The Labor Market and Female Crime*

Bryan Engelhardt  Guillaume Rocheteau
University of Iowa  Federal Reserve Bank of Cleveland

Peter Rupert
Federal Reserve Bank of Cleveland

January 24, 2007

Abstract

The same forces that lead to changes in participation in the labor market can also affect the extent of criminal activity. To analyze such interaction we construct a search-theoretic model where labor market participation, labor market outcomes and crime are determined jointly. The model is calibrated to US data focusing on females. The main finding is that changes affecting the labor market, such as changes in productivity or in preferences toward market activities, can have significant effects on criminal behavior.

*We thank Marco Cozzi, Dale Mortensen, Victor Rios-Rull and Randall Wright for their comments. We also thank the seminar participants at the Federal Reserve Bank of Cleveland and at the universities of Texas, Iowa, Pennsylvania, Santa Barbara and Western Ontario. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Cleveland or the Federal Reserve System.
1 Introduction

Crime statistics in the U.S. over the past several decades reveal several interesting trends. First, there has been a substantial decline in the rate of property crimes. Second, crime rates of men and women look very different.

Since 1960, the fraction of property offenses perpetrated by women has increased by a factor of 5. In 1960 women committed about 3 crimes per every one thousand persons, by 2003 that number increased to roughly 15. Although property crimes committed by males have also increased over this time period, the rise has not been nearly as large, increasing by a factor of 1.3–from 25 crimes per thousand to about 34 crimes per thousand. Moreover, since 1975 there has been a large decline in the property crime rate of males while female crimes have stayed roughly constant.1

The last several decades have also seen much different patterns of labor force participation between the sexes. Labor force participation of women rose substantially after 1960 and then began to level off in the early 1990’s, while that for men has shown a long steady decline.

In this paper we examine whether these two phenomena might be linked. Empitically, Witt and Witte (2000) find that “...a one percentage point rise in the female labor force participation rate increases the crime rate by just over 5 percent.” This is obviously relevant for an understanding of female crime given that the female labor force participation rate has risen substantially over the last 50 years, from about 40 percent in 1960 to more than 60 percent in 2003.

Understanding how labor market outcomes and crimes are determined jointly calls for a theoretical model in which unemployment, participation in the labor force, wages and criminal activity are endogenous. The labor market follows the canonical description proposed by Pissarides (2000), extending it in a very natural way to account for criminal activity. This model was chosen in part because we think that changes that may affect the availability of jobs can matter for unemployed workers’ incentives to commit crimes. We are then able to obtain endogenous crime rates for individuals in any state, i.e., employed, unemployed or out of the labor force. In the data, more than 50 percent of females convicted of criminal activities were employed prior to their arrest. Therefore, in our model, all individuals receive random opportunities to commit crime. The crime opportunities have different values and individuals choose which ones to undertake and which ones to leave aside.

1The overall property crime rate looks much like that for males because males still commit a much larger share of crimes.
We do not take a stand on the driving force behind the increase in female labor force participation. What is relevant for our paper is that there has been a change in the relative valuation of staying at home versus working in the market.\footnote{See, Fortin (2005), Fernandez, Fogli, and Olivetti (2004) or Greenwood, Seshadri, and Yorukoglu (2005) for theories underlying the rise in female labor force participation.}

The model is calibrated to U.S. data focusing on females. The crimes considered here are property crimes as defined by the Federal Bureau of Investigation. With the calibrated model in hand, we quantify the effects of several experiments. We show that the same forces that have likely driven the rise in female labor market participation can account for a 39 percent increase in their crime rate. We also consider skill-biased technological progress (an event that is thought to have increased wage inequality), and changes in workers’ bargaining power that could reflect changes in discriminatory behavior.

In a related paper Englehardt, Rocheteau, and Rupert (2007), examine various policy experiments—changes in unemployment compensation, wage subsidies, and changes in apprehension probability, to show how labor market outcomes and crime are related. The model here differs in that we include a household sector and participation decision as well as calibrate the model to females.

Burdett, Lagos, and Wright (2003) – BLW hereafter, is also somewhat related. While BLW adopt the wage posting framework of Burdett and Mortensen (1998), we employ the Pissarides model where wages are determined via bilateral bargaining. What is key, however, is that we allow for endogenous entry and exit of firms because the availability of jobs may be relevant for crime decisions. In addition, we endogenize the decision to participate in the labor force by introducing a home sector.

Huang, Liang, and Wang (2004) is also related to our model in that they employ a search-theoretic framework with bilateral bargaining. Their description of criminal activities is, however, very different. In their model individuals specialize in criminal activities. As a consequence of this assumption employed workers never commit crimes, a result that is at odds with the evidence. Also, they do not formalize participation decisions but they include an endogenous human capital choice.
2 Model

The environment is similar to Pissarides (2000) extended to allow for criminal activity.\(^3\) Time, \(t\), is continuous and goes on forever. The economy is composed of a unit-measure set \(\mathcal{K}\) of infinitely-lived individuals indexed by \(\kappa\) and a large measure of firms. There is one final good produced in the market by firms and workers. Each individual is endowed with one indivisible unit of time. This unit of time has three alternative, mutually exclusive, uses. It can be used to search for a job \((\ell_u = 1)\), to work for a firm \((\ell_e = 1)\), or to stay out of the labor force and work or enjoy leisure at home \((\ell_o = 1)\).

The utility function of an individual at time 0 is:

\[
\mathbb{E}_0 \int_0^\infty c(t) e^{-rt} dt,
\]

where \(c(t)\) is the consumption flow of the final good, or the utility flow in a given state, and \(r > 0\) is the rate of time preference. Individuals are not liquidity constrained and have access to a competitive market for private loans.

