, reducing employment frictions by half could reduce crime and recidivism by more than five percent. Note you can see the effect is purely employment driven as the average wage is constant.

The elasticity of a job placement program might seem "small." However, the policy is primarily affecting a small part of the population, the unemployed. In addition, U.S. law enforcement observes roughly ten million crimes per year. Therefore, a five percent reduction would eliminate more than a half of a million crimes annually. Finally, other anti-crime policies have a "small" elasticity such as an increase in incarceration. Therefore, the costs are essential in evaluating the success of a job placement program.

Table 1.9: Changes in the Unemployed Job Arrival Rate (λ_0)

	λ_0		
	0.108	0.215	0.43
Unemployed Criminals (%)	17.4	10	5.4
Incarcerated Criminals (%)	21.9	20.1	18.9
Employed Criminals (%)	60.7	69.9	75.6
Crime Index	109	100	94.39
Rec_{12} (%)	21.6	18.7	16.1
Rec_{36} (%)	44.5	39.9	36.9
Average Wage of Criminals	1202.67	1202.67	1202.67

Note: Crime is indexed because π is not uniquely identified.

Job placement programs can take many different forms. Consider the costs and benefits of a residential re-entry center (RRC). RRC's provide a structured environment for convicts being released from jail. In particular, they limit the time individuals are outside of the center. The time individuals are allowed outside of the center is closely monitored and used mainly for job searching or employment.

The cost-benefit analysis of a RRC using the estimated model is insightful.

The costs of an RRC can range widely between one and three thousand dollars per person per month depending upon the location and environment. The benefits can range widely as well. As shown above, the benefit a RRC provides in reducing crime depends upon an individual's labor force status because the unemployed commit twice as much crime as those employed. In evaluating the benefits of a RRC, assume they deter agents from committing crime and the probability of being caught and incarcerated is 2.5%. In addition, the average cost of a crime(excluding murder) is roughly $4,255.[15] The bottom line is benefits from a RRC, or the reduction in crime, is worth $4,425 per month for those unemployed as they commit roughly 1.03 crimes per month. In addition, the benefits for an employed criminal type is between $1,020-2,040 as they would commit on average between 0.24 and 0.48 crimes per month depending upon their wage. Therefore, the benefits discussed above are greater than the costs when the resident of a RRC is unemployed but not necessarily while employed.

The benefits might not outweigh the costs of holding an employed individual in a RRC. However, what is the effect of an increase in the job finding rate for an employed individual? The purpose would be to reduce the crime rate of the employed by finding them higher paying jobs. The results are found in Table 1.10. First notice the expected wage rises as individuals are finding better paying jobs at a faster rate. Second, the policy has very little affect on the short run recidivism rate as those exiting jail take time to find their first job let alone a second. Third, the equilibrium

[15]The average cost is taken from Cohen (1988) and adjusted for inflation using the CPI.

crime rate falls only slightly as the number of individuals finding a high productivity firm, or "low crime" job, is small. As a result, halving the time it takes to receive a new job offer reduces the crime rate by roughly 1%.

Table 1.10: Changes in the Employed Job Arrival Rate (λ_1)

	λ_1		
	0.006	0.011	0.022
Unemployed Criminals (%)	10.1	10	10
Incarcerated Criminals (%)	20.2	20.1	19.8
Employed Low Wage Criminals (%)	58.3	57	54.7
Employed High Wage Criminals (%)	11.5	12.9	15.5
Crime Index	100.68	100	98.72
Rec_{12} (%)	18.7	18.7	18.7
Rec_{36} (%)	40	39.9	39.8
Average Wage of Criminals	933.59	1202.67	1655.25

Note: Crime is indexed because π is not uniquely identified.

As a potential critique of the analysis, one might argue the correlation between unemployment and criminal behavior is not causal in the sense assumed in the paper. For instance, a "career" or "hard core" criminal might not seek employment. In such a situation, we might find the unemployed committing more crime because hard core criminals are always unemployed.

In response, the estimation procedure is not constrained to result in a negative correlation between the incarceration rate and employment status. The maximum of the likelihood function could be located where there is no correlation as the model contains an equilibrium where employment and higher wages do not deter crime. In addition, a model incorporating a career criminal would presumably find the difference in incarceration rates of the unemployed and employed fall as education rises. However, I find the difference to be insignificant as education rises. Finally, the estimation is based on individuals who are searching for employment, and in fact a large fraction of them find jobs. In the end, the idea regarding a career criminal could be incorporated into the model by assuming another type of agent with a value of leisure b_{cc} where $b_{cc} < b_c$.

1.5 Conclusion

I have proposed an on-the-job search model that incorporates heterogeneous agents, firms and crime opportunities. The heterogeneity produces a Pareto improving equilibrium, a better estimate of wage dispersion, allows for agents to commit crime at different rates and results in a proportion of unemployed agents declining criminal opportunities based on their individual value of leisure.

Furthermore, I have developed a procedure to estimate the model. The major result is that economic incentives, in particular employment frictions and wages, affect crime.

Given the incentives between crime, unemployment and wage inequality, I argue policies aimed at reducing employment frictions, potentially implemented during incarceration, can improve the labor market for criminals and in turn decrease crime. What I find is a successful job placement program, one capable of cutting the average length of unemployment in half, can reduce crime and recidivism by more than five percent.

CHAPTER 2
CRIME AND THE LABOR MARKET: A SEARCH MODEL WITH OPTIMAL CONTRACTS

2.1 Introduction

According to Becker (1968), participation in illegal activities is driven by many of the same economic forces that motivate legitimate activities. Therefore, changes in labor market policies that affect individuals' incomes and prospects are likely to affect their criminal behavior as well. A case in point is the Job Seeker's Allowance introduced in the United Kingdom in 1996. The program was instituted to reduce unemployment by decreasing the duration of unemployment benefits. According to Machin and Marie (2004), this reform had the unfortunate effect of increasing crime. Similarly, Fougere et al. (2003) present some (mild) evidence that workers in France who do not receive unemployment benefits tend to commit more property crime. More generally, Hoon and Phelps (2003) advocate the use of labor market policies, such as wage subsidies, to reduce the enrollment of low-skilled workers in criminal activities.

Turning the Becker argument on its head suggests that changes in the crime sector could affect the labor market. In the U.S., sentence lengths have been increased in several states, sentencing guidelines have become tougher, and some states have moved to "three-strikes" rules. While it is intuitively plausible that increased deterrence and/or punishment should reduce criminal activity, there is scant research on how this might affect job duration, employment, wages and other outcomes of the labor market.

In this paper we develop a tractable model where crime and labor market outcomes are determined jointly. We use this model to assess, qualitatively and quantitatively, the effects of various labor market and crime policies. Therefore, we adopt the description of the labor market proposed by Pissarides (2000) where the terms of the employment contract are determined via bilateral bargaining and where a free-entry condition of firms makes the job finding rate endogenous. Both worker's bargaining strength and the exit rate out of unemployment are important determinants of the trade-off that workers face when deciding whether to undertake crime opportunities.

In the model all individuals receive random crime opportunities. The willingness to commit an illegal act is represented by a reservation value for crime opportunities above which individuals commit crime. This reservation value depends on current income, prospects for future income and so on. It also depends on the punishment that an individual faces if caught, which occurs with some probability.

Since detected crimes are punished by periods of imprisonment, employed workers' involvement in criminal activities imposes a negative externality on firms by reducing average job duration. This type of externality, which is well understood in models with on-the-job search (crime can certainly be thought of in a similar way), can lead to inefficient separations if the contract space is restricted to flat wages.[1] We take the approach that employees and employers face no liquidity constraints

[1]See Burdett and Mortensen (1998), the extensions by Burdett and Coles (2003) and Stevens (2004).

and can write contracts that generate efficient turnover from the point of view of a worker and employer. As shown by Stevens (2004) in a related context, the optimal contract involves an up-front payment by the worker and a constant wage equal to the worker's productivity. One can think of this optimal contract approximating features of existing contracts, such as probationary periods or an upward sloping wage profile.[2]

We prove that equilibrium exists and provide simple conditions for uniqueness.[3] Individuals' willingness to engage in criminal activities can be ranked according to their labor force status, with unemployed workers being the least choosy in terms of which crime opportunities to undertake. To highlight the tractability of the model, we provide a two-dimensional representation of the equilibrium similar in spirit to that in Mortensen and Pissarides (1994). This tractability allows us to study analytically a broad range of policies. In addition, we calibrate the model to U.S. data to examine the quantitative effects of policy.

We show analytically that a more generous unemployment insurance system reduces the crime rate of unemployed workers but the effect on the crime rate of employed workers depends on the difference between the average length of jail sentences and the average job duration. Quantitatively, the total crime rate decreases, although the effect is small.

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[2]For the sake of completeness, and to assess the extent to which the assumption of an optimal contract matters, we also work out in a companion working paper, Engelhardt et al. (2007), a version of the model with an exogenous rent sharing rule.

[3]In Engelhardt et al. (2007) we consider extensions of the model that are susceptible to generating multiple equilibria, e.g., by endogenizing workers' human capital; however, we find it interesting that a benchmark version of the model predicts a unique equilibrium.

The effects of a change in worker compensation are also investigated.[4] Higher worker's bargaining power leads to higher unemployment but it has ambiguous (and highly nonlinear) effects on the crime rates of employed and unemployed workers. The quantitative effects on total crime are large, coming mainly from the sharp reduction in the job-finding rate. Because of the endogeneity of the distribution of crime opportunities, the total crime rate falls substantially as bargaining power becomes large.

A wage subsidy reduces the unemployment rate and overall crime. Hiring subsidies that reduce the cost of advertising vacancies can raise the crime rate of employed workers.

From a normative standpoint, our analysis suggests that most labor market policies have a negative effect on welfare: the distortions they introduce in the labor market outweigh the potential benefits in terms of crime. A noticeable exception is the wage subsidy case, having a significant and positive effect on welfare by reducing crime, as suggested by Hoon and Phelps (2003).

We also examine policies that affect the likelihood of catching criminals and the length of jail sentences. The probability of apprehension and sentence lengths have large effects on crime with virtually no effect on the labor market.

The closest paper to ours is that of Burdett et al. (2003)– BLW hereafter. There are several key differences between the two formalizations. First, while BLW adopt the wage posting framework of Burdett and Mortensen (1998), we employ

[4] See Freeman (1999) for an extensive review on the relationship between crime and workers' compensation.

the Pissarides model for the reasons stated above. Second, in contrast to BLW we consider optimal employment contracts that internalize the effect of workers' crime decisions on the duration of a match. In BLW the employment contract is restricted to a constant wage which leads to a wage distribution and multiple equilibria. Third, the endogenous participation of firms in our model provides a channel through which criminal activities can distort the allocation and lower welfare. In contrast, the distortions introduced by crime in BLW are due solely to the policy that consists of sending criminals to jail. Fourth, the value of crime opportunities in our model are random draws from a distribution; this allows us to formalize crime behavior as a standard sequential search problem and to obtain endogenous crime rates for individuals in different states.

Huang et al. (2004) is also related to our analysis in that they employ a search-theoretic framework with bilateral bargaining. In their model individuals specialize in criminal activities while we let all agents, irrespective of their labor status, receive crime opportunities and commit crimes. This distinction is important since in the data all types of individuals, in particular employed ones, commit crimes.

İmrohoroğlu et al. (2004) calibrate an equilibrium model of crime to explore potential explanations for the decline in property crime over the past few decades. Their model does not have an explicit description of the labor market and is not set up to address how changes in the criminal sector affects the labor market.[5]

[5]There is also an empirical literature on the relationship between the labor market and crime. See, for instance, Grogger (1998) or Machin and Meghir (2004). Going further, Lochner and Moretti (2004) find empirical evidence that policies aimed at improving la-

2.2 Model

2.2.1 Environment

Time, t, is continuous and goes on forever. The economy is composed of a unit-measure of infinitely-lived individuals and a large measure of firms. There is one final good produced by firms. Each individual is endowed with one indivisible unit of time that has two alternative, mutually exclusive uses: search for a job, work for a firm.

Individuals are risk-neutral and discount at rate $r > 0$. They are not liquidity constrained and can borrow and lend at rate r. An unemployed worker who is looking for a job enjoys utility flow b, which we interpret as the utility from not working.

Upon entering an employment relationship, a worker pays a hiring fee, ϕ, and receives a constant wage, w, thereafter. We establish below that this type of contract is Pareto-optimal for a worker and a firm. The pair (ϕ, w) will be determined through some bargaining solution.[6]

Firms are composed of a single job, either filled or vacant, and discount future profits at rate $r > 0$. Vacant firms are free to enter and pay a flow cost, $\gamma > 0$, to advertise a vacancy. Vacant firms produce no output while filled jobs produce $y > b$.

The labor market is subject to search-matching frictions. The flow of hires is

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bor market opportunities, specifically increasing graduation rates, can substantially reduce crime.

[6] Implicit in this formulation is that the firm commits to the terms of the employment contract. In particular, once the worker pays the hiring fee the firm does not renege on the promised future wage. Note also that firms have no incentive to fire their workers once the hiring fee has been paid since their expected profits from opening a new vacancy is zero.

given by the aggregate matching function $\zeta(U,V)$ where U is the measure of unemployed workers actively looking for jobs and V is the measure of vacant jobs. The matching function, $\zeta(\cdot,\cdot)$, is continuous, strictly increasing, strictly concave with respect to each of its arguments and exhibits constant returns to scale. Furthermore, $\zeta(0,\cdot) = \zeta(\cdot,0) = 0$ and $\zeta(\infty,\cdot) = \zeta(\cdot,\infty) = \infty$. Following Pissarides' terminology, we define $\theta \equiv V/U$ as labor market tightness. Each vacancy is filled according to a Poisson process with arrival rate $\frac{\zeta(U,V)}{V} \equiv q(\theta)$. Similarly, each unemployed worker finds a job according to a Poisson process with arrival rate $\frac{\zeta(U,V)}{U} = \theta q(\theta)$. Filled jobs receive negative idiosyncratic productivity shocks, with a Poisson arrival rate s, that render matches unprofitable. The measures of employed and unemployed workers are denoted n_e and n_u, respectively.

A crime is described as a transfer of utility (or wealth) from the victim to the offender. Each dollar stolen by criminals corresponds to a loss of $1+\omega$ dollars incurred by victims. If $\omega = 0$ crime is a pure transfer; whereas $\omega > 0$ means that victims also suffer a nonpecuniary cost when robbed. Crimes occur as follows. Each individual meets a potential offender who is unemployed with Poisson rate $n_u\lambda_u$, and a potential offender who is employed with Poisson rate $\lambda_e n_e$.[7] The variables λ_i can be interpreted as the (exogenous) intensities with which an individual in state i (where $i = u$ if unemployed and $i = e$ if employed) looks for an opportunity to commit a

[7]The assumption that all individuals, including those in jail, are subject to crime is meant to capture the fact that all individuals, even those in jail, can have their property stolen. Furthermore, it guarantees that being in jail does not provide an advantage in terms of the security of one's property that could make jail more attractive. Our results would not be affected significantly if prisoners are not subject to theft.

crime. The potential offender has the opportunity to steal from his victim, but the value of his crime opportunity is εm where ε is a random draw from a distribution $G(\varepsilon)$ with support $[0, \bar{\varepsilon}]$. We treat the scale parameter m as exogenous for the time being but will endogenize it below.[8] Since the model is agnostic about the distribution of wealth, we simply assume that the distribution of crime opportunities is independent of the victim's labor force status.[9] Hence, the expected loss from crime is

$$\tau^c = n_u \lambda_u (1 + \omega) \mathbb{E}_u [\varepsilon] + \lambda_e n_e (1 + \omega) \mathbb{E}_e [\varepsilon] , \tag{2.1}$$

where $\mathbb{E}_i [\varepsilon]$ is the (endogenous) expected value of the crime committed by an individual with labor force status $i \in \{u, e\}$. Firms do not suffer directly from criminal activities.

A worker who commits a crime is caught and sent to jail with probability π.[10] The measure of those in prison is denoted by n_p. When in jail an individual cannot make any productive use of time but receives a flow of utility x (which can be negative). A prisoner exits jail according to a Poisson process with arrival rate δ. We assume that the average time spent in jail is independent of the value of the crime,

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[8]An interpretation of m being exogenous is that of a local labor market where crime opportunities come from outside the economy.

[9]The loss due to crime is independent of one's wealth, and in principle could be larger than one's income or wealth. For instance, an individual can be the victim of credit card fraud, or can have his car stolen even if he does not own it (e.g., the car is leased).

[10]Note that in our framework the probability of being caught is independent of the value of the crime. An alternative is to have π as a function of the value of the crime, for example by assigning more police to larger crimes. We do not know of any data in this regard to support one particular assumption over another.

εm.[11]

Finally, individuals have to pay taxes, τ^g, to the government. In order to avoid taxes affecting crime decisions directly, we assume that the burden of taxes falls on all workers including those in jail. We denote $\tau = \tau^c + \tau^g$.

2.2.2 Discussion

A distinctive feature of our model relative to the standard Pissarides model, or the existing search models of crime (e.g., BLW), is the form of the employment contract. Typically, search models of the labor market assume that the employment contract involves only a constant wage: There is no hiring fee or tenure-dependent compensation. In most instances, these restrictions on the contract space are innocuous because the only thing that matters for the risk-neutral workers and firms is the division of the match surplus (e.g. Shimer (1996)). Put differently, the same division of the match surplus can be achieved with a constant wage, or with a hiring fee and a constant wage, or with some other, more elaborate, wage-tenure contract.

The exact form of the employment contract is more relevant when workers can take actions that affect the duration of the match, such as through on-the-job search or crime opportunities. As pointed out by Shimer (2005a) and Stevens (2004), a constant wage may fail to achieve a pairwise Pareto-efficient outcome. Similarly, the restriction

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[11] The length of incarceration has more to do with the violent nature of the crime and the number of past offenses than the value of the crime. For example, the Sentencing Commission Guidlines suggests a period of incarceration ranging from 0 to 6 months for larceny less than \$10,000 (75% of thefts are under \$10,000) and the criminal has not been convicted more than once. If it is the second or third offense then the suggested penalty is 4-10 months. If the theft is violent, such as a robbery, and the crime is still less than \$10,000, the guidelines suggest incarceration for 33-41 months.

to flat-wage contracts in the wage-posting model of Burdett et al. (2003) generates an inefficient turnover of workers and, for some parameter values, a nondegenerate distribution of wages. Moreover, standard bargaining solutions cannot always be used when the contract is restricted to a constant wage since the bargaining set need not be convex (Bonilla and Burdett (2005); Shimer (2005a)). As we show below, an employment contract composed of a hiring fee and a constant wage generates a pairwise optimal outcome in our context. Given that this is the type of contract our model calls for, it is the one we choose to adopt.[12]

Despite the adoption of the optimal contract being theoretically elegant, it may not be empirically relevant. One may wonder if a hiring fee has any counterpart in reality. Since the presence of liquidity constraints (especially for young and less skilled workers) reduces the feasibility of such contracts. Our view is that contracts with hiring fees approximate in a tractable way some features of existing contracts. For instance, a contract with an upfront payment by the worker is just an extreme version of a contract with an upward sloping wage profile over time. Moreover, many employment contracts have an initial probationary period during which wages are lower.[13]

Engelhardt et al. (2007) describes a version of the model without a hiring fee and where the wage is set according to some ad-hoc rent sharing rule. A more

[12]The fact that a constant wage may be suboptimal when workers can engage in some opportunistic behavior (such as crime opportunities or search on the job) mirrors the discussion about the "bonding critique" in the efficiency wage literature. See Carmichael (1985) and Ritter and Taylor (1997)

[13]For a related discussion, see Chapter 5 in Mortensen (2003).

realistic approach would be to allow for risk-aversion and liquidity constraints (see, e.g., Burdett and Coles (2003)). While these assumptions would likely generate a smoother wage-tenure contract, and an interesting relationship between job tenure and crime involvement, tractability would be lost.

2.3 Bellman equations

This paper focuses on steady-state equilibria where the distribution of individuals across states, n_e, n_u and n_p, and market tightness, θ, are constant over time. As a consequence, matching probabilities and crime rates are also time-invariant. In this section we write down the flow Bellman equations for individuals and firms and characterize the employment contract.

2.3.1 Individuals

An individual is in one of the following three states: unemployed (u), employed (e), or in prison (p). The value of being an individual in state $i \in \{u, e, p\}$ with zero net wealth is denoted $\mathcal{V}_i$. The flow Bellman equations for individuals' value functions are

$$r\mathcal{V}_u = b - \tau + \theta q(\theta)\left(\mathcal{V}_e - \mathcal{V}_u - \phi\right) + \lambda_u \int \left[\varepsilon m + \pi(\mathcal{V}_p - \mathcal{V}_u)\right]^+ dG(\varepsilon), \quad (2.2)$$

$$r\mathcal{V}_e = w - \tau + s\left(\mathcal{V}_u - \mathcal{V}_e\right) + \lambda_e \int \left[\varepsilon m + \pi\left(\mathcal{V}_p - \mathcal{V}_e\right)\right]^+ dG(\varepsilon), \quad (2.3)$$

$$r\mathcal{V}_p = x - \tau + \delta\left(\mathcal{V}_u - \mathcal{V}_p\right), \quad (2.4)$$

where $[x]^+ = \max(x, 0)$. Equation (2.2) has the following interpretation. An unemployed worker enjoys a utility flow of $b-\tau$ where b is the utility flow from not working and τ is the sum of the (expected) cost of being victimized and taxes. A job is found with an instantaneous probability $\theta q(\theta)$. Upon taking a job an individual pays a hiring fee, ϕ (or receives an up-front payment if $\phi < 0$), and enjoys the capital gain $\mathcal{V}_e - \mathcal{V}_u$. When unemployed the individual receives an opportunity to commit a crime with instantaneous probability λ_u. The value of the crime opportunity is drawn from the cumulative distribution $G(\varepsilon)$. If a worker chooses to commit a crime she enjoys utility εm but is at risk of being caught and sent to jail with probability π, in which case she suffers a capital loss, $\mathcal{V}_p - \mathcal{V}_u$. From (2.3), an employed worker receives a wage w, loses her job with an instantaneous probability s and has the opportunity to commit a crime with an instantaneous probability λ_e. According to (2.4), an imprisoned worker receives consumption flow x, suffers the loss τ, and exits jail with an instantaneous probability δ. After release a prisoner joins the unemployment pool.

From (2.2) and (2.3) an individual in state i chooses to commit a crime whenever $\varepsilon \geq \varepsilon_i$ where

$$\varepsilon_u m = \pi(\mathcal{V}_u - \mathcal{V}_p), \tag{2.5}$$

$$\varepsilon_e m = \pi\left(\mathcal{V}_e - \mathcal{V}_p\right), \tag{2.6}$$

From (2.5)-(2.6) the value of the marginal crime that makes an individual in a given state indifferent between undertaking the crime or not, $\varepsilon_i m$, is equal to the expected cost of punishment, $\pi(\mathcal{V}_i - \mathcal{V}_p)$.

2.3.2 Firms

Firms participating in the market can be in either of two states: they can hold a vacant job (v) or a filled job (f). Firms' flow Bellman equations are

$$r\mathcal{V}_v = -\gamma + q(\theta)\left(\phi + \mathcal{V}_f - \mathcal{V}_v\right), \tag{2.7}$$

$$r\mathcal{V}_f = y - w - s\left(\mathcal{V}_f - \mathcal{V}_v\right) - \lambda_e \pi \left[1 - G(\varepsilon_e)\right]\left(\mathcal{V}_f - \mathcal{V}_v\right). \tag{2.8}$$

According to (2.7), a vacancy incurs an advertising cost γ; finds an unemployed worker with an instantaneous probability $q(\theta)$ in which case it receives the hiring fee, ϕ and enjoys the capital gain $\mathcal{V}_f - \mathcal{V}_v$. According to (3.3), a filled job enjoys a flow profit $y - w$ and is destroyed if a negative idiosyncratic productivity shock occurs, with an instantaneous probability s, or if the worker commits a crime and is caught, an event occurring with an instantaneous probability $\lambda_e \pi[1 - G(\varepsilon_e)]$. Free-entry of firms implies $\mathcal{V}_v = 0$ and therefore, from (2.7),

$$\mathcal{V}_f + \phi = \frac{\gamma}{q(\theta)}. \tag{2.9}$$

From (2.9), the firms' surplus from a match, the sum of the value of a filled job and the hiring fee, is equal to the average recruiting cost incurred by the firm.

2.3.3 Employment contract

To determine the details of the employment contract we define $\mathcal{S} \equiv \mathcal{V}_e - \mathcal{V}_u + \mathcal{V}_f$ as the total surplus of a match (Recall that $\mathcal{V}_v = 0$). From (2.3) and (3.3),

$$r\mathcal{S} = y - \tau - r\mathcal{V}_u - s\mathcal{S} + \lambda_e \int_{\varepsilon_e}^{\bar{\varepsilon}} \left[\varepsilon m - \pi\mathcal{S} - \pi(\mathcal{V}_u - \mathcal{V}_p)\right] dG(\varepsilon). \tag{2.10}$$

Equation (2.10) has the following interpretation. A match generates a flow surplus, $y - \tau - r\mathcal{V}_u$, composed of the output of the job minus taxes (including the loss due to victimization of the worker) and the permanent income of an unemployed person, $r\mathcal{V}_u$. The match is destroyed if an exogenous shock occurs, at Poisson rate s, or if the worker commits a crime and is caught. In the latter case, the value $\mathcal{S}$ of the match is lost and the worker goes to jail which generates an additional capital loss $\mathcal{V}_u - \mathcal{V}_p$. The value of the match also incorporates the crime opportunities undertaken by the employed worker.

Suppose a worker and a firm could *jointly* determine the crime opportunities undertaken by the worker. It can be seen from (2.10), that the surplus of the match is maximized if

$$\varepsilon_e m = \pi(\mathcal{S} + \mathcal{V}_u - \mathcal{V}_p) = \pi\left(\mathcal{V}_e + \mathcal{V}_f - \mathcal{V}_p\right). \tag{2.11}$$

Comparison of (2.6) and (2.11) reveals that if $\mathcal{V}_f > 0$, the worker's choice of which crime opportunities to undertake and the choice that maximizes the match surplus differ, i.e. the total surplus of the match is not maximized. Employed workers commit "too much crime" because they do not internalize the negative externality they impose on the firm if they are sent to jail.

We show that by allowing the employment contract to include an upfront fee, ϕ, the worker and the firm can reach a pairwise-efficient outcome. The employment contract (ϕ, w) is determined by the generalized Nash solution where the worker's bargaining power is $\beta \in [0, 1]$. The contract satisfies

$$(\phi, w) = \arg\max\left(\mathcal{V}_e - \mathcal{V}_u - \phi\right)^{\beta}\left(\mathcal{V}_f + \phi\right)^{1-\beta}. \tag{2.12}$$

Lemma 2.1. *The employment contract solution to (2.12) is such that*

$$w = y, \tag{2.13}$$

$$\phi = (1-\beta)\left(\mathcal{V}_e - \mathcal{V}_u\right). \tag{2.14}$$

Proofs of the lemmas and propositions can be found in the appendix. According to Lemma 2.1, the wage is set to be equal to the worker's productivity.[14] Since the worker gets the entire output generated by the match, and hence $V_f = 0$, this wage setting guarantees that the worker internalizes the effect of his crime decision on the total surplus of the match. The up-front payment is used to split the surplus of the match according to each agent's bargaining power.[15]

2.4 Equilibrium

In this section we derive conditions for existence and uniqueness of an active (positive employment) equilibrium. We establish that the model has a simple recursive structure and can be reduced to two equations and two unknowns, market tightness (θ) and the reservation value for crime opportunities (ε_u).

The free-entry condition of firms allows us to express the worker's and firm's surpluses from a match as functions of market tightness. From (2.9), $\mathcal{V}_f = 0$ implies

$$\phi = \frac{\gamma}{q(\theta)}. \tag{2.15}$$

[14] Since the firm makes no profit after the hiring fee has been paid, it has no incentive to fire the worker as the value of a vacancy is no greater than the value of a filled job, i.e., $\mathcal{V}_f = \mathcal{V}_v = 0$.

[15] Alternatively, the optimal contract could take the form of a constant wage, w, and a payment from the worker to the firm (a fine) if the worker is caught committing a crime. This transfer would exactly compensate the firm for its lost surplus.

The gain from filling a vacancy is equal to the up-front payment, ϕ, which equals the average recruiting cost incurred by the firm to fill a vacancy. From (2.14), the expected surplus received by an unemployed worker who finds a job is

$$\mathcal{V}_e - \mathcal{V}_u - \phi = \frac{\beta}{1-\beta}\phi = \frac{\beta\gamma}{(1-\beta)q(\theta)}. \tag{2.16}$$

The worker's surplus from a match is $\frac{\beta}{1-\beta}$ times the expected recruiting costs incurred by firms.

Second, using the Bellman equations (2.2), (2.3) and (2.4), as well as the expression for the worker's surplus, (2.16), the crime decisions (2.5)-(2.6) can be rewritten as follows:

$$\begin{aligned} \left(\frac{r+\delta}{\pi}\right)\varepsilon_u m &= b - x + \frac{\beta}{1-\beta}\theta\gamma + \lambda_u m \int_{\varepsilon_u}^{\bar{\varepsilon}} [1-G(\varepsilon)]\, d\varepsilon, \quad &(2.17)\\ \left(\frac{r+\delta}{\pi}\right)\varepsilon_e m &= y - x + \frac{(\delta - s)\gamma}{q(\theta)(1-\beta)} + \lambda_e m \int_{\varepsilon_e}^{\bar{\varepsilon}} [1-G(\varepsilon)]\, d\varepsilon. \quad &(2.18)\end{aligned}$$

Given θ, (2.17)-(2.18) determine a unique pair $(\varepsilon_u, \varepsilon_e)$. Notice that (2.17)-(2.18) correspond to standard optimal stopping rules. Also, (2.17) gives the first relationship between ε_u and θ.

Next, we turn to the determination of market tightness. Substituting (2.16) into (2.2) and integrating the integral term in (2.2) by parts, gives the permanent income of an unemployed worker as:

$$r\mathcal{V}_u = b - \tau + \frac{\beta}{1-\beta}\theta\gamma + \lambda_u m \int_{\varepsilon_u}^{\bar{\varepsilon}} [1-G(\varepsilon)]\, d\varepsilon. \tag{2.19}$$

From (2.3) and (2.19) and using the fact that $\mathcal{V}_e - \mathcal{V}_u = \gamma/\left[(1-\beta)q(\theta)\right]$, market tightness satisfies

$$\frac{(r+s)\,\gamma}{(1-\beta)q(\theta)} = y - b - \frac{\beta}{(1-\beta)}\theta\gamma - \lambda_u m \int_{\varepsilon_u}^{\bar{\varepsilon}} [1 - G(\varepsilon)]\, d\varepsilon + \lambda_e m \int_{\varepsilon_e}^{\bar{\varepsilon}} [1 - G(\varepsilon)]\, d\varepsilon. \tag{2.20}$$

Given the thresholds ε_u and ε_e, (2.20) determines a unique θ. Note that, up to the last two terms on the right-hand side, (2.20) is identical to the equilibrium condition in the Pissarides model. If crime activities are more valuable for unemployed workers than for employed ones, i.e., the sum of the last two terms is negative, then the presence of crime opportunities tends to reduce market tightness. Using (2.6)

$$\varepsilon_e m = \varepsilon_u m + \frac{\pi\gamma}{(1-\beta)q(\theta)}. \tag{2.21}$$

Substituting ε_e by its expression given by (2.21) into (2.20) we obtain a relationship between ε_u and θ,

$$\begin{aligned} \frac{(r+s)\,\gamma}{(1-\beta)q(\theta)} &= y - b - \frac{\beta}{(1-\beta)}\theta\gamma - \lambda_u m \int_{\varepsilon_u}^{\bar{\varepsilon}} [1 - G(\varepsilon)]\, d\varepsilon \\ &\quad + \lambda_e m \int_{\varepsilon_u + \frac{\pi\gamma}{m(1-\beta)q(\theta)}}^{\bar{\varepsilon}} [1 - G(\varepsilon)]\, d\varepsilon. \end{aligned} \tag{2.22}$$

Equation (2.22) gives the second relationship between ε_u and θ. According to (2.22), if $\lambda_u[1 - G(\varepsilon_u)] > \lambda_e[1 - G(\varepsilon_e)]$ then θ increases with ε_u. This condition is satisfied, for instance, if $\lambda_u = \lambda_e$.

Finally, we characterize the steady-state distribution of individuals across states. The distribution (n_u, n_e, n_p) is determined by the following steady-state conditions:

$$sn_e + \delta n_p = \{\theta q(\theta) + \lambda_u \pi [1 - G(\varepsilon_u)]\}\, n_u, \tag{2.23}$$

$$\theta q(\theta) n_u = \{s + \lambda_e \pi [1 - G(\varepsilon_e)]\}\, n_e, \tag{2.24}$$

$$n_e + n_u + n_p = 1. \tag{2.25}$$

According to (2.23) the flows in and out of unemployment must be equal. The measure of individuals entering unemployment is the sum of the employed workers who lose their jobs, sn_e, and the criminals who exit jail, δn_p. The flow of individuals exiting unemployment corresponds to individuals finding jobs, $\theta q(\theta) n_u$, or unemployed individuals committing crimes and sent to jail, $\lambda_u \pi [1 - G(\varepsilon_u)] n_u$. Similarly, (2.24) prescribes that the flows in and out of employment must be equal in steady state. According to (2.25), individuals are either employed, unemployed, or in jail. Figure 2.1 diagrams the above-mentioned flows.