Individuals out of the labor force enjoy utility flow \(\kappa p\) (expressed in terms of consumption of the final good) where \(\kappa \geq 0\) is individual-specific and \(p \geq 0\) is common across all individuals. Individuals are heterogeneous in terms of their utilities at home. The distribution of the \(\kappa\)'s across individuals is \(H(\kappa)\). The common component \(p\) is used to capture how society perceives women’s work at home and in the market, as well as the productivity of the technology in the home sector.\(^4\)

We assume that \(\kappa\) does not affect the utility of unemployed workers because of indivisibilities in the use of time.

An unemployed worker who is looking for a job enjoys a utility flow \(b\). One can interpret \(b\) as the utility from not working or as unemployment benefits paid by the government. When an unemployed worker and a vacant job meet they negotiate the terms of the employment relationship. The decision to engage in criminal activities can affect the tenure of the job. We consider an optimal employment contract, composed of a hiring fee, \(\phi\), and a constant wage, \(w\), that internalizes this effect.\(^5\)

\(^3\)In particular, Chapter 7 includes a participation decision.

\(^4\)According to Fortin (2005), “…female attitudes towards working women are developed in youth, influenced by parental education and religious affiliation.” Or, following Fernandez et al. (2004), \(p\) could reflect women’s spouses attitudes toward working women. Following Greenwood et al. (2005) we can also interpret \(p\) as representing the productivity in the home sector. See the Appendix for such an interpretation.

\(^5\)See Englehardt et al. (2007) for a derivation and proofs of optimality.
Firms are composed of a single job, either filled or vacant. Vacant firms are free to enter the labor market. There is a flow cost, $\gamma$, to advertise a vacancy. The production flow of a filled job is $y > b$. Firms are risk-neutral and discount future utility at rate $r > 0$.

The labor market is subject to search-matching frictions. The flow of hirings is given by the aggregate matching function $m(U, V)$ where $U$ is the measure of unemployed workers actively looking for jobs and $V$ is the measure of vacant jobs. The matching function $m(\cdot, \cdot)$ is strictly increasing and strictly concave with respect to each of its arguments and it exhibits constant returns to scale. Furthermore, $m(0, \cdot) = m(\cdot, 0) = 0$ and $m(\infty, \cdot) = m(\cdot, \infty) = \infty$. 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 $\frac{m(U, V)}{V} \equiv q(\theta)$. Similarly, each unemployed worker finds a job according to a Poisson process with arrival rate $\frac{m(U, V)}{U} = \theta q(\theta)$. Filled jobs receive negative idiosyncratic productivity shocks, with a Poisson arrival rate $s$, that render matches unprofitable.\(^6\)

We allow for the possibility that individuals in the economy, irrespective of their labor market status, receive an opportunity to commit a crime according to a Poisson process with arrival rate $\lambda_i$, where $i$ indicates the individual’s state: $i = u$ if unemployed, $i = e$ if employed and $i = o$ if out of the labor force.\(^7\) The value of a crime is $\varepsilon$, where $\varepsilon$ is a random draw from a distribution $G(\varepsilon)$ with support $[0, \bar{\varepsilon}]$. A worker who commits a crime is caught with probability $\pi$ and is sent to jail. For simplicity, a criminal not caught instantly is never caught. Being in jail means that the individual cannot make any productive use of time. Workers in jail receive a flow of utility $x$. A prisoner exits jail according to a Poisson process with arrival rate $\delta$. We assume that the average time spent in jail is independent of the value $\varepsilon$ of the crime.\(^8\)

Since the model is agnostic about the distribution of wealth, we simply assume that all individuals incur the same expected instantaneous loss, $\tau^c$, from being victimized and is independent of one’s labor force status. Firms do not suffer directly from criminal activities. Finally, individuals

\(^6\)One could adopt a more explicit description of the idiosyncratic shocks received by firms and endogenize $s$. See Mortensen and Pissarides (1994).

\(^7\)The fact that individuals can have different arrival rates for crime opportunities depending on their status in the labor force can be justified in various ways. For instance, one may think that opportunities to steal are more frequent for individuals participating in the market. Also, assuming different arrival rates for crime opportunities can be seen as an indirect way to relax the assumption that time is indivisible.

\(^8\)According to the U.S. Sentencing Commission Guidelines Manual 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 a larceny less than $10,000 — 75\%$ of thefts are under $10,000 —$, and if the criminal has 0-1 past convictions, the Sentencing Commission Guidelines suggest 0-6 months of incarceration. If it is the criminals 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.
also have to pay taxes, $\tau^g$, to the government. In order to avoid having taxes affecting crime decisions directly, we assume that the burden of taxes falls on all workers including those in jail. We denote $\tau = \tau^c + \tau^g$. We impose a “balanced budget” requirement according to which the aggregate amount stolen by criminals is equal to the aggregate cost of being victimized.

3 Bellman equations

We focus on steady state equilibria where the distribution of individuals across states is constant over time.

3.1 Individuals

An individual is in one of the following four states: Out of the labor force ($o$), unemployed ($u$), employed ($e$), or in prison ($p$). The value of being an individual in state $i \in \{o, u, e, p\}$ is denoted $\mathcal{V}_i$. The flow Bellman equations for individuals’ value functions are

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

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

$$r \mathcal{V}_o = \kappa p - \tau + \lambda_o \int [\varepsilon + \pi (\mathcal{V}_p - \mathcal{V}_o)]^+ dG(\varepsilon),$$

$$r \mathcal{V}_p = x - \tau + \delta [\max(\mathcal{V}_u, \mathcal{V}_o) - \mathcal{V}_p].$$

where $[x]^+ = \max(x, 0)$. When there is no ambiguity we omit the dependence of the value functions on $\kappa$. Equation (1) has the following interpretation. An unemployed worker enjoys a flow revenue of $b - \tau$ where $b$ is the income of unemployed workers and $\tau$ is the cost of being victimized. A job is found with an instantaneous probability $\theta q(\theta)$. Upon taking a job an individual pays a hiring fee, $\phi$ (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 $\lambda_u$. 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 $\varepsilon$ but is at risk of being caught and sent to jail with probability $\pi$, in which case there is a capital loss, $\mathcal{V}_p - \mathcal{V}_u$.