The equilibrium unemployment rate, u, is defined as the fraction of individuals not in jail who are unemployed, i.e., $u \equiv n_u/(n_e + n_u)$. From (2.24), it satisfies

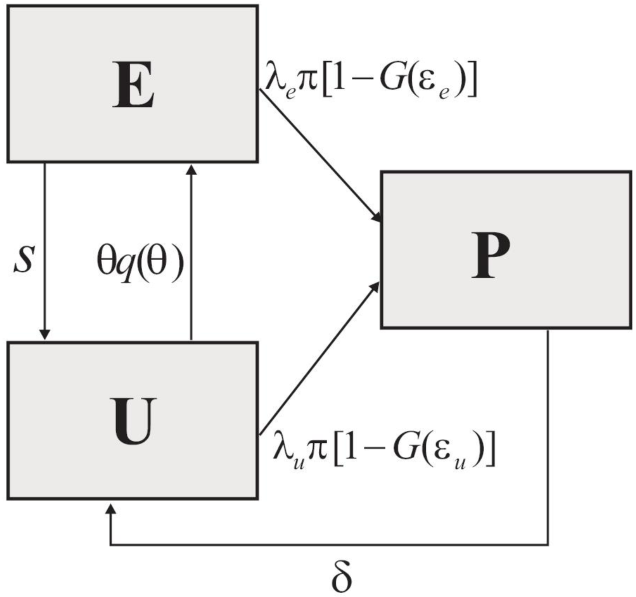
$$u = \frac{s + \lambda_e \pi \left[1 - G(\varepsilon_e)\right]}{\theta q(\theta) + s + \lambda_e \pi \left[1 - G(\varepsilon_e)\right]}. \tag{2.26}$$

As in Mortensen and Pissarides (1994), the unemployment rate decreases with market tightness and increases with the job destruction rate, which is endogenous, and depends on ε_e.

We close the model by computing the expected instantaneous loss incurred by individuals from being victimized. From (2.1),

$$\tau^c = (1 + \omega) m \left[\lambda_e n_e \int_{\varepsilon_e}^{\bar{\varepsilon}} \varepsilon dG(\varepsilon) + \lambda_u n_u \int_{\varepsilon_u}^{\bar{\varepsilon}} \varepsilon dG(\varepsilon) \right]. \tag{2.27}$$

Figure 2.1: Worker Flows



We are now ready to define an equilibrium for the model.

Definition 2.1. *A steady-state equilibrium is a list* $\{\theta,\ \varepsilon_u,\ \varepsilon_e,\ n_e,\ n_u,\ n_p, \tau^c\}$ *such that:* θ *satisfies (2.22);* $\{\varepsilon_u,\ \varepsilon_e\}$ *satisfies (2.17)-(2.18);* $\{n_e,\ n_u,\ n_p\}$ *satisfies (2.23)-(2.25) and* τ^c *satisfies (2.27).*

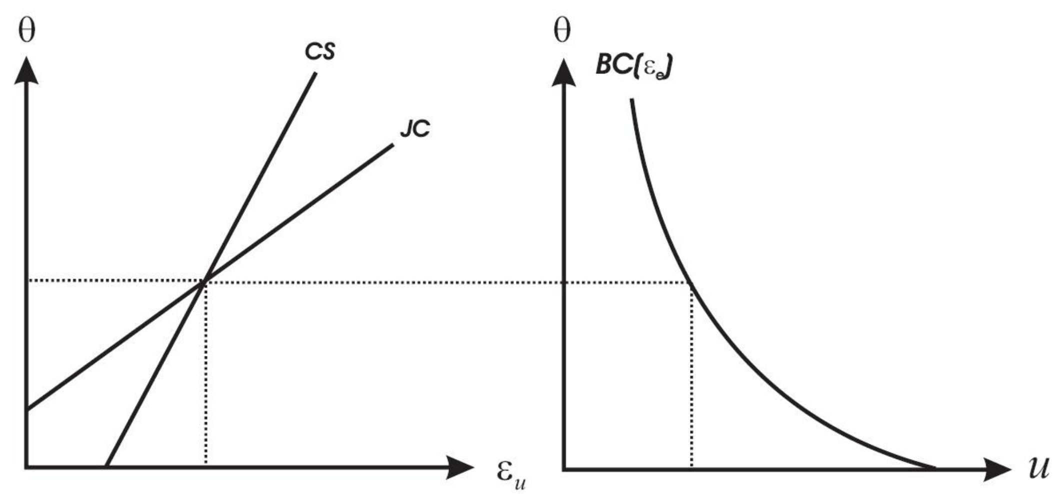
As indicated above, the model is recursively solvable. First, the pair (θ, ε_u) is determined jointly from (2.17) and (2.22). Second, knowing (θ, ε_u), one can use (2.21) to find ε_e. Finally, given $(\theta, \varepsilon_u, \varepsilon_e)$ the steady-state distribution (n_e, n_u, n_p) is obtained from (2.23)-(2.25).

Figure 2.2 represents the determination of the pair (θ, ε_u). We denote CS (crime schedule) as the curve representing (2.17) and JC (job creation) as the curve representing (2.22). Recall that CS always slopes upward while JC can slope upward or downward, depending on the values of λ_e and λ_u. In the case where $\lambda_u = \lambda_e$, the case we will focus on in the quantitative section, the two curves slope upward. Along CS, as the number of vacancies per unemployed increases, unemployed workers are less likely to commit crimes. Along JC, as the frequency of crime by the unemployed falls, the supply of vacancies in the market increases. The Beveridge curve (2.26) is denoted $BC(\varepsilon_e)$. It shifts with the reservation value ε_e which, from (2.21), is uniquely determined from θ and ε_u.

In Figure 2.2, the curves CS and JC intersect once. The following lemma establishes that this result holds in general.

Lemma 2.2. *In the space (ε_u, θ) the curve JC intersects the curve CS from above.*

Figure 2.2: Equilibrium



The determination of equilibrium is reminiscent of the one in Mortensen and Pissarides (1994) where labor market tightness and the job destruction rate are determined jointly. The CS curve in our model is analogous to the job destruction curve in the Mortensen-Pissarides model in that workers' crime decisions affect the duration of a job.

The following proposition provides a simple condition under which there is a unique equilibrium with a positive number of jobs. Denote ε_u^0 as the value of ε_u that solves (2.17) when $\theta = 0$.

Proposition 2.1. *There exists a unique equilibrium such that $\theta > 0$ if*

$$y - b + (\lambda_e - \lambda_u)m \int_{\varepsilon_u^0}^{\bar{\varepsilon}} [1 - G(\varepsilon)]d\varepsilon > 0. \tag{2.28}$$

In any such equilibrium, $\varepsilon_e > \varepsilon_u$.

Proposition 2.1 shows that an equilibrium exists and is unique. So despite the possibility of strategic complementarities between individuals' crime decisions and firms' entry decisions, there is no multiple steady-state equilibria in this model. The condition (2.28) for firms entering the market requires that the rate at which unemployed workers receive crime opportunities is not too high compared to the arrival rate of crime opportunities for employed workers; obviously, it is satisfied if $\lambda_e = \lambda_u$ in which case (2.28) reduces to $y > b$.

Proposition 2.1 also shows that unemployed workers are less picky than other individuals when choosing which crime opportunities to accept. To see this, note that employed workers are paid their productivity, which is larger than the income they receive when unemployed. Therefore, the opportunity cost of being caught and sent to jail is higher for employed workers. In the particular case where $\lambda_u = \lambda_e$ the crime rate of unemployed workers is larger than the crime rate of employed workers, a fact that is present in the data.[16]

The following Proposition provides a condition under which the equilibrium is characterized by no criminal activities. Denote $\hat{\theta}$ the value of market tightness that solves

$$\frac{(r+s)\,\gamma}{q(\hat{\theta})} = (1-\beta)\,(y-b) - \beta\hat{\theta}\gamma. \tag{2.29}$$

This is the market tightness that would prevail in an economy without crime.

Proposition 2.2. *If*

$$\frac{(r+\delta)}{\pi}\bar{\varepsilon}m \leq b - x + \frac{\beta}{1-\beta}\hat{\theta}\gamma \tag{2.30}$$

then the equilibrium is such that $\theta = \hat{\theta}$ *and no crime occurs.*

According to Proposition 2.2, there is no crime equilibrium provided that the probability of being caught is sufficiently high and the time spent in jail is sufficiently long. In this case the model reduces to the Pissarides model.

So far we have taken the distribution of crime opportunities, $mG(\varepsilon)$, as exogenous. This assumption is reasonable if one envisions the economy as a local labor market and the crime opportunities as coming from outside the neighborhood. If one thinks of an entire economy, the distribution of crime opportunities is presumably endogenous and depends on the distribution of wealth, income and other characteristics of the economy. We capture this idea by assuming that m is a continuous function, μ,

[16]Data from the Survey of Prison Inmates in State and Federal Correction Facilities gives the labor force status at the time of arrest. This allows us to calculate that the probability of committing a crime when unemployed as 17% and when employed as 3%.

of the endogenous variables $(\varepsilon_e, \varepsilon_u, \theta)$. This is consistent with several interpretations. For instance, m could be the aggregate output in the economy, $m = n_e y$ where n_e is an implicit function of θ and ε_e.[17] We will assume that $\mu(\varepsilon_e, \varepsilon_u, \theta) > 0$ if and only if $\theta > 0$ –there are crime opportunities as long as the labor market is active.

Proposition 2.3. *Assume $m = \mu(\varepsilon_e, \varepsilon_u, \theta)$, where μ is continuous, bounded above and strictly positive iff $\theta > 0$. Then there exists an active equilibrium ($\mu > 0$ and $\theta > 0$) provided that $y > b$.*

As long as workers' productivity is greater than the income of unemployed workers there exists an equilibrium with an active labor market. While we can show existence of equilibrium for an endogenous distribution of crime opportunities, we can no longer guarantee uniqueness.

To investigate the implications of various policies on welfare in the quantitative section, we define welfare using an approach similar to that of Hosios (1990) and Pissarides (2000). Letting $\mathcal{W}$ be the sum of all agents' utility flows in steady state we have,

$$\mathcal{W} = n_u (b - \theta\gamma) + n_e y + n_p x - \tau^g - \omega m \left[\lambda_e n_e \int_{\varepsilon_e}^{\bar{\varepsilon}} \varepsilon dG(\varepsilon) + \lambda_u n_u \int_{\varepsilon_u}^{\bar{\varepsilon}} \varepsilon dG(\varepsilon)\right]. \quad (2.31)$$

[17] Alternatively, output could be defined as $n_e y - v\gamma$, where $v\gamma$ represents the hiring costs incurred by firms.

2.5 Calibrated example

The unit of time corresponds to one year and the rate of time preference is set to $r = 0.048$. The output from a match is normalized to $y = 1$. The flow of utility when unemployed is $b = 0.4$.[18]

The matching function is assumed to be Cobb-Douglas, $\zeta(U,V) = AU^{\eta}V^{1-\eta}$ with constant returns to scale and we set $\eta = 0.5$, so that workers' and firms' contributions to the matching process are symmetric. We set the bargaining power of the worker $\beta = 0.5$ so that the division of the match surplus internalizes the externalities associated with firms' entry decisions (see Hosios, 1990).[19]

The parameters A and γ are chosen to match the average job finding rate and the average $v - u$ ratio while s is chosen to match the separation rate. For the years 1951-2003 the job finding rate, taken from Shimer (2005b), is 0.45 per month, implying that the annualized expected number of job offers, $\theta q(\theta)$, is 5.40. For a given job finding rate, $\theta q(\theta)$, θ and γ appear as a product in the equilibrium conditions (2.17) and (2.22). Hence, one can normalize θ to one without loss of generality; this yields $A = 5.40$ and $\gamma = 0.513$. The monthly job separation rate, also taken from Shimer (2005b), 0.034, implying an annualized rate of 0.408, i.e., jobs last, on average, about 2 years.

Turning to the crime sector, the crimes considered are Type I property crimes

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[18]The choice of the value for b, taken from Shimer (2005b), is somewhat controversial, see Hagedorn and Manovskii (2006) for an alternative calibration.

[19]However, it does not guarantee that equilibrium is constrained-efficient because of the presence of crime opportunities. Our value for η is in the ballpark of estimates in the literature (see Petrongolo and Pissarides, 2001), Shimer (2005b) and Flinn (2006).

as defined by the FBI, which include larceny, burglary, and motor vehicle theft.[20] The total number of property crimes, the crime rate (per 1000 persons), and the total dollar amount lost from crime are taken from the Uniform Crime reports (Tables 1 and 24).[21]

The distribution $G(\varepsilon)$, characterizing the crime opportunities, is assumed to be exponential with mean μ_g and is chosen to target the average amount stolen, approximately \$1243 in the data. The scaling factor, m, that endogenizes crime opportunities is taken to be the aggregate output of the economy, $n_e y$. The parameters $\lambda_e = \lambda_u$ target the overall crime rate, which is 42.4 per 1000 persons. Therefore, $\mu_g = 0.0118$ and $\lambda_e = \lambda_u = 0.417$. Finally, Cohen (1988) calculates the average costs of property crime to the victim, including pain and suffering, to be \$1374. We calculate the cost of crime to the victim by weighting the loss for each type of property crime (adjusted by the CPI) by their proportion of Type I property crimes. Therefore, we set $\omega = 0.105$.

The probability of being caught is derived from the number sent to prison (we exclude those sentenced to probation) divided by the number of crimes, implying $\pi = 0.019$. The mean length of incarceration for those convicted of a property crime was 16 months in 2002, so that $\delta = 0.75$. Since we do not have much information on

[20]We note at the outset of this section that many of the parameters and targets differ depending on the population of interest. For example, the job destruction rate is three times the average for those aged 16-24 (those more at risk of committing crime) and the unemployment rate is substantially higher than for the sample using all workers. Therefore, the quantitative findings depend upon the group being observed.

[21]The FBI defines Forgery, Fraud, and Embezzlement as a Type II offense and does not collect the number of these types of crimes.

the utility or disutility from being in jail, we let $x = 0$.

For welfare calculations, we assume that the technology to catch criminals is costly, and maintaining individuals in jail involves some real resources. Following İmrohoroğlu et al. (2000), the cost (not normalized by the wage) corresponding to a technology, π, to catch criminals is given by

$$C(\pi) = (1-\pi)^{-\frac{1}{\nu}},$$

and we use their estimate of $\nu = 0.044$. The cost of a prisoner is estimated to be \$22,650.[22] In our model we assume both types of expenditures are financed by lump-sum taxes.

We normalize all dollar figures in the data (taxes, average amount stolen, cost of imprisonment, etc.) by annualized median weekly earnings in the CPS. In our model the counterpart is taken to be

$$\bar{w} = y - \{r + s + \lambda_e \pi [1 - G(\varepsilon_e)]\}\phi. \tag{2.32}$$

which is equivalent in discounted terms to the wage profile of a worker including the payment of the hiring fee. Using the chosen parameters gives $\bar{w} = 0.96$. Median weekly earnings in the CPS after converting to an annual basis is $\bar{w} = \$31,616$. Therefore, \$31,616/0.96 = \$33,051, corresponds to y in our model.

In the tables that follow, the total crime rate is the expected number of crimes per 1000 workers and the crime rates for each type (unemployed or employed) are the

[22]The estimate for the cost of a prisoner comes from the survey of State Prison Expenditures (2001) which includes the operating and capital costs of holding an inmate.

expected number of crimes each type commits times 1000. Note that the total crime rate is the weighted average of the unemployed and employed crime rates.

Table 2.1 recapitulates the parameters and functional forms used in the calibration.

Table 2.1: Calibrated Parameters

r	0.048	real interest rate
b	0.400	unemployed utility flow
β	0.500	bargaining power of workers
η	0.500	elasticity of matching function
γ	0.513	recruiting cost
s	0.408	job destruction rate
A	5.400	efficiency of matching technology
x	0.000	utility flow when in jail
π	0.019	apprehension probability
δ	0.750	rate of exit from jail
$\lambda_e = \lambda_u$	0.417	flow of crime opportunities
μ_g	0.0118	mean of exponential crime distribution
ω	0.105	dead-weight loss from crime
ν	0.044	elasticity of apprehension technology

2.6 Labor market policies

In this section we examine qualitatively and quantitatively how changes in several labor market policies affect crime and labor market outcomes. The policies we analyze are those that have been mentioned in the literature to reduce crime. Machin and Marie (2004) and Fougere et al. (2003) show that changes in unemployment benefits affects crime in the U.K. and France. Gould et al. (2002) document that workers' compensation is an important determinant of crime. Hoon and Phelps (2003) advocate the use of wage subsidies as a policy instrument to reduce the enrollment of low-skilled workers in criminal activities.

For our qualitative results (Propositions 2.4 – 2.8), we assume that the distribution of crime opportunities, and hence m, are exogenous. In contrast, our quantitative results are obtained for an endogenous distribution of crime opportunities ($m = n^e y$).

2.6.1 Unemployment benefits

To illustrate the effects of unemployment benefits in our model, we consider an increase in the income flow, b, received by unemployed workers financed by an increase in τ^g. Note that, according to our interpretation, b is composed of the utility of not working, 0.4, and unemployment benefits received from the government.[23]

Proposition 2.4. *An increase in b reduces θ, raises ε_u and decreases ε_e if $\delta > s$ and*

[23] Unemployment insurance benefits, in practice, require certain eligibility conditions and are usually terminated after a fixed number of periods. We abstract from these in the model and calibration. For a more detailed treatment, see Holmlund (1998).

increases it if $\delta < s$.

For given θ, an increase in b provides unemployed workers with lower incentives to commit crimes. In Figure 2.2, the curve CS shifts to the right. For given ε_u, an increase in b raises the threat point of workers when bargaining so that fewer firms enter the market: the curve JC shifts downward. Although the overall effect seems ambiguous, Proposition 2.4 establishes that the measure of vacancies per unemployed falls as does the unemployed workers' incentives to commit crimes (recall that this result is established under the assumption that m is exogenous.).

The crime rate of employed workers depends on the average jail sentence and job duration because employed workers and individuals in jail will ultimately end up in the pool of unemployed, and enjoy $\mathcal{V}_u$.[24] The transition from employment to unemployment occurs at rate s, while the transition from jail to unemployment occurs at rate δ. If $\delta > s$ and $\mathcal{V}_u$ increases then the value of being in jail tends to increase relatively more, raising the incentive to commit crimes. In contrast, if $\delta < s$ then employed workers commit fewer crimes.

Quantitatively, δ is almost twice s, therefore the employed accept lower and lower valued crime opportunities as b rises, given m. However, when m is endogenous (and equal to $n^e y$) their willingness to commit more crime is offset by the falling return to crime due to the degradation of the labor market and the associated loss in output. As a result, the employed crime rate is almost constant (until $b = 0.6$) but the aggregate crime rate falls due to the drop in the unemployed crime rate, as

[24] A related result can be found in Burdett, Lagos and Wright (2003).

can be seen in Table 2.2. In terms of welfare, changing b has a negative effect by distorting firms' entry decisions, and for our numerical example, the distortionary effect outweighs the reduction in crime.

Table 2.2: Effects of Changing Unemployment Benefits (b)

	b				
	0.2	0.3	0.4	0.5	0.6
	Labor Force				
Employed (%)	93.8	93.4	92.9	92.2	91.3
Unemployed (%)	6.1	6.5	7	7.7	8.6
	Crime				
Employed Crime Rate	41.3	41.4	41.3	41.2	40.9
Unemployed Crime Rate	60.5	59	57.5	55.6	53.5
Total Crime Rate	42.5	42.5	42.4	42.3	41.9
Change in Welfare	-0.09%	-0.02%	–	-0.04%	-0.2%

2.6.2 Workers' bargaining strength

In the next two subsections, we will consider two different policies that affect payments to workers. We start with the effect of a change in workers' bargaining power. While β may not necessarily be viewed as a policy parameter, it may be influenced by government's tolerance vis-a-vis unions, for instance.

Proposition 2.5. *An increase in β:*

- *reduces θ;*
- *increases ε_u if $\beta < \eta(\theta)$ and decreases it if $\beta > \eta(\theta)$;*
- *increases ε_e if $\delta > s$ and $\beta > \eta(\theta)$ or $\delta < s$ and $\beta < \eta(\theta)$, and decreases it otherwise.*

An increase in β has two effects on unemployed worker's utility. On the one hand, workers enjoy a larger share of the match surplus which tends to make them better-off (they pay a lower hiring fee). On the other hand, a higher β reduces firms' incentives to open vacancies, and therefore also reduces the job finding rate of workers. The former effect dominates if $\beta < \eta$. In this case, ε_u increases so that the unemployed workers are less likely to engage in crime, and more agents participate in the labor force. If $\beta > \eta$ then the opposite happens.

The effect of changing β on the crime rate of employed workers is analogous to that of unemployment benefits described above, i.e., it depends on the ordering of δ to s.

Quantitatively, the relationship between the total crime rate and β is non-monotonic and highly non-linear.[25] Table 2.3 shows that reducing workers' bargaining power from 0.5 to 0.01, corresponding to a reduction of workers' compensation

[25]In Engelhardt et al. (2007) we have worked out a version of the model with no hiring

(compensation is $\bar{w}$, defined in (2.32)) of about 30%, generates a reduction in the total crime rate of about 20%. On the other hand, raising workers' bargaining power from 0.5 to 0.99, which corresponds to an increase in workers' compensation of 5%, decreases total crime roughly three-fold. These non-linearities are explained by the asymmetric response of the workers' job finding rate. Unemployment decreases from 5% to 1% as β is reduced from 0.5 to 0.01 but it increases from 5% to 28% as β is increased to 0.99. Moreover, as β increases from 0.5 to 0.99 the value of crime opportunities plummets due to a fall in employment (and hence, m).

Welfare is maximized for β close to 0.5. A change of β away from 0.5 distorts the entry of jobs —the Hosios (1990) condition no longer holds. The welfare loss associated with this distortion outweights any potential gain in terms of reducing criminal activities.

2.6.3 Wage subsidies

Suppose now that the government pays a (flow) wage subsidy $\varphi > 0$ per unit of time to each employed worker. This subsidy is financed by a lump-sum tax of size $n_e\varphi$. The Bellman equation for an employed worker becomes

$$r\mathcal{V}_e = w + \varphi - \tau + s\left(\mathcal{V}_u - \mathcal{V}_e\right) + \lambda_e \int \left[\varepsilon m + \pi\left(\mathcal{V}_p - \mathcal{V}_e\right)\right]^+ dG(\varepsilon). \tag{2.33}$$

The terms of the employment contract are still $w = y$ and $\phi = (1-\beta)\left(\mathcal{V}_e - \mathcal{V}_u\right)$. In the equilibrium conditions (2.18), (2.20) and (2.22), y is replaced by $y+\varphi$, suggesting that

fee. The effects of workers' bargaining strength on total crime are significantly different from the one we obtain under optimal contracts. In particular, for a calibrated version of the model, the crime rate is always decreasing with β.

Table 2.3: Changes in Bargaining Power (β)

β	0.01	0.05	0.10	0.50	0.90	0.95	0.99
$\bar{w}$	0.682	0.829	0.876	0.957	0.986	0.991	0.997
			Labor Force				
Employed (%)	98.9%	98%	97.3%	92.9%	80.6%	73.2%	49.5%
Unemployed (%)	1%	1.9%	2.6%	7%	19.3%	26.7%	50.5%
			Crime				
Employed Crime Rate	33.3	40.4	42.5	41.3	26.5	18.4	2.7
Unemployed Crime Rate	104.5	77.2	69.8	57.5	48.3	43.7	26.3
Total Crime Rate	34	41.1	43.1	42.4	30.7	25.1	14.6
Change in Welfare	-22.72%	-9.03%	-4.89%	–	-5.08%	-9.45%	-24.43%

an increase in the wage subsidy is equivalent to an increase in workers' productivity (except for welfare considerations).

Proposition 2.6. *An increase in φ raises θ, ε_e and ε_u.*

A wage subsidy has two effects on the equilibrium. It has a direct effect on the crime rate of the employed. Since the flow payment to the employed worker (including the wage subsidy) is higher, employed workers incur a larger opportunity cost if sent to jail, and hence they tend to commit fewer crimes. The wage subsidy also has a direct effect on firms' decision to open vacancies. Indeed, through the payment of the hiring fee the firm is able to capture a fraction of the wage subsidy paid to employed workers. Therefore, firms with vacant jobs have higher incentives to enter the market. Graphically, the JC curve shifts upward and both θ and ε_u increase.

The calibration adds another dimension to the relationship between the wage subsidy and the crime rate. Specifically, as the subsidy rises so does the value of crime opportunities (because of the increased employment). Therefore, the opportunity cost of committing crime is rising at the same time as the average benefit. Quantitatively, as seen in Table 2.4, a wage supplement equal to 5% of worker's yearly output reduces the crime rate by about 10%. The optimal wage subsidy is 0.084.

As previously indicated, the effects of an increase in φ on the equilibrium are equivalent to those of an increase in y. This is relevant because a large literature (e.g., Lochner (2004)) has emphasized policies aimed at increasing workers' human capital, and hence their productivity. (See Engelhardt et al. (2007) for a methodology to endogenize y).

Table 2.4: Effects of Wage Subsidies (φ)

	φ				
ϕ	0.025	0.05	0.084	0.15	0.2
Labor Force					
Employed (%)	93	93.2	93.3	93.6	93.8
Unemployed (%)	6.9	6.8	6.6	6.3	6.1
Crime					
Employed Crime Rate	39.2	37.1	34.6	30	26.9
Unemployed Crime Rate	54.8	52.3	49.1	43.3	39.4
Total Crime Rate	40.2	38.1	35.5	30.8	27.7
Change in Welfare	0.011	0.018%	0.021%	0.011%	-0.009%

2.6.4 Subsidies to vacancy creation

Consider a policy that subsidizes the creation of vacancies. We interpret such a policy in our model as a reduction in γ financed by a lump sum tax.

Proposition 2.7. *A decrease in γ raises θ and ε_u; decreases ε_e if $\delta > s$ and increases it if $\delta < s$.*

By reducing the cost to open vacancies, hiring subsidies promote job creation. Unemployed workers benefit from a higher job finding rate and therefore reduce their involvement in crime. Employed workers commit more crimes if $\delta > s$. (The intuition is similar to the one for an increase in b or β.) So the overall effect on crime is ambiguous. Quantitatively, shown in Table 2.5 reducing the hiring cost from .51 to .41 leads to an increase in crime of about 3%. (This result is surprisingly different from the one derived for the wage subsidies.) For our calibration, the introduction of hiring subsidies lowers welfare.

Table 2.5: Effects of Hiring Subsidies (γ)

	γ				
	0.31	0.41	0.51	0.61	0.71
Labor Force					
Employed (%)	94.4	93.6	92.9	92.2	91.6
Unemployed (%)	5.5	6.3	7	7.7	8.3
Crime					
Employed Crime Rate	44.2	42.7	41.3	40.2	39.1
Unemployed Crime Rate	57.1	57.3	57.5	57.6	57.7
Total Crime Rate	44.8	43.5	42.4	41.5	40.6
Change in Welfare	-0.28%	-0.05%	–	-0.04%	-0.13%

2.7 Crime policies

The government can have a direct effect on criminal activity by imposing harsher punishments on criminals or investing in police surveillance and technologies to solve crimes.[26] However, such policies also affect the labor market by modifying the outside options of the workers, their employment contract and job duration.

2.7.1 Apprehension

In our model, the effects of an increase in π on the labor market (job duration and market tightness) are ambiguous. On the one hand, a higher π tends to reduce employed workers' incentives to commit crimes. On the other hand, criminals are caught more often, which increases the rate of job destruction.

The quantitative findings with respect to π are substantial as seen in Table 2.6. Increasing the probability of being caught committing a crime by about 10% cuts the total crime rate by about 20%. A higher probability of catching criminals raises market tightness, but the effect is small.[27]

2.7.2 Jail sentences

Crime deterrence involves some degree of punishment for convicted criminals. Sentence lengths have been increased in several states, sentencing guidelines have

[26] Levitt (2004) argues that crime has fallen in the 90's because of an increase in police surveillance. Bedard and Helland (2000) find sizeable deterrence effects of custody rate and punitiveness changes on female crime.

[27] For a given δ, the optimal value of π, 0.0637, is given in the last column of the table; however, it is sensitive to the assumption that all individuals receive crime opportunities at the same rate and the estimate for the cost function $C(\pi)$.

Table 2.6: Changes in Criminal Apprehension (π)

	π					
π	0.017	0.018	0.019	0.02	0.021	0.0637
	Labor Force					
Employed (%)	92.8	92.9	92.9	92.9	92.9	93
Unemployed (%)	7.0	7.0	7.0	7.0	7.0	7.0
	Crime					
Employed Crime Rate	52.7	46.7	41.3	36.6	32.4	0.2
Unemployed Crime Rate	70.8	63.8	57.5	51.8	46.7	0.5
Total Crime Rate	53.9	47.8	42.4	37.6	33.4	0.2
Change in Welfare	-0.03%	-0.02%	–	0.01%	0.03%	0.21%

become tougher, and some states have moved to “three-strikes” rules. The next proposition characterizes the effect of punishment on the labor market and crime.

Proposition 2.8. *Assume $\lambda_e = \lambda_u$. An increase in δ decreases θ, ε_e and ε_u.*

An increase in δ, the Poisson rate at which an individual exits jail, moves the CS curve to the left. Since the punishment for committing crimes is weaker, both unemployed and employed workers commit more crimes and firms open fewer vacancies.

While crime policies have strong effects on criminal behavior they do not affect significantly labor market outcomes. The quantitative findings with respect to δ are substantial as seen in Table 2.7. Increasing the rate of release after incarceration from 0.75 to 0.8 (corresponding to a decline of about one month in jail) increases the total crime rate by about 15%.[28]

Table 2.7: Changes in Jail Sentences (δ)

	δ					
δ	< 0.03	0.65	0.7	0.75	0.8	0.85
Labor Force						
Employed (%)	93	92.9	92.9	92.9	92.9	92.8
Unemployed (%)	7.0	7.0	7.0	7.0	7.0	7.0
Crime						
Employed Crime Rate	0	31.1	36.2	41.3	46.5	51.5
Unemployed Crime Rate	0	43.3	50.3	57.5	64.6	71.6
Total Crime Rate	0	32	37.2	42.4	47.7	52.9
Change in Welfare	0.22%	0.03%	0.02%	–	-0.01%	-0.03%

[28]For a given π the optimal value for δ is small, less than 0.03. As indicated earlier, this result depends on our assumption that $\lambda_e = \lambda_u$ as well as our estimate for the cost of maintaining an individual in jail.

2.8 Conclusion

A search-theoretic model is constructed and calibrated in which labor market outcomes and crimes are determined jointly. The description of the labor market follows the canonical model of Pissarides (2000). Criminal activities are described in accordance with Becker (1968). Individuals' willingness to commit crimes is endogenous and depends on their labor status, current and future expected incomes, the probability of apprehension as well as the expected jail sentence if caught.

We show existence and uniqueness of equilibrium under simple conditions. The model generates crime rates that differ across labor force status - the unemployed have the highest propensity to commit crime compared to the employed - a feature that is present in the data. The tractability of the model allows us to qualitatively and quantitatively assess the effects that changing labor market policies (such as unemployment benefits, wage and hiring subsidies) have on the equilibrium.

Engelhardt et al. (2007) extends the benchmark model in two ways that seem relevant for the relationship between the labor market and crime. First, since the accumulation of human capital by workers is an important determinant of both labor market outcomes and crime decisions, we consider a simple extension of our model that endogenizes workers' productivity. Unemployed workers choose a training intensity that determines their level of productivity when matched with a firm. The worker's investment in human capital tends to be too low because of a holdup problem. Moreover, because of strategic complementarities between workers' training choices and firms' decisions to open vacancies, the model can exhibit multiple equilibria. While these complementarities are not new, in the presence of crime they provide another rationale for why policies aimed at reducing workers' training cost can be desirable.

Second, it is a well known fact (from the Survey of Inmates) that a significant fraction of property crimes are committed by individuals who are neither employed nor searching actively for a job. So, we also extend our model to account for participation decisions in the labor force along the lines of Pissarides (2000). As individuals' utility out of the market increases, they commit fewer crimes. Moreover, unemployed workers are less picky than individuals out-of-the-labor-force when choosing which crime opportunities to commit. Hence, the crime rate of the unemployed is larger than the crime rate of workers out of the labor force, in accordance with the evidence. We show that a decline in preferences towards work at home that generates an increase in the participation rate from 40% to 60% (the magnitude of the increase in female participation over the last 50 years) leads to a 40% rise in crime (female crime more than doubled over the period).

The model could also be extended to take into account additional aspects of crime. For example, firms might observe part of a worker's crime history, leading to the possibility of stigma effects. Another extension would allow for some depreciation of skills while in prison, thus increasing the cost of incarceration. It would also be of interest to allow for ex-ante heterogeneity across workers, which would require taking into account the distribution of wealth across agents.

CHAPTER 3
CRIME NETWORKS WITH BARGAINING AND BUILD FRICTIONS

3.1 Introduction

Classical theory argues that any type of punishment increases the cost and reduces the quantity of crime. Furthermore, crime can be reduced through policies that target the key player in a network. This paper introduces a third diminesion, the importance of the timing of anti-crime policies. For example, should law enforcement intervene when wholesale drug dealers are distributing to retail dealers or when retailers are selling to consumers? What I show is the type, target and timing of the intervention will have different and sometimes counterintuitive results in terms of fighting crime.

Three features shape the results. First, there is a network consisting of a wholesaler who authorizes or facilitates a criminal transaction and a retailer who carries out the act. Second, the retailer faces frictions in finding a wholesaler and crime opportunity where crime can be thought of as things such as selling drugs, prostitution or motor-vehicle theft. The last feature of the model is wholesalers and retailers bargain over the surplus of the criminal activity. Frictions are assumed to exist due to the illicit nature of the activity, and as a result, the network bargains over the surplus from crime.

The results show anti-crime policies have a range of effects depending upon their type, target and timing. As an extreme example, I find certain policies used to increase the criminal's costs could raise the aggregate level of crime. For example, consider the tactic of plea bargaining with a retailer in exchange for evidence that leads to the prosecution of a wholesaler. In other words, a policy that increases the costs of apprehension to the wholesale dealer after the initial wholesale-retail connection is established. The result of such a policy distorts the retail-wholesale bargaining in favor of retail dealers. Intuitively, the wholesaler's threat point is lower and he provides additional surplus to the retailer. All in all, an increase in retail profits increases the number of retailers and in turn the amount of crime.