From (2), an employed worker receives a wage $w$, loses the job with an instantaneous probability $s$ and has the opportunity to commit a crime with an instantaneous probability $\lambda_e$. 


As can be seen in (3), an individual out of the labor-force enjoys the utility \( \kappa p \) and receives an opportunity to commit crime with an instantaneous probability \( \lambda_o \).

According to (4), an imprisoned worker receives consumption flow \( x \), suffers the loss \( \tau \), and exits jail with an instantaneous probability \( \delta \). After release a decision has to be made whether to participate in the labor force as an unemployed worker or to be out of the labor force. In steady-state a prisoner who was previously in the labor force returns to the labor force upon release from jail. Similarly, a prisoner who was previously out of the labor-force returns to home production activities after exiting jail.

From (1), (2) and (3), an individual \( \kappa \) in state \( i \) chooses to commit a crime whenever \( \varepsilon \geq \varepsilon_i \) where

\[
\varepsilon_u = \pi (\gamma_u - \gamma_p), \tag{5}
\]
\[
\varepsilon_e = \pi (\gamma_e - \gamma_p), \tag{6}
\]
\[
\varepsilon_o(\kappa) = \pi [\gamma_o(\kappa) - \gamma_p(\kappa)]. \tag{7}
\]

From (5)-(7) the value of the marginal crime, \( \varepsilon_i m \), is the expected cost of punishment, \( \pi (\gamma_i - \gamma_p) \).

An individual chooses to stay at home if \( \gamma_o(\kappa) \geq \gamma_u \). From (3) the utility from staying at home is increasing with \( \kappa \). Hence, there exists a threshold \( \kappa_u \) such that an individual chooses not to participate in the labor force if \( \kappa \geq \kappa_u \). This threshold satisfies \( \gamma_o(\kappa_u) = \gamma_u \). From (5) and (7), \( \varepsilon_o(\kappa_u) = \varepsilon_u \). Therefore, from (1) and (3), and using the fact that \( \int_{\varepsilon_i}^{\varepsilon_e} (\varepsilon - \varepsilon_i) dG(\varepsilon) = \int_{\varepsilon_i}^{\varepsilon_e} [1 - G(\varepsilon)] d\varepsilon \) from integration by parts,

\[
\kappa_u p = b + \theta q(\theta) (\gamma_e - \gamma_u - \phi) + (\lambda_u - \lambda_o) \int_{\varepsilon_u}^{\varepsilon_e} [1 - G(\varepsilon)] d\varepsilon. \tag{8}
\]

According to (8), the reservation utility, \( \kappa_u \), below which individuals choose to participate in the labor market is such that the instantaneous surplus from staying at home, the left-hand side of (8), is equal to the the sum of the income flow received by an unemployed worker, the expected surplus from finding a job and the difference of the returns from criminal activities for unemployed individuals and individuals out-of-the-labor-force, the right-hand side of (8). Other things being equal, as the labor market becomes tighter individuals have higher incentives to participate in the market. Also, if there are more opportunities to commit crimes when unemployed (\( \lambda_u > \lambda_o \)) then individuals tend to participate more. If \( \lambda_u = \lambda_o \) then crime opportunities do not affect participation decisions.
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

\[ rV_v = -\gamma + q(\theta) \left( \phi + V_f - V_v \right), \]

\[ rV_f = y - w - s \left( V_f - V_v \right) - \lambda \pi \left[ 1 - G(\epsilon) \right] V_f. \]

According to (9), a vacancy incurs an advertising cost $\gamma$; finds an unemployed worker with an instantaneous probability $q$ in which case it enjoys the capital gain $\phi + V_f - V_v$. According to (10) a filled job enjoys an instantaneous profit $y - w$ and is destroyed if a negative shock occurs, with an instantaneous probability $s$, or if the worker commits a crime and is caught, an event occurring with an instantaneous probability $\lambda \pi \left[ 1 - G(\epsilon) \right]$. Free-entry of firms implies $V_v = 0$ and therefore, from (9),

\[ V_f + \phi = \frac{\gamma}{q(\theta)}. \]

From (11), the value of the filled job plus the up-front payment is equal to the average recruiting cost incurred by the firm.

4 Equilibrium

The model admits a simple recursive structure. To see this, rearrange the conditions determining individuals’ crime decisions. Using the Bellman equations (1), (2) and (4), the crime decisions (5)-(7) can be rewritten as follows:

\[ \left( \frac{r + \delta}{\pi} \right) \epsilon_u = b - x + \frac{\beta}{1 - \beta} \theta \gamma + \lambda u \int^{\bar{\epsilon}}_{\epsilon_u} [1 - G(\epsilon)] d\epsilon, \]

\[ \left( \frac{r + \delta}{\pi} \right) \epsilon_e = y - x + \frac{(\delta - s)\gamma}{q(\theta)(1 - \beta)} + \lambda e \int^{\bar{\epsilon}}_{\epsilon_e} [1 - G(\epsilon)] d\epsilon. \]

\[ \left( \frac{r + \delta}{\pi} \right) \epsilon_o(\kappa) = \kappa p - x + \lambda_o \int^{\bar{\epsilon}}_{\epsilon_o(\kappa)} [1 - G(\epsilon)] d\epsilon. \]

Given $\theta$, (12)-(14) determine a unique list $[\epsilon_u, \epsilon_e, \epsilon_o(\kappa)]$ of critical values for crime decisions. Notice that (12)-(14) correspond to standard optimal stopping rules where the left-hand side represents the gain from stopping and the right-hand side is the gain from continuing to search for opportunities.
From (12), as the labor market becomes tighter the probability that an unemployed worker commits a crime falls. Also, for given $\theta$, an unemployed worker is less likely to commit a crime if: the probability to be caught is high; the time spent in jail is high; the income when unemployed is high; the worker’s bargaining power is high. According to (13) an increase in $\theta$ raises $\varepsilon_e$ if $\delta > s$ and it reduces $\varepsilon_e$ if $\delta < s$. From (14) individuals out-of-the-labor-force are more likely to commit crime if the instantaneous utility from being at home, $\kappa p$, is low.

Using (6) the crime decision of an employed worker can also be described by

$$\varepsilon_e = \varepsilon_u + \frac{\pi \gamma}{(1 - \beta) q(\theta)}. \quad (15)$$

So, for a given $\varepsilon_u$, employed workers are also less likely to commit crimes as market tightness increases.

In order to determine market tightness, use the condition $\gamma'_{e} - \gamma'_u = \gamma/[(1 - \beta) q(\theta)]$. Integrating by parts the integral term in (1), the permanent income of an unemployed worker obeys

$$r\gamma_{u} = b - \tau + \frac{\beta}{1 - \beta} \theta \gamma + \lambda_u \int_{\varepsilon_u}^{\bar{\varepsilon}} [1 - G(\varepsilon)] d\varepsilon. \quad (16)$$

From (2) and (16) market tightness satisfies

$$\frac{(r + s) \gamma}{(1 - \beta) q(\theta)} = y - b - \frac{\beta}{1 - \beta} \theta \gamma - \lambda_u \int_{\varepsilon_u}^{\bar{\varepsilon}} [1 - G(\varepsilon)] d\varepsilon + \lambda_e \int_{\varepsilon_e}^{\bar{\varepsilon}} [1 - G(\varepsilon)] d\varepsilon. \quad (17)$$

Given the thresholds $\varepsilon_u$ and $\varepsilon_e$, (17) determines a unique $\theta$. Up to the last two terms on the right-hand side, (17) 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. This will be the case if the arrival rates of crime opportunities are the same for employed and unemployed workers, $\lambda_e = \lambda_u$, since $\varepsilon_e > \varepsilon_u$. Using (15), we obtain a relationship between $\varepsilon_u$ and $\theta$,

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

$$+ \lambda_e \int_{\varepsilon_u + \frac{\pi \gamma}{(1 - \beta) q(\theta)}}^{\bar{\varepsilon}} [1 - G(\varepsilon)] d\varepsilon. \quad (18)$$

According to (18), if $\lambda_u [1 - G(\varepsilon_u)] > \lambda_e [1 - G(\varepsilon_e)]$ then $\theta$ increases with $\varepsilon_u$. This condition is satisfied, for instance, if $\lambda_u = \lambda_e$. 9
From (8), the reservation utility at home, below which individuals participate in the labor force satisfies
\[
\kappa_u = b + \frac{\beta}{1 - \beta} \theta \gamma + (\lambda_u - \lambda_o) \int_{\kappa_u}^{\kappa} [1 - G(\varepsilon)] d\varepsilon.
\]
(19)
Notice that \(\tau\), the cost of being victimized, does not appear in the equilibrium conditions (12), (15), (18) and (19). Therefore, the requirement that the losses incurred by victims are the gains of the criminals is irrelevant for the equilibrium.

Finally, we characterize the steady-state distribution of individuals across states. Denote \(n_i(\kappa)\) the density measure of individuals in state \(i \in \{e, u, o, p\}\). More precisely, \(\int_{\kappa} E n_i(\kappa) d\kappa\) is the measure of individuals in state \(i\) whose utility at home is \(\kappa \in E \subseteq \mathcal{K}\). Consider individuals who do not participate in the labor force, \(\kappa \geq \kappa_u\). The condition that the flows in and out of each state are equal implies
\[
\begin{align*}
n_o(\kappa)\lambda_o \pi [1 - G(\varepsilon_o(\kappa))] &= \delta n_p(\kappa), \quad (20) \\
n_o(\kappa) + n_p(\kappa) &= g(\kappa). \quad (21)
\end{align*}
\]
According to (20) the flow of individuals from out-of-the-labor-force to jail, \(n_o(\kappa)\lambda_o \pi [1 - G(\varepsilon_o(\kappa))]\), has to be equal to the flow of individuals from jail to out-of-the-labor-force, \(\delta n_p(\kappa)\).

Consider next workers who participate in the labor market \((\kappa < \kappa_u)\). The distribution \([n_u(\kappa), n_e(\kappa), n_p(\kappa)]\) is determined by the following steady-state conditions:
\[
\begin{align*}
&sn_e(\kappa) + n_p(\kappa)\delta = \{\theta q(\theta) + \lambda_u \pi [1 - G(\varepsilon_u)]\} n_u(\kappa), \quad (22) \\
&\theta q(\theta)n_u(\kappa) = \{s + \lambda_e \pi [1 - G(\varepsilon_e)]\} n_e(\kappa), \quad (23) \\
&n_e(\kappa) + n_u(\kappa) + n_p(\kappa) = g(\kappa). \quad (24)
\end{align*}
\]
According to (22) the flows in and out of unemployment must be equal. The measure of individuals (with home-productivity \(\kappa\)) entering unemployment is the sum of the employed workers who lose their jobs, \(sn_e(\kappa)\), and the criminals who exit jail, \(n_p(\kappa)\delta\). The flow of individuals exiting unemployment corresponds to individuals finding jobs, \(\theta q(\theta)n_u(\kappa)\), or unemployed individuals committing crimes and sent to jail, \(\lambda_u \pi [1 - G(\varepsilon_u)]n_u(\kappa)\). Similarly, (23) prescribes that the flows in and out of employment must be equal in steady state. Figure 1 diagrams the above-mentioned flows.