Although the effects of certain policies go against the classical framework of supply and demand, many of my findings support other research that uses the canonical model. Specifically, if the value or revenue from crime goes up then the level of crime rises. As another example, take drug trafficking and a policy in which law enforcement officers pose as wholesale dealers in order to sell and bust retailers. Such a policy targets the retailer by increasing the likelihood of apprehension during the initial stage of the networking process. The result of such a policy raises the retailer's fixed cost. In other words, the policy would decrease the quantity of retailers, and in turn crime, while leaving the bargained price between the wholesaler and retailer unaffected. Therefore, many of the classical results from the supply and demand model still hold. However, I find policy makers must pay careful attention to how they impose costs on criminal networks as they could distort the allocation of recourses within the network and potentially increase crime.

In relation to the literature, I find stacking two different frictions results in significantly different outcomes than search models of crime that posses one friction.

For instance, Engelhardt et al. (2007) finds unequivocally that increasing the length of incarceration decreases crime. In addition, the results differ from the literature dealing with how a network augments a single matching function, such as Calvó-Armengol and Zenou (2005), where their results highlight how the rate of matching changes within a network. Also, the frictions distinguish how the *timing* and *type* of policies effect supply rather than simply how *targeting* the key player will change the equilibrium as discussed in Ballester et al. (2006). As a final comparison, my results differ significantly from the related literature regarding retail/wholesale drug networks. Chiu et al. (1998) argue "the choice of battlefield(retail/wholesale) on which to fight the war on drugs is likely to be of only secondary importance." Poret (2003) argues their results are dependent upon the linear cost function the retailers and wholesalers face. Alternatively, she determines the vertical structure of the market matters but argues targeting the retailer could increase consumption. I find the alternative where targeting the wholesaler increases consumption.

As an application, the model can explain the counter-intuitive facts observed in the U.S. cocaine market during the 1980's. During the period, the U.S. "War on Drugs" effectively doubled the annual number of arrests and increased eight fold the number incarcerated for a drug related offense. At the same time, U.S. cocaine prices fell and consumption rose.[1] In the classical model of supply and demand, it

[1]The Criminal Justice Statistics provides the number of incarcerations and arrests. Office of National Drug Control Policy (2001) provides evidence the price of cocaine fell. Drug Abuse Warning Network (1996, 2002) provides evidence cocaine consumption rose during the 1980's.

is difficult to reconcile these observations. Specifically, an increase in the cost of supplying drugs should lead to a fall in consumption and a rise in price. However, the model below provides evidence that anti-drug policies could have distorted the market and increased the aggregate level of drugs hitting the street. Intuitively, the U.S. government's action increased the likelihood and costs for those trafficking across state lines. As a result, the wholesale dealer's bargaining position fell. As evidence, we observe an increase in surplus going to the street level dealer. Hence, an increase in the retail surplus increased the number of retail dealers and in turn consumption. In Section 3.5, I discuss the argument in further detail.

In the next section, I introduce the model's environment and characterize the resulting equilibrium. Section 3.3 analyzes the effects from changing the expected costs to the network. Finally, Section 3.4 evaluates the efficiency of different policies.

3.2 Model

3.2.1 Environment

Time, t, is continuous and goes on forever. The economy is composed of a unit-measure of infinitely-lived wholesalers and a large measure of retailers. Both wholesalers and retailers are risk neutral and discount at rate $r > 0$. The two types of players network in three stages.

In the first stage, retailers and wholesalers pay to search for each other where the cost of search is $\pi_0 F_0^v$ and $\pi_0 F_0^w$, respectively. The parameter π_0 represents the probability of apprehension during the initial period of searching while F_0^v and

F_0^w represents the cost of being apprehended for the retailer and wholesaler, respectively. The wholesalers match with a large measure of retailers through the technology $m_0(w_0, v_0)$, where v_0 and w_0 represents the mass of the retailers and wholesalers engaged in the initial search process. In accordance with the related literature, the matching function is strictly increasing, strictly concave with respect to each of its arguments, and exhibits constant returns to scale. Furthermore, $m_0(0, \cdot) = m_0(\cdot, 0) = 0$ and $m_0(\infty, \cdot) = m_0(\cdot, \infty) = \infty$.

In the second stage, retailers and wholesalers risk being caught at the rate π_1, and if caught, pay F_1^v and F_1^w, respectively. If the retail-wholesale pair is apprehended then the network is destroyed. As in the first stage, the retail-wholesale network finds a crime opportunity through the technology $m_1(v_1, c_1)$ where v_1 is the measure of retailers with a wholesaler and c_1 is the measure of untaken crime opportunities. Crime opportunities can be thought of as a street corner where criminals can continuously pickpocket, or a drug user who is continuously buying drugs. Following the benchmark, $m_1(\cdot, \cdot)$ is assumed to have the same characteristics as $m_0(\cdot, \cdot)$. In addition, I assume retailers do not interfere with crime opportunities already being taken by other retailers.[2]

In the third stage, the wholesaler facilitates the crime at a fixed cost, y_p, and the crime produces output y for the wholesale-retail pair. At this point, the pair uses Nash bargaining to divide the surplus y. As a result, the retailer receives y_v share

[2]The underlying idea is retailers protect their turf, where I refer to turf as the retailers clientele/local.

of the surplus while the wholesaler receives $y_w \equiv y - y_v - y_p$. At the same time, the retailer and wholesaler risk the loss of the crime opportunity in two ways. The network loses the crime opportunity exogenously at rate λ but keeps their association. Alternatively, the retailer and wholesaler run the risk of apprehension at rate π_2, lose the criminal opportunity along with their association, and pay the cost of being apprehended F_2^v and F_2^w, respectively.

This paper focuses on steady-state equilibrium where the distribution of crime opportunities and the measure of retailers is constant over time. Following Pissarides (2000) notation, the market tightness of the initial stage, $\theta_0 = \frac{v_0}{w_0}$, and second stage, $\theta_1 = \frac{v_1}{c_1}$ are time invariant. Therefore, a wholesaler matches with a retailer according to a Poisson process with arrival rate $\frac{m_0(v_0,w_0)}{w_0} \equiv \theta_0 q_0(\theta_0)$. Similarly, each retailer matches with a crime opportunity according to a Poisson process with arrival rate $\frac{m_1(v_1,c_1)}{v_1} \equiv q_1(\theta_1)$ and the retailer matches with the wholesaler at rate $\frac{m(v_0,w_0)}{v_0} \equiv q_0(\theta_0)$.

3.2.2 Bellman equations

In this section, I write down the flow Bellman equations for the retailers and wholesalers. A retailer is in one of the following three states: searching for a wholesaler, v_0, matched with a wholesaler and searching for an opportunity, v_1, or taking the crime opportunity and splitting the surplus with the wholesaler, v_2. The value of being in each state $i \in \{0, 1, 2\}$ is denoted $\mathcal{V}_i$. The flow Bellman equations for a retailer is

$$r\mathcal{V}_0 = \pi_0 \left[-F_0^v - \mathcal{V}_0\right] + q_0(\theta_0) \left[\mathcal{V}_1 - \mathcal{V}_0\right], \tag{3.1}$$

$$r\mathcal{V}_1 = \pi_1 \left[-F_1^v - \mathcal{V}_1\right] + q_1(\theta_1) \left[\mathcal{V}_2 - \mathcal{V}_1\right], \ and \tag{3.2}$$

$$r\mathcal{V}_2 = y_v + \pi_2 \left[-F_2^v - \mathcal{V}_2\right] + \lambda \left[\mathcal{V}_1 - \mathcal{V}_2\right]. \tag{3.3}$$

Equation 3.1 has the following interpretation. Initially, the retailer searches for a wholesaler to facilitate a criminal action. He finds the wholesaler at rate $q_0(\theta_0)$ at which time he enjoys a utility flow $[\mathcal{V}_1 - \mathcal{V}_0]$. However, at the same time he faces the likelihood of apprehension, π_0, and if caught, would pay the cost F_0^v as well as losing the asset value of being in the initial state. The second stage follows the same logic except the retailer is searching for a criminal opportunity. Finally, in Equation (3.3) the retailer finds a criminal opportunity and receives the benefit y_v. However, he faces the probability of being caught and suffering the disutility of losing his network, $\pi_2 \left[-F_2^v - \mathcal{V}_2\right]$, or he could lose the crime opportunity and have to search for a new one, $\lambda \left[\mathcal{V}_1 - \mathcal{V}_2\right]$.

The wholesaler progresses through three states: searching for a retailer, has a retailer and waiting for the retailer to discover an opportunity, or transacting with the retailer and facilitating the crime. The value of being in each state $i \in \{0, 1, 2\}$ is denoted $\mathcal{W}_i$. The flow Bellman equations for a wholesaler is

$$r\mathcal{W}_0 = \pi_0 \left[-F_0^w - \mathcal{W}_0\right] + \theta_0 q_0(\theta_0) \left[\mathcal{W}_1 - \mathcal{W}_0\right], \tag{3.4}$$

$$r\mathcal{W}_1 = \pi_1 \left[-F_1^w - \mathcal{W}_1\right] + q_1(\theta_1) \left[\mathcal{W}_2 - \mathcal{W}_1\right], \textit{ and} \tag{3.5}$$

$$r\mathcal{W}_2 = y_w + \pi_2 \left[-F_2^w - \mathcal{W}_2\right] + \lambda \left[\mathcal{W}_1 - \mathcal{W}_2\right]. \tag{3.6}$$

The interpretation of the wholesaler's problem is similar to the retailer's with the exception of the matching function in the first stage and the payoff in the last. As wholesalers are matching with retailers, they find matches at rate $\theta_0 q_0(\theta_0)$. In addition, they receive the payoff $y_w \equiv y - y_v - y_p$ where y_v share of the surplus goes to the retailer and y_p is the exogenous cost of facilitating the transaction. In terms of cocaine trafficking, one can consider y_p as the cost of buying cocaine on a centralized market and the transport costs to distribute the drugs to the retailer. In using the same example, one can think of y as the reservation value of the cocaine user.

3.2.3 Bargaining, free entry and networking flows

In this section, I discuss three key features of the model: how the surplus from crime is split between the wholesaler and retailer; how the free entry of retailers affects payoffs; how the networking of process affects the aggregate crime rate.

The contract between the retailer and wholesaler is determined by the generalized Nash solution. The contract satisfies

$$y_v = \arg\max(\mathcal{V}_2 - \mathcal{V}_1)^{\beta}(\mathcal{W}_2 - \mathcal{W}_1)^{1-\beta}, \tag{3.7}$$

where the retailer's bargaining power is $\beta \in [0, 1]$. The assumption relies on the idea that the illicit network negotiates their contract at the time of the transaction.

From (3.1)-(3.3), one can see the return to crime for retailers is decreasing as market tightness increases. Therefore, given free entry of retailers then

$$\mathcal{V}_0 = 0. \tag{3.8}$$

Also, the model can be solved with a free entry condition for wholesalers as an alternative to a fixed size. The results are in the appendix.

The model's flows come in two types. The first is how retailers match with wholesalers and then match with crime opportunities. The second type of flows relate how the number of available crime opportunities are found and lost. In the steady-state, the distribution of retailers at each stage is

$$q_0(\theta_0)v_0 + \lambda v_2 = [\pi_1 + q_1(\theta_1)]v_1, \textit{ and} \tag{3.9}$$

$$q_1(\theta_1)v_1 = (\pi_2 + \lambda)v_2. \tag{3.10}$$

According to (3.9), the mass of retailers who flow into the state where they match with crime opportunities must be equal to the number flowing out of the same state. The measure flowing into the state are those who just found a wholesaler, $q_0(\theta_0)v_0$, and those who just lost a crime opportunity but not their wholesaler, λv_2. The flow of individuals exiting the same state are those who have been apprehended plus those who found a new crime opportunity, $[\pi_1 + q_1(\theta_1)]v_1$. Similarly, (3.10) prescribes that the flows into and out of the state where crime is taking place must be equal.

The second set of flows captures the amount of crime taking place. As a result of the fixed number of crime opportunities and the assumption criminals do not interfere with each other turf, the total number of opportunities must equal the sum of the ones being taken (c_2) and the opportunities remaining available (c_1), or

$$c_1 + c_2 = \kappa, \tag{3.11}$$

where κ is the fixed quantity of crime opportunities. In addition, the number of opportunities being found must equal the quantity being lost in the steady state, or

$$\theta_1 q_1(\theta_1) c_1 = (\pi_2 + \lambda) c_2. \tag{3.12}$$

To reiterate, a crime opportunity is thought to be a street corner where pick-pocketing occurs or a drug user who is continuously buying drugs. Hence, the quantity of crime on a per period basis is equivalent to the amount of opportunities being taken,

$$c_2 = \left(\frac{\theta_1 q_1(\theta_1)}{\theta_1 q_1(\theta_1) + \pi_2 + \lambda} \right) \kappa. \tag{3.13}$$

3.2.4 Equilibrium

The steady-state equilibrium of the model can be defined as follows.

Definition 3.1. *A steady-state equilibrium consists of* $\{y_v, v_0, v_1, v_2, c_2\}$ *such that retail surplus* (y_v) *satisfies (3.7);* (v_0, v_1, v_2) *satisfies the free entry condition (3.8), and the flows (3.9)-(3.10); and the quantity of crime* (c_2) *is deduced from (3.13).*

Solving for the equilibrium can be done in steps. First, the share of the surplus going to the retailer can be deduced, y_v. Following the first step, two conditions arise from the free entry condition and the of flow retailers within the networking process. These two conditions lead to a solution of the two equilibrium levels of market tightness (θ_0,θ_1). Once the market tightness is known, the quantity of crime can be solved as well as the mass of retailers at each level of the networking process.

In determining retail surplus, it is straight forward to reduce the flow Bellman equations of the retailer and wholesaler into functions of the model's parameters and market tightness, θ_0 and θ_1. Given the substitution, (3.7) implies the surplus of the crime going to the retailer is

$$y_v = \beta y + \frac{\pi_1(\pi_2 + r)(\beta F_1^w - F_1^v(1-\beta)) - \pi_2(\pi_1 + r)(\beta F_2^w - F_2^v(1-\beta))}{r + \pi_1}. \quad (3.14)$$

As the reader can see, the retail surplus is a weighted share of total output, βy, plus what I will refer to as a distortionary term.

At first sight, the distortionary term seems cumbersome. However, upon closer inspection one realizes the distortion would be zero if the retailer and wholesaler had an equivalent level of bargaining power and paid the same costs of apprehension. In addition, the term is simplified due to the fact that the utility gain from taking the crime opportunity is discounted at the same rate by both the wholesaler ($[\mathcal{W}_2 - \mathcal{W}_1]$) and retailer ($[\mathcal{V}_2 - \mathcal{V}_1]$). As a result, the equilibrium rates of matching do not affect the way the surplus is split.

Taking the retailer's share of the surplus as given, one can use the free entry condition to find

$$q_0(\theta_0) = \pi_0 F_0^v \frac{q_1(\theta_1)(r+\pi_2) + (r+\pi_1)(r+\pi_2+\lambda)}{q_1(\theta_1)(y_v - \pi_2 F_2^v) - \pi_1 F_1^v(r+\pi_2+\lambda)}, \tag{3.15}$$

which I refer to as the "Network Creation" curve and label $q_0(\theta_0) = NC[q_1(\theta_1)]$. The NC curve captures the fact that as the cost of being caught or searching rises, $\pi_i F_i^v$ for $i \in \{0, 1, 2\}$, then fewer retailers enter the market and create new networks. As a result, the matching rate of the retailers increases. In the same way, an increase in the retailer's surplus increases the mass of retailers and as a result it becomes increasingly difficult for a retailer to find a wholesaler. In general, the NC curve captures how retailers enter the market, and more specifically, the rate at which they match within the networking process.

Similarly, the flows (3.9)-(3.10) and (3.11)-(3.12) imply a "Network Flow" curve

$$\theta_0 q_0(\theta_0) = \frac{(q_1(\theta_1)\pi_2 + \pi_1\pi_2 + \pi_1\lambda)\theta_1\kappa}{(\theta_1 q_1(\theta_1) + \pi_2 + \lambda)}, \tag{3.16}$$

which I will refer to implicitly as $q_0(\theta_0) = NF[\theta_1 q_1(\theta_1)]$. The NF curve captures the relationship between the number of crime opportunities, κ, and the measure being taken given the inherent frictions retailers face when establishing a network and locating a crime opportunity.

The NC and NF curves, given y_v from (3.14), reduce the equilibrium to two equations and two unknowns. As a result, they can be used to prove the following proposition.

Proposition 3.1. *An equilibrium exists and is unique if*

1. $0 < y_v - \pi_2 F_2^v$

2. $0 < \mathcal{W}_0$.

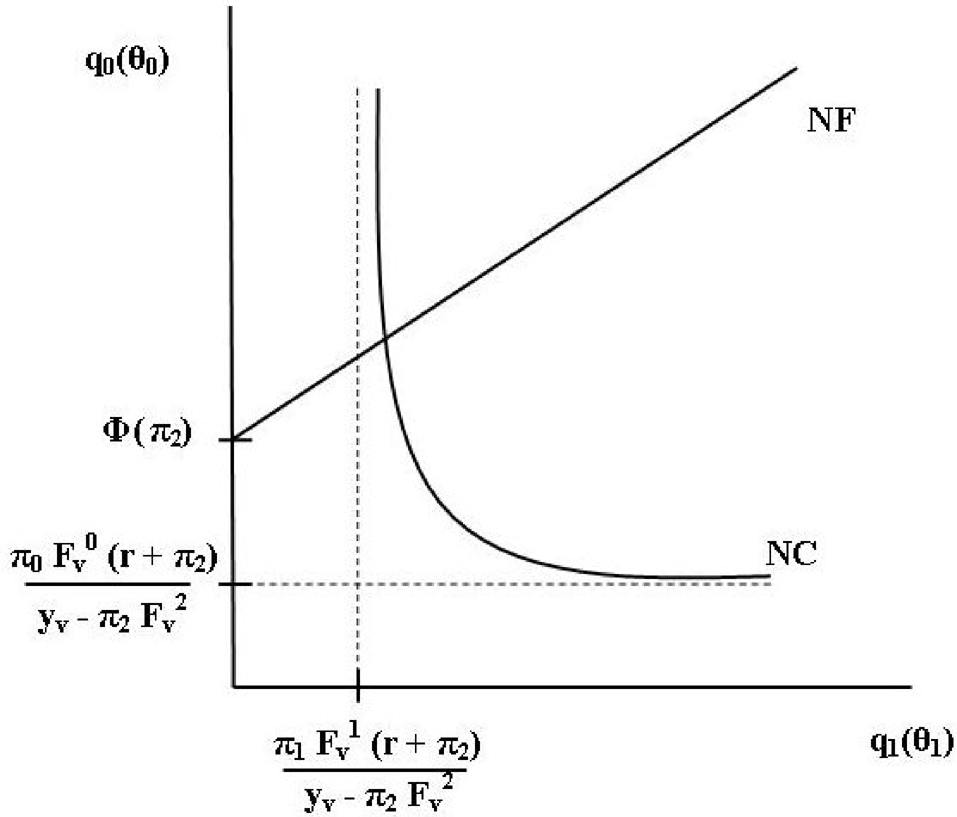
where y_v *satisfies (3.14).*

The proof is in the appendix. The two conditions for existence and uniqueness can be easily interpreted. Condition 1 states the surplus from the crime must outweigh the expected cost of apprehension. As you can see, the cost of being caught in the first two stages of networking are irrelevant to the existence and uniqueness of the equilibrium as the length of time spent in each stage decreases to zero as the mass of retailers falls. Condition 2 captures the simple fact that wholesalers must earn a profit. It is a sufficient condition for $y_w > 0$.

A nice feature about the equilibrium is it can be illustrated as seen in Figure 3.1.[3] The figure captures the rate the retailer goes from the initial process of looking for a wholesaler to the final step of finding the criminal opportunity. On the y-axis, we see the rate retailers find a wholesaler and on the x-axis the rate they find the crime opportunity. The illustration demonstrates how the NF curve slopes upward because if fewer retailers are in the market, or $q_0(\theta_0)$ is higher, then fewer will be in the second stage and therefore $q_1(\theta_1)$ is higher. This fact is driven completely by the flow equations. The second equilibrium condition, the NC curve, slopes downward because of the crowding out effect from the free entry condition. In other words,

[3] $\Phi(\pi_2)$ is the value of $q(\theta_1)$ when $\theta_1 q(\theta_1) = \pi_2$.

Figure 3.1: Equilibrium Matching



as more retailers enter the market then the length of time spent searching for a wholesaler rises (or $q_0(\theta_0)$ falls). However, if $q_0(\theta_0)$ falls then the profitability of entering the market falls. Therefore, if $q_0(\theta_0)$ falls then the free entry condition requires an offsetting effect of $q_1(\theta_1)$ rising, or an increase in the speed of finding the criminal opportunity.

3.3 Policy

I begin by analyzing changes in the cost of apprehension, or F_i^j for $i \in \{0, 1, 2\}$ and $j \in \{v, w\}$. These comparative statics are straight forward to analyze as they effect only the NC curve. After examining the effects of increasing the costs of apprehension given the timing and target, I will look at the effects from altering the likelihood of apprehension, or π_i for $i \in \{0, 1, 2\}$.

3.3.1 Costs of apprehension

As expressed in the introduction, increasing the cost of apprehension can have counter-intuitive implications.

Result 3.1. *A change in F_0^w has no effect on y_v, the quantity of retailers or crime.*

Simply put, F_0^w is a fixed cost to wholesalers who are making positive profits. Hence, altering the fixed cost has no effect on crime.[4] The result changes if a free entry conditions for wholesalers is introduced. For further discussion, refer to the appendix.

At this stage, the retail market is competitive and fixed costs affect their decisions.

Result 3.2. *An increase in F_0^v decreases the quantity of retailers and crime while leaving y_v unchanged.*[5]

In words, F_0^v is a fixed cost to retailers and doesn't change the surplus sharing although it reduces the quantity being produced.

[4]The result is conditional on the fact the equilibrium exists, or Conditions 1 and 2 in Proposition 3.1 are satisfied. However, it is feasible to set F_0^w where a condition for existence is violated.

[5]The retailer's share of the surplus is unchanged because of the assumption on the timing of the bargaining. If the retailer and wholesaler bargained over any future realization of a crime when they initially met then Result C.1 would change. Therefore, the assumption on the timing of the bargaining plays a key role in determining how policy distorts supply.

The most counter-intuitive result of a change in policy relates to increasing the cost of apprehension when the criminal network is established but is not engaging in crime.

Result 3.3. *An increase in F_1^w leads to an increase in y_v, the quantity of retailers and crime.*

A key feature of the model is how the bargaining between the criminal types can be altered by anti-crime policies. In the extreme, anti-crime policies can distort bargaining in a way that leads to an increase in crime.

The remaining results carry over from the classical model. Specifically, if policy makers increase costs then crime falls.

Result 3.4.

- *A decrease in y (or an increase in y_p) decreases y_v, the mass of retailers and crime.*
- *An increase in F_1^v decreases y_v, the mass of retailers and crime.*
- *An increase in F_2^v decreases the mass of retailers and crime while y_v increases.*
- *An increase in F_2^w decreases y_v, the mass of retailers and crime.*

3.3.2 Likelihood of apprehension

Changing the likelihood of apprehension has two effects on the model. First, it decreases the return to retailers, which decreases the number entering the market and shifts the NC curve. Second, it destroys networks and inhibits the amount of crimes being taken. In terms of the model, the NF curve shifts.

The model has been constructed to consider three different types of apprehension.

Result 3.5. *An increase in π_0 decreases the mass of retailers and crime while leaves y_v unchanged.*

Again, π_0 is a fixed cost as is F_0^v and F_0^w . Hence, an increase in π_0 increases the costs to retailer, reduces their willingness to enter the market and decreases crime.

Instead of inhibiting network creation through π_0, anti-crime policies can target existing retail-wholesale networks.

Result 3.6. *An increase in π_1 decreases y_v if and only if $(1-\beta)F_1^v > \beta F_1^w$. If an increase in π_1 decreases y_v then crime decreases.*

The result hinges on how the surplus is split. If y_v falls then it guarantees a decrease in the retailer surplus, a fall in the mass of retailers, or in other words a shift to the right in the NC curve. On the other hand, if y_v rises and a large mass of retailers enter the market, enough for the shift in the NC curve to outweigh the falling NF curve (which captures the destruction in matches) then it is possible for crime to increase.

Attacking an established crime opportunity by increasing π_2 has a similar effect as attacking the network, or π_1. However, whether π_2 decreases crime hinges on nearly the opposite condition that guarantees a decrease in crime from π_1.

Result 3.7. *An increase in* π_2 *decreases* y_v *if and only if* $(1-\beta)[F_2^v - F_1^v \frac{\pi_1}{r+\pi_1}] < \beta[F_2^w - F_1^w \frac{\pi_1}{r+\pi_1}]$. *If an increase in* π_2 *decreases* y_v *then crime decreases.*

The condition in Result 3.7 would be the exact opposite of the one in Result 3.6 if $F_2^w = F_1^w$ and $F_2^v = F_1^v$.

In general, the timing of apprehension plays a key role in anti-crime policy. It is critical because it can alter the way the surplus from crime is split and in turn the number of criminals on the street committing crime.

3.4 Efficiency

In the standard matching model, efficiency is discussed in terms of the Hosios condition as found in Hosios (1990). In summary, the bargaining power determines the efficient level of market activity. In terms of a crime network with bargaining and build frictions, the efficient level of bargaining power is where the least amount of crime occurs.

Result 3.8. *Given an equilibrium exists, if* β *decreases then crime decreases.*

Hence, setting the lowest level of bargaining power results in the most efficient level or smallest amount of crime. The proof is in the appendix but the result is intuitive. As β decreases, the surplus going to the retailer falls. As a result, fewer retailers enter the market and carry out criminal acts. However, it is possible to set β high enough to where monopolists make negative profits and in turn eliminate the crime equilibrium.

Although it is interesting to consider changes in bargaining power, the applicable question is the relative effectiveness of government policies. For instance, how does raising F_2^w compare to raising F_2^v.

Result 3.9. *Increasing F_2^w or F_2^v by one unit decreases crime by equal amounts.*

The equivalence result might be surprising. However, bargaining plays the key role. In other words, retailers help compensate the wholesalers by decreasing y_v when F_2^w increases. On the flip side, wholesalers compensate retailers by increasing y_v when F_2^v increases although not enough to completely offset the additional costs. In either case, bargaining guarantees any additional cost in the final stage is shared evenly between each player and results in an equivalent drop in crime.

The equivalency result is not what the model predicts in general. Obviously, increasing F_1^w is ineffecient in terms of anyother policy aimed at increasing costs as it increases crime. Increasing F_0^w is the second worst policy as it has no influence on crime. Other comparisons of crime policies rely critically on the parameterization of the model and are excluded here. However, the comparisons raise the question about the most effective timing, target and type of anti-crime policies.

3.5 Discussion

As an application, the model allows a policy maker to think about if the "War on Drugs" might have distorted the cocaine market and increased consumption. To begin the discussion, Figure 3.2 illustrates the dynamics of the market.

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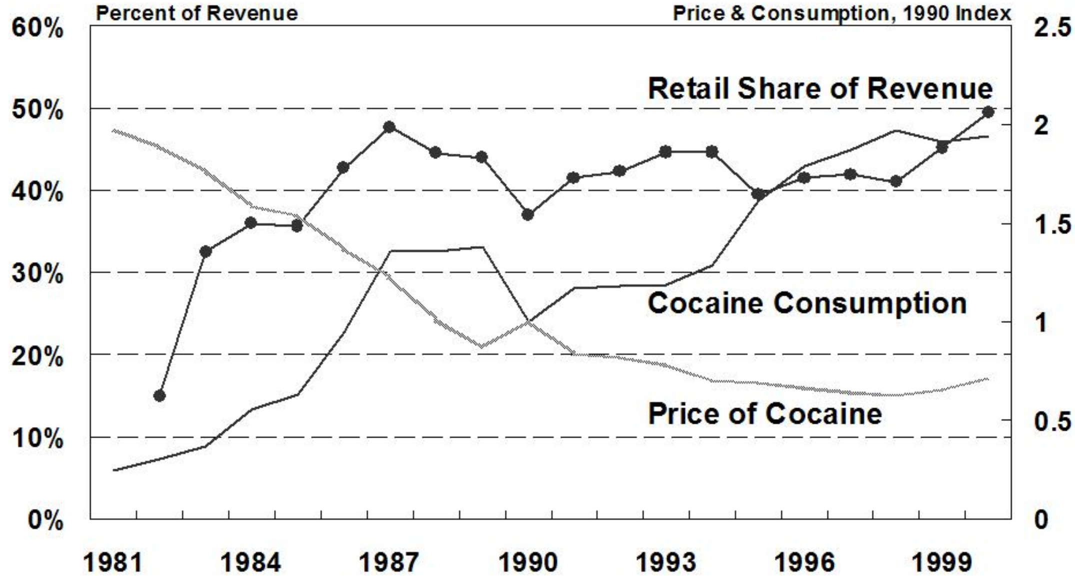
[6]Consumption is *non-crack* cocaine proxied by the quantity of emergency room mentions published by Drug Abuse Warning Network (1996, 2002). Non-crack cocaine is measured by the percent of mentions that state the substance was not smoked. I plot non-crack cocaine

Figure 3.2: Overview of U.S. Cocaine Market[6]



Although I use a proxy for consumption and the price measure has drawn criticism, I argue three trends about the market can be deduced.[7] First, the price of drugs fell. Second, the quantity rose significantly. Finally, the share of the revenue from the sale went increasingly from the wholesaler to the retailer.

From these three facts, I argue the "War on Drugs" might have increased drug consumption following Result 3.3. For the argument to hold, the proposition requires the "War on Drugs" targeted the wholesaler by increasing the cost of apprehension after the retail-wholesale connection was made. In regards to the targeting the

in order to control for the technological innovation that is argued to have caused widespread use. Price data comes from Office of National Drug Control Policy (2001). A wholesale drug dealer is defined as someone selling 100 or more grams.

[7]Due to these issues, I am constrained to an illustrative example.

wholesaler, the federal government's "War on Drugs" consistently penalized wholesale dealers due to their jurisdiction being those trafficking across state lines. Also, Glaeser et al. (2000) shows the Federal Government has a higher tendency to target high profile dealers. The second requirement is the "War on Drugs" needed to have been targeting dealers who had established a retail connection. The implication seems plausible as one of the main techniques used by the DEA is to have retail level dealers provide evidence against wholesalers after a crime has taken place. Finally, the cost of apprehension (mainly the length of incarceration) looks to have increased for federal prosecutions over this time period.

In the end, the empirically evidence is insufficient to provide confidence in such a claim as the "War on Drugs" increased drug consumption. However, the model supports the idea that revenue sharing plays a key role. This feature of the model is highlighted by the fact that revenue went increasingly to the retailer over the period when cocaine consumption rose the most.

3.6 Conclusion

In this paper, I incorporate build frictions into the formation of a simple network. In turn, the players within the network bargain over the surplus from working together. These two features demonstrate how the timing of anti-crime policies can play a critical role in determining their effects on crime. In the extreme, anti-crime policies aimed at a network can increase crime. However in general, we see increasing the costs of distribution will decrease crime albeit at different rates depending upon the target, timing, and type of policy.

As an application, the model provides an explanation for the rising distribution costs, rising consumption and falling prices which was observed in the U.S. cocaine market during the 1980's. The argument is the "War on Drugs" distorted the networks revenue sharing, a distortion that lead to an increase in the number of retail dealers and in turn consumption.

APPENDIX A
THE EFFECT OF EMPLOYMENT FRICTIONS ON CRIME: THEORY AND ESTIMATION

A.1 Criminal and non-criminal agents

An agents value of leisure/freedom can partition him into one of two types, those who commit crime and those who do not.

Proof of Proposition 1.1 It is sufficient to show as b_k increases then the difference between the value of being unemployed and being incarcerated increases unbounded. If true, it implies the cost of crime is to high for a particular $\bar{b} \leq b_k$. As the reader can see, the difference between the welfare of being unemployed and in jail, up to a constant, is

$$b - z + \lambda_0 \int_R^\infty \frac{1 - F(x)}{\delta + \lambda_1(1 - F(x))} dx.$$

Hence, the difference increases as b increases without bound given $\lambda_1 < \lambda_0$ and p_L is sufficiently large. It can be seen by plugging in the reservation wage equation, then using the Implicit Function Theorem along with the Fundamental Theorem of Calculus. Therefore, there exists a point where the cost of the crime outweighs any benefit $g_j \in \mathcal{G}$. ■

A.2 Wage dispersion

At this point I develop the remaining part of the model required in estimation. Specifically, I develop $F_C(w)$. The development of $F_C(w)$ follows from the work of Burdett et al. (2004) and Mortensen (1990). The distribution of wages posted for the non-criminal market is derived in Mortensen (1990) and therefore excluded.

To reiterate, I am analyzing the criminal market with two types of firms and one type of agent. Proposition **??** justifies why I am able to look at the criminal market exclusively and Proposition 1.1 justifies why only one type of agent is needed to estimate the model.

To begin, I provide Lemma A.1 in order to characterize $F_C(w)$. Lemma A.1 is stated generically with the understanding some cases are "vacuous." Let $\underline{w}_c$ be the lower support of $F_C(w)$, $\underline{w}_{i,c}$ and $\overline{w}_{i,c}$ is the lowest and highest wage paid by a firm of type i, $\Pi_i(\cdot)$ is firm i profit, $C_k(g_j)$ is the reservation wage necessary to deter an agent from crime g_j, and $L_C(w)$ is the amount of labor for a firm offering wage w.