The equilibrium unemployment rate \(u\) is defined as the fraction of individuals in the labor force
who are unemployed,

\[ u = \frac{\int_{0}^{\kappa_u} n_u(\kappa) d\kappa}{\int_{0}^{\kappa_u} n_e(\kappa) d\kappa + \int_{0}^{\kappa_u} n_u(\kappa) d\kappa}. \] (25)

From (23), it satisfies

\[ u = \frac{s + \lambda_e \pi [1 - G(\varepsilon_e)]}{\theta q(\theta) + s + \lambda_e \pi [1 - G(\varepsilon_e)]}. \] (26)

The unemployment rate decreases with market tightness and increases when employed workers commit crimes at a higher frequency, that is, \( \varepsilon_e \) decreases. As in Mortensen and Pissarides (1994) the rate at which jobs are destroyed is endogenous. In our model it depends on employed workers’ decision to commit crimes.

The participation rate is computed as the fraction of individuals who are not in jail who choose to participate in the labor market. It satisfies

\[ P = \frac{\int_{0}^{\kappa_u} n_e(\kappa) d\kappa + \int_{0}^{\kappa_u} n_u(\kappa) d\kappa}{1 - \int_{0}^{\kappa_p} n_p(\kappa) d\kappa}. \] (27)

The following defines an equilibrium.

**Definition 1** A steady-state equilibrium is a list \( \{\theta, \kappa_u, \varepsilon_u, \varepsilon_e, \varepsilon_o(\kappa), n_e(\kappa), n_u(\kappa), n_o(\kappa), n_p(\kappa)\} \) such that: \( \theta \) satisfies (18); \( \kappa_u \) satisfies (19); \( \{\varepsilon_u, \varepsilon_e, \varepsilon_o(\kappa)\} \) satisfies (12), (15), (14); \( \{n_e(\kappa), n_u(\kappa), n_o(\kappa), n_p(\kappa)\} \) satisfies (20)-(24).
The model can now be solved recursively. First, the crime decisions of individuals out of
the labor force are determined independently of other endogenous variables by (14). Second, the
pair \((\theta, \varepsilon_u)\), are determined jointly from (12) and (18). Third, knowing \((\theta, \varepsilon_u)\), one can use (15)
and (19) to find \(\varepsilon_e\) and \(\kappa_u\). Finally, knowing \(\{\theta, \kappa_u, \varepsilon_u, \varepsilon_e, \varepsilon_o(\kappa)\}\) the steady-state distribution
\(\{n_e(\kappa), n_u(\kappa), n_o(\kappa), n_p(\kappa)\}\) is obtained from (20)-(24).

Figure 2 represents the determination of the pair \((\theta, \varepsilon_u)\). We denote \(CS\) (crime schedule) the
curve representing (12) and \(JC\) (job creation) the curve representing (18). Recall that \(CS\) always
slopes upward while \(JC\) can slope upward or downward depending on the the values of \(\lambda_e\) and
\(\lambda_u\). In the case where \(\lambda_u = \lambda_e\) the two curves are upward sloping. Along \(CS\), as the number of
vacancies per unemployed increases, workers are less likely to commit crimes. Along \(JC\), as the
frequency of crime falls the number of jobs in the market increases. The Beveridge curve (26)
is denoted \(BC(\varepsilon_e)\). It shifts with the reservation value \(\varepsilon_e\) which from (15) is uniquely determined
from \(\theta\) and \(\varepsilon_u\). The following Lemma establishes that if \(JC\) and \(CS\) intersect then they intersect
once. This result is illustrated in Figure 2.

**Lemma 2** *In the space \((\varepsilon_u, \theta)\) the curve \(JC\) intersects the curve \(CS\) from above.*

**Proof.** See Appendix. ■

Interestingly, the determination of equilibrium is reminiscent of the one in the *Mortensen and
Pissarides (1994)* model where labor market tightness and the job destruction rate are determined
jointly through two conditions that can be represented graphically. 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. Denote $\epsilon^0_u$ the value of $\epsilon_u$ that solves (12) when $\theta = 0$.

**Proposition 3** There exists a unique equilibrium such that $\theta > 0$ if

$$y - b + (\lambda_e - \lambda_u) \int_{\epsilon_u^0}^{\bar{\epsilon}} [1 - G(\epsilon)] d\epsilon > 0.$$  \hspace{1cm} (28)

**Proof.** See the Appendix. ■

Proposition 3 shows that 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 (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; moreover, it is satisfied if $\lambda_e = \lambda_u$.

**Proposition 4** In any equilibrium where $\theta > 0$ then $\epsilon_e > \epsilon_u$ and $\epsilon_o(\kappa) \geq \epsilon_u$ for all $\kappa \geq \kappa_u$.

**Proof.** The result according to which $\epsilon_e > \epsilon_u$ comes from (15). From (14), $\epsilon_o(\kappa)$ is nondecreasing in $\kappa$. Since $\epsilon_o(\kappa_u) = \epsilon_u$ we have $\epsilon_o(\kappa) \geq \epsilon_u$ for all $\kappa \geq \kappa_u$. ■

Proposition 4 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 marginal product 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. Also, individuals who choose not to participate in the labor force have a higher expected utility than individuals who are unemployed. Consequently, those individuals suffer a higher cost of being sent to jail than unemployed workers. In the particular case where $\lambda_u = \lambda_e = \lambda_o$ Proposition 4 implies that the crime rate of unemployed workers is larger than the crime rates of employed workers and individuals out of the labor force.

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

$$\frac{(r + s) \gamma}{q(\hat{\theta})} = (1 - \beta) (y - b) - \beta \hat{\theta} \gamma.$$  \hspace{1cm} (29)

This is the market tightness that would prevail in an economy without crime.
Proposition 5  If
\[
\frac{(r + \delta)}{\pi} \bar{\varepsilon} \leq b - x + \frac{\beta}{1 - \beta} \hat{\theta} \gamma
\]  \tag{30}
then the equilibrium is such that \( \theta = \hat{\theta} \) and no crime occurs.

Proof. From Proposition 4, no crime occurs in equilibrium iff \( \varepsilon_u \geq \bar{\varepsilon} \). From (17) if \( \varepsilon_u \geq \bar{\varepsilon} \) then \( \theta = \hat{\theta} \). From (12) the condition \( \varepsilon_u \geq \bar{\varepsilon} \) requires (30). \( \blacksquare \)

According to Proposition 5, there is no crime in equilibrium provided that the probability of being caught is sufficiently high and the time spent in jail is sufficiently long.

5 Calibration

The model is calibrated to the U.S. labor market along the lines of Shimer (2005); however, the focus is on females due to the large changes in participation in the labor force and crime. 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 \( b = 0.4 \). The matching function, \( m(U, V) = AU^\eta V^{1-\eta} \), is assumed to be Cobb-Douglas with constant returns to scale and we set \( \eta = 0.72 \).\(^9\) To ensure search externalities are internalized through the wage mechanism, we impose the Hosios (1990) condition, i.e., \( \beta = \eta = 0.72 \).\(^{10}\) The distribution of returns in the home sector is exponential, \( g(\kappa) = e^{-\kappa} \). We calibrate \( p \) so the model’s participation rate matches the female participation rate in 2003, which was 59%.

To calibrate the job finding rate, we use total female unemployment as well as female short term unemployment, i.e., those unemployed less than 5 weeks.\(^{11}\) Let \( u_t^s \) denote the number of workers unemployed for less than one month in month \( t \), and \( u_t \) be the total number of unemployed women in month \( t \). The job finding rate is defined as
\[
f_t = 1 - \frac{u_{t+1} - u_t^s}{u_t} \tag{31}\
\]
For the years 1976-2004 (the only years this data is available for females) \( f_t = 0.434 \) per month, implying the annualized expected number of job offers, \( \theta q(\theta) \), is 5.208. We infer the job separation rate for females using the two unemployment series given above. In the data, when a worker

\(^9\)For a survey of the literature on the aggregate matching function, see Petrongolo and Pissarides (2001).

\(^{10}\)The Hosios condition emerges endogenously if wages are posted and search is directed. See Moen (1997).

\(^{11}\)The female data series which began in 1976 can be found at http://www.bls.gov/cps. Implicitly, our assumption that the job finding rate is gender specific implies that the labor market is segmented by gender. This may reflect the fact that males and females are specialized by occupations.
is separated from her job, she has on average half a month to find a new job before she is recorded as unemployed. Therefore, letting $e_t$ be the number of women employed in month $t$ we calculate the separation rate as

$$s_t = \frac{u_{t+1}^e}{e_t (1 - \frac{1}{2} f_t)},$$

which is 0.038 for females over 1976-2004. This implies an annualized rate of 0.456, i.e., jobs last, on average, about 2 years. The parameters $A$ and $\gamma$ are chosen to match the average job finding rate and the average $v - u$ ratio. In the model the vacancy to unemployment ratio, $\theta$, is arbitrary and normalized to one. Therefore, we set $A = 5.208$ and $\gamma = 0.2056$.

The crimes considered are Type I property crimes as defined by the FBI, which includes larceny, burglary, and motor vehicle theft. We exclude violent crimes because they are not necessarily driven by economic incentives. We do not include drug related crimes because of the difficulty in capturing addictive behavior inherent in all types of drug crimes. Finally, the FBI defines Forgery, Fraud, and Embezzlement as a Type II offense and does not collect the number of these types of crimes.

The female property crime rate is calculated as the product of the total number of property crimes and the percent of female arrests. The probability of being caught is derived from the number of females sent to prison divided by the number of female crimes, implying $\pi = 1.5\%$. We exclude those sentenced to probation when calculating the probability of being caught because individuals on probation or parole may not be forced out of employment and/or home production. Fines, mandatory volunteer service, and other types of punishments that do not involve jail have not been modeled given they are constructed to allow individuals to continue to participate in the labor market. The annual number of females sent to prison is the product of the total number of convictions, the percentage of the total who were female, and the percent of those females who were incarcerated. The average length of incarceration for women convicted of a property crime was 17 months in 2002, so that $\delta = 0.706$. The average per capita loss from crime, $\tau$, is set to 0.001. Since we do not have much information on the utility or disutility from being in jail, we

---

12 See Cozzi (2005) for an analysis on the link between drugs and crime.
13 See Heimer (2000) for further information on the calculation of the female crime rate.
14 The values are taken from the most recent survey “State Court Sentencing of Convicted Felons, 2002,” Tables 1.1, 2.1, and 2.4, respectively. These numbers represent both state and federal convictions. The Bureau of Criminal Justice Statistics collects data at the state level and then estimates that another six percent are convicted at the federal level.
15 The total number of property crimes is reported in the Uniform Crime Reports, 2003, Table 1. The percent of female arrests is located in Table 42 of the 2003 Uniform Crime Reports. The percent of females convicted to jail or
let $x = 0$.

We assume that the distribution of the value of crime opportunities $G(\mu_g, \sigma_g)$ is log normal.

The average amount stolen in the data is approximately $800, calculated as the ratio of the dollar value stolen and not recovered divided by the number of crimes. To target this amount we need to choose values for $\sigma_g$, $\mu_g$ and $m$. First, we normalize $m = 1$. Next we choose values for $\sigma_g$ and $\mu_g$ to target the average amount stolen, given by $E_G[\epsilon|\epsilon > \epsilon_i]$ for $i = e, u, o$. Targetting the amount stolen in our model means that choices for $\sigma_g$ will affect the arrival rates of crime. That is, the values of $\lambda_e, \lambda_u$, and $\lambda_o$ are calibrated to target the probability an individual commits a crime given they are in a particular state. The crime rates for employed, unemployed, and non-participants, (which correspond to $\lambda_i[1 - G(\epsilon_i)]$ in the model) are 2.5%, 17.7%, and 2% respectively. Unfortunately, there is little direct evidence to assist in choosing $\sigma_g$. The benchmark calibration sets $\sigma_g = 1$, and weighting the three expectations by the proportion of crime committed in each state, gives $\mu_g = -6.33$.