Lemma A.1. *1. $F_C(w)$ has no mass points, 2. $\underline{w}_c = R_c$ or $\underline{w}_c = C_k(g_j)$ for a $g_j \in \mathcal{G}$, 3. there are no gaps in $F_C(w)$ except on the intervals $(C_k(g_j) - \varepsilon_{C_k(g_j)}, C_k(g_j))$, where $\varepsilon_{C_k(g_j)} > 0$ and all $g_j \in \mathcal{G}$, 4. $\overline{w}_{L,c} = \underline{w}_{H,c}$ or $\underline{w}_{H,c} = C_k(g_j)$, and 5. $L_C(w)$ is increasing.*

Proof. 1. Suppose $F^C(w)$ has a mass point at w', then by offering $w' + \varepsilon$ the firm would increase their labor market supply by a discrete amount, implying $w' + \varepsilon$ has a larger profit and firms deviate to the slightly higher wage until no mass point exists.

2. Suppose all firms offer $R_c + \varepsilon \leq w$ where $\varepsilon > 0$. A firm paying $R_c + \varepsilon$ would deviate to paying R_c because they would be paying the worker less while they would lose workers at the same rate, therefore increasing profits. The identical

argument can be made but replacing R_c with $C_k(g)$. Also,

$$\underline{w}_c = \begin{cases} R_c & \text{if} \quad \Pi_i(R_c) > \Pi_i(C_k(g_j)) \\ C_k(g) & \text{if} \quad \Pi_i(R_c) \leq \Pi_i(C_k(g_j)) \end{cases}$$

3. Suppose a firm offers $w' - \varepsilon$ arbitrary close to $C_k(g_j)$, then by offering $C_k(g_j)$ the firm could decrease their job destruction rate by a discrete amount because they would not be losing workers to prison, implying an increase in profits. Therefore, no firms offer wages within $(C_k(g_j) - \varepsilon_{C_k(g_j)}, C_k(g_j))$.

4. Same argument as Lemma A.1.3.

5. First, considering $L(w) \in [\underline{w}_{L,c}, \overline{w}_{L,c}]$ or $[\underline{w}_{H,c}, \overline{w}_{H,c}]$ separately allows one to apply the proof of Mortensen(1990) Proposition 3. Second, $L_C(C_k(g_j) - \varepsilon_{C_k(g_j)}) < L_C(C_k(g_j))$ holds because for both to exist then $\Pi_i(C_k(g_j) - \varepsilon_{C_k(g_j)}) \leq \Pi_i(C_k(g_j))$ and $C_k(g_j) - \varepsilon_{C_k(g_j)} < C_k(g_j)$ implying $L_C(C_k(g_j) - \varepsilon_{C_k(g_j)}) < L_C(C_k(g_j))$.

□

I refer several times in the body of the text to the fact higher productive firms pay more than lower productive firms. Here, I restate Proposition 1.3 as

Lemma A.2. $p_i < p_{i+1} \Rightarrow w_{i,c} \leq w_{i+1,c}$.

Proof. The proof is in two steps. First, I show it holds for wages offered within $[C_k(g_j), C_k(g_{j+1})]$. Second, I show it holds across any crime wage $C_k(g_j)$.

1. For firms i and $i+1$ offering wages in $[C_k(g_j), C_k(g_{j+1})]$ then $\overline{w}_{i,c} \leq \underline{w}_{i+1,c}$

because $L(w) \in [\underline{w}_{L,c}, \overline{w}_{L,c}]$ or $[\underline{w}_{H,c}, \overline{w}_{H,c}]$ is continuous and increasing in w implying Mortensen (1990) Proposition 3 applies.

2. Suppose there are two firms (i and $i+1$), paying above and below $C_k(g_j)$, then $\exists\ \underline{w}_{C_k(g_j)} < C_k(g_j)$ and $C_k(g_j) < \overline{w}_{C_k(g_j)}$ such that $\Pi_i(\underline{w}_{C_k(g_j)}) = \Pi_i(\overline{w}_{C_k(g_j)})$ and $\Pi_{i+1}(\underline{w}_{C_k(g_j)}) = \Pi_{i+1}(\overline{w}_{C_k(g_j)})$, but if

$(p_i - \underline{w}_{C_k(g_j)})L(\underline{w}_{C_k(g_j)}) = (p_i - \overline{w}_{C_k(g_j)})L(\overline{w}_C) \Rightarrow$

$\overline{w}_{C_k(g_j)}L(C) - \underline{w}_{C_k(g_j)}L(\underline{w}_{C_k(g_j)}) = p_i(L(\overline{w}_{C_k(g_j)}) - L(\underline{w}_{C_k(g_j)})) \Rightarrow$

$\overline{w}_{C_k(g_j)}L(\overline{w}_{C_k(g_j)}) - \underline{w}_{C_k(g_j)}L(\underline{w}_{C_k(g_j)}) < p_{i+1}(L(\overline{w}_{C_k(g_j)}) - L(\underline{w}_{C_k(g_j)})) \Rightarrow$

$(p_{i+1} - \underline{w}_{C_k(g_j)})L(\underline{w}_{C_k(g_j)}) < (p_{i+1} - \overline{w}_{C_k(g_j)})L(\overline{w}_{C_k(g_j)})$

$\Rightarrow$ no $i+1$ firm would offer $\underline{w}_{C_k(g_j)} \Rightarrow \sigma_{i+1}(g_j) = 1$.

$\square$

I have proven $F_C(w)$ is continuous on the support except below the points $C_k(g_j)$ for all $g_j \in \mathcal{G}$. From Lemma A.2, I will break down the distribution of $F_C(w)$ into parts

$$F_C^i(w_{i,c}) = F_C(w|\underline{w}_{i,c} < w < \overline{w}_{i,c}). \tag{A.1}$$

It is key to derive the wages being paid, $G_C(w)$, in order to back out $F_C(w)$. Therefore, define $G_C(w)$ as

$$G_C^i(w_{i,c}) = G_C(w|\underline{w}_{i,c} < w < \overline{w}_{i,c}), \tag{A.2}$$

where $G_C(w)$ is defined explicitly for the two firms as[1]

$$G_C^L(w_{L,c}) = \frac{F_C^L(w_{L,c})}{(1+\kappa_1(1-F_C^L(w_{L,c}))}, \textit{ and}$$

$$G_C^H(w_{H,c}) = \frac{F_C^H(w_{H,c})}{1+\kappa_2(1-F_C^H(w_{H,c}))}, \tag{A.3}$$

where $\kappa_1 = \frac{\lambda_1\varphi}{\delta+\mu\pi\overline{\Gamma}(g_{e,L})+\lambda_1(1-\varphi)}$ and $\kappa_2 = \frac{\lambda_1(1-\varphi)}{\mu\pi\overline{\Gamma}(g_{e,H})+\delta}$.

The rest of the necessary steps in attaining $F_C(w)$ in closed form can be summarized in two steps. The first is to derive $L_C(w)$ from $L_C^L(w_{L,c}) = e_{L,c}\frac{\frac{dG_C^L(w_{L,c})}{dw}}{\frac{dF_C^L(w_{L,c})}{dw}}$ and $L_C^H(w_{H,c}) = e_{H,c}\frac{\frac{dG_C^H(w_{H,c})}{dw}}{\frac{dF_C^H(w_{H,c})}{dw}}$. The second and final step in attaining $F_C(w)$ plugs $L_C(w)$ into the profit function of a firm, $\Pi_i(w_{i,c})$, then sets the equilibrium condition that firms of the same type make the same profit, $\Pi_i(\underline{w}_{i,c}) = \Pi_i(w_{i,c})$, along with $F_C^i(\underline{w}_{i,c}) = 0$. The result is

[1]Setting the time derivatives equal to zero gives you equation A.3

$$\begin{aligned}
\frac{d}{dt}G_C^L(w_{L,c})e_{L,c} &= \lambda_0 u_k\varphi F_C^L(w_{L,c}) \\
&\quad -(\delta+\mu\pi\overline{\Gamma}(g_{e,L})+\lambda_1(1-\varphi)+\lambda_1\varphi(1-F_C^L(w_{L,c})))e_{L,c}G_C^L(w_{L,c}) \\
\frac{d}{dt}G_C^H(w_{H,c})e_{H,c} &= (\lambda_0 u_k+\lambda_1 e_{L,c})(1-\varphi)F_C^H(w_{H,c}) \\
&\quad -(\delta+\mu\pi\overline{\Gamma}(g_{e,H})+\lambda_1(1-\varphi)(1-F_C^H(w_{H,c})))e_{H,c}G_C^H(w_{H,c}),
\end{aligned}$$

where the steady state flows are:

$$\begin{aligned}
&u_k = (\delta+\mu\pi\overline{\Gamma}(g_{e,L})+\lambda_1(1-\varphi))\rho(\delta+\mu\pi\overline{\Gamma}(g_{e,H}))/\Omega, \\
&e_{L,c} = \lambda_0\varphi\rho(\delta+\mu\pi\overline{\Gamma}(g_{e,H}))/\Omega, \\
&e_{H,c} = (\delta+\mu\pi\overline{\Gamma}(g_{e,L})+\lambda_1)(1+\varphi)\rho\lambda_0/\Omega,
\end{aligned}$$

and $\Omega = u_k + n_k + e_{L,c} + e_{H,c}$.

$$F_C^L(w_{L,c}) = \tfrac{1+\kappa_1}{\kappa_1}(1-\sqrt{\tfrac{(p_1-w_{L,c})}{(p_1-\underline{w}_{L,c})}}),$$

$$F_C^H(w_{H,c}) = \tfrac{1+\kappa_2}{\kappa_2}(1-\sqrt{\tfrac{(p_2-w_{H,c})}{(p_2-\underline{w}_{H,c})}}), \tag{A.4}$$

and $\overline{w}_{L,c}$ and $\overline{w}_{H,c}$ are derived using $F_C^L(\overline{w}_{L,c}) = 1$ and $F_C^H(\overline{w}_{H,c}) = 1$, or

$$\overline{w}_{L,c} = p_1 - (p_1 - \underline{w}_{L,c})(\tfrac{1}{1+\kappa_1})^2,$$

$$\overline{w}_{H,c} = p_2 - (p_2 - \underline{w}_{H,c})(\tfrac{1}{1+\kappa_2})^2. \tag{A.5}$$

Therefore, the necessary equation in estimation is

$$F_C(w) = \begin{cases} 0 & \text{if } \ w < \underline{w}_{L,c} \\ \varphi F_C^L(w_{L,c}) & \text{if } \ \underline{w}_{L,c} \leq w \leq \overline{w}_{L,c} \\ \varphi & \text{if } \ \overline{w}_{L,c} \leq w \leq \underline{w}_{H,c} \\ \varphi + (1-\varphi)F_C^H(w_{H,c}) & \text{if } \ \underline{w}_{H,c} \leq w \leq \overline{w}_{H,c} \\ 1 & \text{if } \ \overline{w}_{H,c} < w \end{cases}, \tag{A.6}$$

which is continuous by Lemma A.1 in the support as defined in equation A.6 and differential except at the points $\underline{w}_{i,c}$ and $\overline{w}_{i,c}$.

A.3 Full Likelihood

In this section, I derive the full likelihood that identifies all of the parameters including

$(b_c, b_{nc}, z, \pi, \Gamma(g))$.[2] The full likelihood requires two additional types of data. In

[2] μ can be normalized to a sufficient large number without loss of generality. Therefore,

addition, I discuss how the parameters I have already estimated are left unchanged when estimating the remaining parameters.

The data necessary to estimate the remaining parameters are

1. the value of crime when an individual is caught,

2. aggregate number of crimes committed, $\mathcal{B}$.

To reiterate, the data is used to estimate the remaining parameters. $\Gamma(g)$ can be deduced using data #1 where the data identifies the discrete pdf, $\gamma(g)$, and is identified when individuals are caught, or

$$\begin{aligned} l(\theta) \;=\; & \rho_0^{d_0^n} e^{-\rho t_0} e^{-(\mu\pi\overline{\Gamma}(g_u)+\lambda_0)t_2} (\mu\pi\overline{\Gamma}(g_u)\gamma(g))^{d_{1,n}} \\ & [\lambda_0 f_C(w) e^{-(\mu\pi\overline{\Gamma}(g_{e,i})+\lambda_1(1-F(\tilde{w}))+\delta)t_2} \\ & (\mu\pi\overline{\Gamma}(g_{e,i})\gamma(g))^{d_{2,n}} (\lambda_1(1-F(\tilde{w})))^{d_{2,e}} \delta^{d_{2,u}}]^{d_{1,e}}, \end{aligned} \tag{A.7}$$

where $\gamma(g)$ is estimated using a clustering type method up to the relative frequency of each occurence in the domain $\mathcal{G}$.

Next, π can be deduced by the aggregate moment

$$\pi = \frac{\pi\mu\overline{\Gamma}_u u + \pi\mu\overline{\Gamma}_{e,L} e_L + \pi\mu\overline{\Gamma}_{e,H} e_H}{\mathcal{B}},$$

where the parameters in the numerator are identified by Equation A.7 and $\mathcal{B}$ is data #2. This arguement is similar to Flinn (2006) who uses an aggregate measure of firm profits to estimate one parameter of the model, specifically bargaining power.

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it is excluded from the discussion.

Finally, (b_c, b_{nc}, z) can be deduced from the previously identified parameters, in particular the super-efficient estimators $\underline{w}_{L,c}$ and $\underline{w}_{H,c}$, and the reservation wages. The reservation wages $[C(g_{e,L}), C(g_{e,H})]$ or $[R, C(g_{e,H})]$ are deduced from the model. To find them, realize the flow Bellman equations of the incarcerated, unemployed and those employed at the smallest wage of low and high wage firms are

$$\begin{aligned}
rJ &= z + \rho(V_0 - J), \\
rV_0 &= b + \mu \sum_{g_i > g_u} \gamma(g_i)(g_i + \pi(J - V_0)) + \lambda_0 \Delta(C_L), \\
rV_1 &= C(g_{e,L}) + \delta(V_0 - V_1) + \mu \sum_{g_i > g_{e,L}} \gamma(g_i)(g_i + \pi(J - V_1)) + \lambda_1 \Delta(C_L), \\
rV_2 &= C(g_{e,H}) + \delta(V_0 - V_2) + \mu \sum_{g_i > g_{e,H}} \gamma(g_i)(g_i + \pi(J - V_2)) + \lambda_1 \Delta(C_H),
\end{aligned}$$

respectively, where

$$\Delta(C_i) = \int_{C_i} \frac{1 - F(x)}{r + \delta + \mu\pi(1 - \Gamma(g_{e,i})) + \lambda_1(1 - F(x))} dx.$$

Also, the threshold values of crime opportunities are

$$\begin{aligned}
V_1 &= J + \frac{g_{e,L}}{\pi}, \\
V_2 &= J + \frac{g_{e,H}}{\pi}.
\end{aligned}$$

As a result, the system can be reduced to two equations and two unknowns, (b_c, z), given the estimated parameters and setting $C(g_{e,L}) = \underline{w}_{L,c}$ and $C(g_{e,H}) = \underline{w}_{H,c}$. I leave it to the reader to show they identify both (b_c, z) given $g_{e,L} \neq g_{e,H}$. Also, it should be noted identification of the remaining two parameters is dependent upon the type of equilibrium deduced in the first stage. For example, the reservation wages should be used as one of the equilibrium conditions to deduce (b_c, z) if $\overline{\Gamma}_u = \overline{\Gamma}_{e,L}$. Finally, b_{nc} is deduced from the non-criminal reservation wage equation which does not include crime.

To conclude, the reader should realize the estimates of these parameters will not affect the ones already estimated in the body of the paper. To see this, notice estimates for $\Gamma(g)$ are independent of the rest of the likelihood. In addition, π is estimated from one aggregate moment. Finally, (b_c, z) are found using the restrictions of the model. Therefore, the estimates of (ρ, λ_0, λ_1, δ, φ, $\mu\pi\overline{\Gamma}(g_u)$, $\mu\pi\overline{\Gamma}(g_{e,L})$, $\mu\pi\overline{\Gamma}(g_{e,H})$,$\underline{w}_{L,c}$, $\underline{w}_{H,c}$, $\overline{w}_{L,c}$, $\overline{w}_{H,c}$) found in Section 1.3.3 are independent of the estimates of (b_c, b_{nc}, z, π, $\Gamma(g)$).