The crime rate of women in a particular state is computed as the product of the number of female crimes and the percent of females incarcerated when in the particular state, divided by the number of females in that state. The implied values of the $\lambda$’s are: $\lambda_e = 3.417$, $\lambda_u = 18.08$, and $\lambda_o = 7.226$. Our interpretation of why they differ here is due to our restrictive assumption on time use—the full unit of time is used in either working, search while unemployed, or producing at home. If we would impose $\lambda_e = \lambda_u = \lambda_o$ then $\lambda_i = 5.54$. Even though $\lambda_e \neq \lambda_u \neq \lambda_o$, the theoretical result that unemployed agents commit more crimes continues to hold in our calibration.

Table 1 provides a summary of the parameters used in the calibration.

---

16 We have tested different values for $x$ and have verified that the calibration is basically unaffected. The threshold values $\epsilon_i$ fall as $x$ rises, which decreases our target for $\mu_g$. The effects on the arrival rates of crime are found to be quite small.

17 An exponential distribution was also tried and the results were not remarkably different. In contrast, using a uniform distribution, the arrival rate of crime opportunities has to be very low, nearly two hundred times lower than under the log normal. This result is due to the fact that with the uniform distribution it is as likely to get a high value crime opportunity as a low value one.

18 Choosing $\sigma_g = 1.25$ leads to arrival rates that are large, for the unemployed it is nearly 200 opportunities per year. While choosing $\sigma_g = .75$ leads to fewer than 3 opportunities per year for the unemployed.

19 The percent of females incarcerated when in labor force status $i = \{e, u, o\}$ is taken from the most recent Survey of Federal and State Correctional Facilities, 1997. The number of females in $i = \{e, u, o\}$ is taken from the Bureau of Labor Statistics for 2003.
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$r$</td>
<td>0.048</td>
<td>real interest rate</td>
</tr>
<tr>
<td>$b$</td>
<td>0.400</td>
<td>unemployed utility flow</td>
</tr>
<tr>
<td>$\beta$</td>
<td>0.720</td>
<td>bargaining power of workers</td>
</tr>
<tr>
<td>$\eta$</td>
<td>0.720</td>
<td>elasticity of matching function</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.205</td>
<td>recruiting cost</td>
</tr>
<tr>
<td>$s$</td>
<td>0.456</td>
<td>job destruction rate</td>
</tr>
<tr>
<td>$A$</td>
<td>5.21</td>
<td>efficiency of matching technology</td>
</tr>
<tr>
<td>$p$</td>
<td>1.04</td>
<td>preferences for non-market activity</td>
</tr>
<tr>
<td>$\tau$</td>
<td>0.001</td>
<td>loss from crime</td>
</tr>
<tr>
<td>$x$</td>
<td>0.00</td>
<td>payment when in jail</td>
</tr>
<tr>
<td>$\pi$</td>
<td>0.015</td>
<td>apprehension probability</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.706</td>
<td>rate of exit from jail</td>
</tr>
<tr>
<td>$m$</td>
<td>1.00</td>
<td>average value of a crime opportunity</td>
</tr>
<tr>
<td>$\mu_g$</td>
<td>−6.33</td>
<td>parameter of log normal crime distribution</td>
</tr>
<tr>
<td>$\sigma_g$</td>
<td>1.00</td>
<td>parameter of log normal crime distribution</td>
</tr>
</tbody>
</table>

### 5.1 Women’s liberation and crime

In this section we examine both qualitatively and quantitatively how changes in some relevant variables affect female crime and female outcomes in the labor market. We distinguish changes in terms of policies and changes in terms of technology or preferences.

Economists are not the first to try and understand the rise in the criminal behavior of women. Sociologists and criminologists have also attempted to understand this phenomenon. As mentioned in Steffensmeier and Streifel (1992), criminologists, among others, have long believed that there is a relationship between gender equality and crime:

> No doubt as woman enters the field of industry formerly occupied by men, and as she takes her part in politics and sits on juries, the percentage of female criminals will rise rapidly. As she takes her place with men she will be more and more judged as men are judged, and will commit the crimes that men commit, and furnish her fair quota of the penitentiaries and jails.


The above quote suggests that as women become more equal with men in labor market choices and outcomes, so too will they become more equal in the crime sector. However, it does not explain the mechanism through which this may occur.
5.1.1 Changes in the home sector

Greenwood et al. (2005) have argued that technological progress in the household sector played a major role in liberating women from the home. Fernandez et al. (2004) and Fortin (2005) emphasize changes in preferences towards market activities to explain the liberation. Changes in welfare programs also affect participation (Blank (2000), Meyer and Rosenbaum (2001)). We examine whether the changes in preferences toward market activities that generated increased participation of women in the labor market can also explain their higher involvement in criminal activities. In our model, changes in preferences towards market activities are represented by the parameter $p$.

**Proposition 6** A decrease in $p$ raises $\kappa_u$ and decreases $\varepsilon_o$. It does not affect $\varepsilon_e$ or $\varepsilon_u$.

According to Proposition 6, as the utility of nonmarket activities falls, participation increases since the benefits of staying at home are smaller. Also, agents out of the labor force have higher incentives to commit crime, $\varepsilon_o$ decreases, because the potential costs of doing so have fallen.

To quantify the increase in the female labor force participation rate witnessed over the last 50 years, rising from 37% to 59%, we assume the average gains from staying at home have fallen relative to market participation. The average gain from staying at home could be falling for several reasons. For our analysis we will assume that preferences toward staying at home, $p\kappa$, have changed. We generate the rise in participation through a drop in $p$. In order to generate the rise in the female participation rate seen in the data, the average gain from staying at home has to fall by roughly half as shown in the upper portion of Table 2.

The lower portion of Table 2 reports the steady-state outcome for crime corresponding to these different values of $p$. The change in preferences that is responsible for the increased participation in the labor market generates a 39% increase in crime. So, the liberating process of women from the home can explain a quantitatively significant increase in female crime.