APPENDIX B
CRIME AND THE LABOR MARKET: A SEARCH MODEL WITH OPTIMAL CONTRACTS

B.1 Proofs of Lemmas and Propositions

Proof of Lemma 2.1 According to Nash's axioms, (ϕ, w) must be pairwise Pareto-efficient. Since the up-front payment ϕ allows the worker and the firm to transfer utility perfectly, the wage, w, must be chosen to maximize the total surplus of the match. The comparison of (2.6) and (2.11) shows that the match surplus is maximized iff $\mathcal{V}_f = 0$. From (3.3), $\mathcal{V}_f = 0$ requires $w = y$. Finally, the first-order condition of (2.12) with respect to ϕ yields (2.14).■

Proof of Lemma 2.2 The slope of CS in the (ε_u, θ) space is

$$\left.\frac{d\theta}{d\varepsilon_u}\right|_{CS} = (1-\beta)m\frac{r+\delta+\lambda_u\pi[1-G(\varepsilon_u)]}{\pi\beta\gamma}.$$

The slope of JC in the (ε_u, θ) space is

$$\left.\frac{d\theta}{d\varepsilon_u}\right|_{JC} = (1-\beta)m\frac{\lambda_u[1-G(\varepsilon_u)]-\lambda_e[1-G(\varepsilon_e)]}{\beta\gamma-\{r+s+\lambda_e\pi[1-G(\varepsilon_e)]\}\frac{q'(\theta)}{[q(\theta)]^2}\gamma}.$$

Observing that

$$\frac{r+\delta}{\pi}+\lambda_u[1-G(\varepsilon_u)] > \lambda_u[1-G(\varepsilon_u)]-\lambda_e[1-G(\varepsilon_e)]$$

and

$$\beta\gamma \leq \{r+s+\lambda_e\pi[1-G(\varepsilon_e)]\}\frac{-q'(\theta)}{[q(\theta)]^2}\gamma+\beta\gamma,$$

it is easy to see that

$$\left.\frac{d\theta}{d\varepsilon_u}\right|_{JC} < \left.\frac{d\theta}{d\varepsilon_u}\right|_{CS}.$$

■

Proof of Proposition 2.1 Summing (2.17) and (2.22) one obtains

$$\frac{(r+s)\,\gamma}{(1-\beta)q(\theta)}+\left(\frac{r+\delta}{\pi}\right)\varepsilon_u m=y-x+\lambda_e m\int_{\varepsilon_u+\frac{\pi\gamma}{m(1-\beta)q(\theta)}}^{\bar{\varepsilon}}[1-G(\varepsilon)]\,d\varepsilon. \tag{B.1}$$

From (B.1), it can be checked that θ is a strictly decreasing function of ε_u. So if a solution to (2.17) and (B.1) exists then it is unique. Denote $\varepsilon_u(\theta)$ the solution ε_u to the equation (2.17). Since $b-x>0$ then $\varepsilon_u(\theta)>0$. Furthermore, $\varepsilon_u(\theta)$ is non-decreasing in θ. Define $\Gamma(\theta)$ as

$$\Gamma(\theta)=y-x+\lambda_e m\int_{\varepsilon_u(\theta)+\frac{\pi\gamma}{m(1-\beta)q(\theta)}}^{\bar{\varepsilon}}[1-G(\varepsilon)]\,d\varepsilon-\frac{(r+s)\,\gamma}{(1-\beta)q(\theta)}-\left(\frac{r+\delta}{\pi}\right)\varepsilon_u(\theta)m.$$

An equilibrium is then a θ that solves $\Gamma(\theta)=0$. Using the expression for $\left(\frac{r+\delta}{\pi}\right)\varepsilon_u(\theta)m$ given by (2.17), we have

$$\Gamma(0)=y-b+(\lambda_e-\lambda_u)\,m\int_{\varepsilon_u^0}^{\bar{\varepsilon}}[1-G(\varepsilon)]\,d\varepsilon.$$

So if (2.28) holds then $\Gamma(0)>0$. Furthermore, $\Gamma(\infty)=-\infty$. Therefore, a solution to $\Gamma(\theta)=0$ exists and it is such that $\theta>0$. Given θ, (2.17) gives a unique ε_u and (2.18) yields a unique ε_e. Finally, given $(\theta,\varepsilon_u,\varepsilon_e)$ the system (2.24)-(2.25) can be solved closed-form to give

$$n_p=\frac{\lambda_u\pi[1-G(\varepsilon_u)]u+\lambda_e\pi[1-G(\varepsilon_e)](1-u)}{\delta+\lambda_u\pi[1-G(\varepsilon_u)]u+\lambda_e\pi[1-G(\varepsilon_e)](1-u)},$$

$$n_u=u(1-n_p),$$

$$n_e=(1-u)(1-n_p),$$

where u is defined in (2.26).

Finally, the result according to which $\varepsilon_e>\varepsilon_u$ comes from (2.21).■

Proof of Proposition 2.2 From Proposition 2.1, no crime occurs in equilibrium iff $\varepsilon_u \geq \bar{\varepsilon}$. From (2.20) if $\varepsilon_u \geq \bar{\varepsilon}$ then $\theta = \hat{\theta}$. From (2.17) the condition $\varepsilon_u \geq \bar{\varepsilon}$ requires (2.30).■

Proof of Proposition 2.3 For any exogenous m, Proposition 2.1 has established that an equilibrium exists and is unique. Hence, there exists a unique triple $[\varepsilon_e(m)$, $\varepsilon_u(m)$, $\theta(m)]$ and $\theta(m) > 0$ if (2.28) holds. With endogenous m, we look for the following fixed point:

$$\mu[\varepsilon_e(m), \varepsilon_u(m), \theta(m)] = m \tag{B.2}$$

From (2.28), if $y > b$ then $\theta(0) > 0$ and hence $\mu[\varepsilon_e(0), \varepsilon_u(0), \theta(0)] > 0$. Furthermore, $\mu[\varepsilon_e(m), \varepsilon_u(m), \theta(m)]$ is a continuous and bounded function of m. Hence, there exists a $m > 0$ solution to (B.2).■

Proof of Proposition 2.4 The pair (ε_u, θ) is uniquely determined by (2.17) and (B.1). Differentiating these two equations, it is straightforward to show that $d\varepsilon_u/db > 0$ and $d\theta/db < 0$. From (2.18) the sign of $d\varepsilon_e/db$ is the same as $s - \delta$.■

Proof of Proposition 2.5 The pair (ε_u, θ) is determined by (2.17) and (B.1). Differentiating these two equations one can establish that $d\theta/d\beta < 0$. In order to determine the effects on ε_u we adopt the following change of variable: $\tilde{\gamma} = \gamma/[(1 -$

$\beta)q(\theta)]$. Equations (2.17) and (B.1) can now be rewritten as

$$\left(\frac{r+\delta}{\pi}\right)\varepsilon_u m = b - x + \frac{\beta}{1-\beta}q^{-1}\left[\frac{\gamma}{(1-\beta)\tilde{\gamma}}\right]\gamma + \lambda_u m \int_{\varepsilon_u}^{\bar{\varepsilon}} [1-G(\varepsilon)]\, d\varepsilon, \tag{B.3}$$

$$(r+s)\,\tilde{\gamma} + \left(\frac{r+\delta}{\pi}\right)\varepsilon_u m = y - x + \lambda_e m \int_{\varepsilon_u + \frac{\pi}{m}\tilde{\gamma}}^{\bar{\varepsilon}} [1-G(\varepsilon)]\, d\varepsilon. \tag{B.4}$$

Equations (B.3) and (B.4) determine ε_u and $\tilde{\gamma}$. The term $\frac{\beta}{1-\beta}q^{-1}\left[\frac{\gamma}{(1-\beta)\tilde{\gamma}}\right]$ on the RHS of (B.3) increases in β if $\beta < \eta(\theta)$. Differentiating (B.3) and (B.4) one can show that $d\varepsilon_u/d\beta > 0$ if $\beta < \eta(\theta)$ and $d\varepsilon_u/d\beta < 0$ if $\beta > \eta(\theta)$. To determine the effect of an increase in β on ε_e we use (2.18) which can be reexpressed as

$$\left(\frac{r+\delta}{\pi}\right)\varepsilon_e m = y - x + (\delta - s)\tilde{\gamma} + \lambda_e m \int_{\varepsilon_e}^{\bar{\varepsilon}} [1-G(\varepsilon)]\, d\varepsilon. \tag{B.5}$$

From (B.4) there is a negative relationship between ε_u and $\tilde{\gamma}$. Therefore, $\text{sign}(d\varepsilon_e/d\beta) = \text{sign}[(s-\delta)d\varepsilon_u/d\beta]$.$\blacksquare$

Proof of Proposition 2.6 As indicated in the text, y is replaced by $y+\varphi$ in the equilibrium conditions (2.18), (2.20) and (2.22). Hence, we can prove the result for a change in y. Equation (2.17) is independent of y. Therefore, it is easy to show from (2.17) and (B.1) that both θ and ε_u increase following an increase in y. From (2.21),

$$\frac{d\varepsilon_e}{dy} = \frac{d\varepsilon_u}{dy} + \frac{\pi\gamma}{m(1-\beta)}\left(\frac{-q'}{q^2}\right)\frac{d\theta}{dy} > 0.$$

$\blacksquare$

Proof of Proposition 2.7 Following the proof of Proposition 2.5, we adopt the following change of variable: $\tilde{\gamma} = \gamma/[(1-\beta)q(\theta)]$. The pair $(\tilde{\gamma}, \varepsilon_u)$ is determined by

(B.3) and (B.4) which can be rewritten as

$$\left(\frac{r+\delta}{\pi}\right)\varepsilon_u m = b - x + \beta p \circ q^{-1}\left[\frac{\gamma}{(1-\beta)\tilde{\gamma}}\right]\tilde{\gamma} + \lambda_u m \int_{\varepsilon_u}^{\bar{\varepsilon}} [1 - G(\varepsilon)]\, d\varepsilon, \tag{B.6}$$

$$(r+s)\,\tilde{\gamma} + \left(\frac{r+\delta}{\pi}\right)\varepsilon_u m = y - x + \lambda_e m \int_{\varepsilon_u + \frac{\pi}{m}\tilde{\gamma}}^{\bar{\varepsilon}} [1 - G(\varepsilon)]\, d\varepsilon. \tag{B.7}$$

where $p(\theta) = \theta q(\theta)$ and $\circ$ is the composition operator. Equation (B.6) gives a positive relationship between ε_u and $\tilde{\gamma}$ while (B.7) defines a negative relationship between ε_u and $\tilde{\gamma}$. It can be checked from (B.6) and (B.7) that $d\varepsilon_u/d\gamma < 0$ and $d\tilde{\gamma}/d\gamma > 0$. From (2.18) the sign of $d\varepsilon_e/d\tilde{\gamma}$ is the same as $\delta - s$. Finally, from (2.17) ε_u increases if $\theta\gamma$ increases which implies $d\theta/d\gamma < 0$.$\blacksquare$

APPENDIX C
CRIME NETWORKS WITH BARGAINING AND BUILD FRICTIONS

C.1 Proofs of the Proposition and Results

Proof of Proposition 3.1 Equation (3.14) solves for y_v. Given y_v, one can think of the NC and NF curves in the space $(q_1(\theta_1), q_0(\theta_0))$. In such a space, the NC curve has the properties

$$\begin{aligned} NC\,'[q_1(\theta_1)] &< 0, && \text{(C.1)} \\ \lim_{q_1(\theta_1)\to\infty} NC[q_1(\theta_1)] &= \frac{F_0^v \pi_0 (r+\pi_2)}{y_v - \pi_2 F_2^v}, && \text{(C.2)} \\ \lim_{q_1(\theta_1)^+ \to \frac{F_1^v \pi_1 (r+\pi_2+\lambda)}{y_v - \pi_2 F_2^v}} NC[q_1(\theta_1)] &= \infty. && \text{(C.3)} \end{aligned}$$

The NF curve has the properties

$$\begin{aligned} NF\,'[q_1(\theta_1)] &> 0, && \text{(C.4)} \\ \lim_{q_1(\theta_1)\to\infty} NF[q_1(\theta_1)] &= \infty, && \text{(C.5)} \\ \lim_{q_1(\theta_1)\to 0} NF[q_1(\theta_1)] &= \Phi(\pi_2), && \text{(C.6)} \end{aligned}$$

where $\Phi(\theta q(\theta)) = q(\theta)$.[1]

Hence, these two equations imply a unique solution to $\{q_1(\theta_1), q_0(\theta_0)\}$ which can be used to solve for the remaining unknowns. ■

[1]For example, a Cobb-Douglas matching function with elasticity η implies $\Phi(x) = x^{-\frac{\eta}{1-\eta}}$.

Proof of Results 3.1-3.8 To solve for the comparative statics, first deduce the change in y_v from (3.14). Next, deduce the changes in the matching frictions from the NC curve (3.15), and NF curve (3.16).

As the results are straightforward to deduce, I talk through a simple example, or Result C.1. First, one finds no effect on y_v or the NF curve, which can be seen by differentiating (3.14) and (3.16) by F_0^v. However, the NC curve shifts out, or to the right. Therefore, as $q_1(\theta_1)$ increases then $\theta_1 q_1(\theta_1)$ decreases, and from (3.13), crime falls. ■

Proof of Result 3.9 Following the previous style of proof,

$$\frac{\partial y_v}{\partial F_2^w} = -\beta\pi_2, \tag{C.7}$$

$$\frac{\partial y_v}{\partial F_2^v} = -(1-\beta)\pi_2. \tag{C.8}$$

Next, realize the NF curve is constant while the NC curve shifts according to

$$\frac{\partial NC}{\partial F_2^w} = -\pi_0 F_0^v \frac{r\left[\lambda + r + q_1(\theta_1)\right]}{\left[q_1(\theta_1)(y_v - \pi_2 F_2^v) - \pi_1 F_1^v (r+\lambda)\right]^2} \frac{\partial y_v}{\partial F_2^w} q_1(\theta_1), \tag{C.9}$$

$$\frac{\partial NC}{\partial F_2^v} = -\pi_0 F_0^v \frac{r\left[\lambda + r + q_1(\theta_1)\right]}{\left[q_1(\theta_1)(y_v - \pi_2 F_2^v) - \pi_1 F_1^v (r+\lambda)\right]^2} \left(\frac{\partial y_v}{\partial F_2^w} - \pi_2\right) q_1(\theta_1). \tag{C.10}$$

Therefore, plugging (C.7) and (C.8) into (C.9) and (C.10), respectively, results in an identical shift in the NC curve and an equivalent change in crime. ■

C.2 Wholesale Free Entry

In this section I discuss how the results change if one assumes a large measure of wholesalers that are given a decision to enter freely.

To begin, several results do not change including the flows (3.9)-(3.12), how y_v is split (refwageeq), and the NC curve (3.15).

However, free entry results in the wholesaler's entering until they are indifferent,

$$\mathcal{W}_0 \quad = \quad 0. \tag{C.11}$$

In the same way, the free entry condition results in a second NC curve, $\mathrm{NC}_{\mathcal{W}}$, which mirrors the original NC curve excpet where the costs are the wholesaler's,

$$\theta q_0(\theta_0) = \pi_0 F_0^w \frac{q_1(\theta_1)(r+\pi_2) + (r+\pi_1)(r+\pi_2+\lambda)}{q_1(\theta_1)(y_w - \pi_2 F_2^w) - \pi_1 F_1^w (r+\pi_2+\lambda)}. \tag{C.12}$$

Most importantly, the left hand side is the frictions the wholesaler faces in making first match. These results lead to similar conclusions.

Proposition C.1. *An equilibrium exists and is unique if*

1. $0 < y_v - \pi_2 F_2^v$
2. $0 < y_w - \pi_2 F_2^w$.
3. $\frac{F_0^v \pi_0 (r+\pi_2)}{y_v - \pi_2 F_2^v} < \Phi\left(\frac{F_0^w \pi_0 (r+\pi_2)}{y_w - \pi_2 F_2^w}\right)$.

where $y_w = y - y_v - y_p$, y_v *satisfies (3.14) and* $\Phi\left(\frac{F_0^w \pi_0 (r+\pi_2)}{y_w - \pi_2 F_2^w}\right)$ *is the value of* $q_1(\theta_1)$ *when* $\theta_1 q(\theta_1) = \frac{F_0^w \pi_0 (r+\pi_2)}{y_w - \pi_2 F_2^w}$.

Proof. Equation 3.14 solves y_v and by definition y_w. Given y_v and y_w, one can think of the NC and NC$_{\mathcal{W}}$ curves implicitly in the space $(q_1(\theta_1), q_0(\theta_0))$. In such a space, the NC curve has the properties specified in (C.1)-(C.3). However, the NC$_{\mathcal{W}}$ curve has the properties

$$NC\,'_{\mathcal{W}}[q_1(\theta_1)] > 0, \tag{C.13}$$

$$\lim_{q_1(\theta_1)\to\infty} NC_{\mathcal{W}}[q_1(\theta_1)] = \Phi\left(\frac{F_0^w \pi_0 (r+\pi_2)}{y_w - \pi_2 F_2^w}\right), \tag{C.14}$$

$$\lim_{q_1(\theta_1)^+ \to \frac{F_1^w \pi_1 (r+\pi_2+\lambda)}{y_w - \pi_2 F_2^w}} NC_{\mathcal{W}}[q_1(\theta_1)] = 0. \tag{C.15}$$

Hence, the NC and NC$_{\mathcal{W}}$ equations imply a unique solution to $\{\theta_0, \theta_1\}$ which can be used to solve for the remaining unknowns. □

The first two conditions of Proposition C.1 are interpreted in the same fashion as Proposition 3.1. The third condition garentees there exists a point where both conditions are satisfied. It can be interpreted as when $q_1(\theta_1)$ increases then more retailers and wholesalers enter the market. However, if to few wholesalers/retailers enter then the market then it may never be worth it for retailers/wholesalers to enter at all.

As discussed in the text, allowing the free entry of wholesalers changes Result 3.1.

Result C.1. *An increase in* F_0^w *decreases the quantity of crime while leaving* y_w *unchanged.*

Proof. The surplus splitting equation and NC curve is unchnaged. However, the $\mathrm{NC}_{\mathcal{W}}$ curve shifts to the left or decreases $q_1(\theta_1)$ while increasing $q_0(\theta_0)$. Hence, crime falls. □

Other results can be discussed. However, adequate evidence has been given regarding the importance of the timing of anti-crime policies.

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