In analyzing the mechanism leading to the rise in female crime, the change can be separated into two effects. The first effect arises from the fact that a woman’s time is relatively less valuable at home. Therefore, the cost of being caught committing a crime is smaller, implying women who stay at home have a higher probability of committing crime. The second effect is due to the change in the composition of the labor force. More women are either employed or unemployed, and both types of women commit crimes at a higher frequency than those not in the labor force, as can be
seen in the crime portion of Table 2. Therefore, as women enter the labor force, the probability of those women committing crime rises.

Table 2: Labor Force Participation and Crime

<table>
<thead>
<tr>
<th></th>
<th>1960</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor Force</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed</td>
<td>34%</td>
<td>54%</td>
</tr>
<tr>
<td>Unemployed</td>
<td>3%</td>
<td>5%</td>
</tr>
<tr>
<td>NILF</td>
<td>63%</td>
<td>41%</td>
</tr>
<tr>
<td>Crime</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pr(Commit Crime</td>
<td>e)</td>
<td>0.025</td>
</tr>
<tr>
<td>Pr(Commit Crime</td>
<td>u)</td>
<td>0.177</td>
</tr>
<tr>
<td>Pr(Commit Crime</td>
<td>o)</td>
<td>0.012</td>
</tr>
<tr>
<td>Total Crime Rate</td>
<td>11.21</td>
<td>15.68</td>
</tr>
</tbody>
</table>

5.1.2 Discrimination

It has been well established that wages are an important determinant in the decision to commit crime. The average hourly earnings for a female worker amounted to about 80 percent of the average for male workers in the US in 2000 compared to about 60 percent in 1960 (see Katz and Autor (1999)). Criminologists have claimed that gains in gender equality in the 60’s and 70’s have reduced the gender gap in terms of involvement in criminal activities. One way to capture the reduction in wage discrimination in our model is to assume that the bargaining power of women in the negotiation of their wages has increased.

**Proposition 7** An increase in $\beta$: reduces $\theta$; raises $\kappa_u$ if $\beta < \eta(\theta)$ and decreases it if $\beta > \eta(\theta)$; increases $\epsilon_u$ if $\beta < \eta(\theta)$ and decreases it if $\beta > \eta(\theta)$; increases $\epsilon_e$ if $\delta > s$ and $\beta > \eta(\theta)$ or $\delta < s$ and $\beta < \eta(\theta)$, and increases it otherwise.

An increase in $\beta$ reduces firms’ expected surplus from a match and therefore the supply of vacancies. The effect of an increase in $\beta$ on the crime behavior of unemployed workers depends

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21 See Blau (2000) for a survey of recent trends for women.
22 See, for example Steffensmeier and Allan (1996).
on how $\beta$ and $\eta$ are ordered. As is well-known from Pissarides (2000), the value of being unemployed, $V_u$, is a nonmonotonic function of $\beta$ that reaches a maximum when $\beta = \eta$, the Hosios Condition. If $\beta = \eta$ then a change in $\beta$ has only a second-order effect on crime. If $\beta < \eta$ an increase in $\beta$ raises the value of being unemployed. As a consequence, $\epsilon_u$ 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. If the average jail sentence is smaller than the average duration of a job then the crime behavior of employed workers varies in the opposite direction as the crime behavior of unemployed workers.

Quantitatively, the results are not monotonic as proven by Proposition 7 and shown in Table 3. Suppose that the worker’s bargaining power increases from a low value, say 0.2, to the value predicted by the Hosios condition, 0.72 in our calibration. The increase in $\beta$ raises the value of being unemployed and therefore it increases $\epsilon_u$, reducing the likelihood of committing crime by unemployed workers. On the other hand, since $\delta > s$ the value of being in jail increases by more than the value of being employed and employed workers are more likely to commit crime. Increasing $\beta$ from .25 to .75 increases the overall crime rate by approximately 10%.

<table>
<thead>
<tr>
<th>$\beta$</th>
<th>Labor Force</th>
<th>Crime Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>E (0.525)</td>
<td>U (0.021)</td>
</tr>
<tr>
<td></td>
<td>E (0.022)</td>
<td>U (0.245)</td>
</tr>
<tr>
<td>0.2</td>
<td>0.544</td>
<td>0.026</td>
</tr>
<tr>
<td>0.3</td>
<td>0.550</td>
<td>0.030</td>
</tr>
<tr>
<td>0.4</td>
<td>0.551</td>
<td>0.034</td>
</tr>
<tr>
<td>0.5</td>
<td>0.551</td>
<td>0.037</td>
</tr>
<tr>
<td>0.6</td>
<td>0.548</td>
<td>0.042</td>
</tr>
<tr>
<td>0.7</td>
<td>0.544</td>
<td>0.047</td>
</tr>
<tr>
<td>0.8</td>
<td>0.537</td>
<td>0.054</td>
</tr>
<tr>
<td>0.9</td>
<td>0.522</td>
<td>0.066</td>
</tr>
<tr>
<td></td>
<td>E (0.025)</td>
<td>U (0.178)</td>
</tr>
</tbody>
</table>

### 5.2 Changes in Productivity

Technological progress in the market sector can lead to a rise in the output from a match. In addition, there has been a large increase in female education levels, thus raising their human capital.
and productivity. \textsuperscript{24}

**Proposition 8** An increase in $y$ raises $\theta, \kappa_u$ and $\varepsilon_i$ for $i = o, u, e$; it reduces unemployment.

As workers become more productive a larger measure of firms enter the market. Graphically, the $JC$ curve shifts upward. Consequently, both $\theta$ and $\varepsilon_u$ increase. The fact that the labor market becomes tighter implies the cost to an unemployed worker of being caught committing a crime increases. As a consequence, unemployed workers commit fewer crimes. Similarly, the wage, which is equal to productivity, increases, raising employed workers’ cost of being caught committing a crime. So the crime rate of employed workers falls. Finally, since productivity in the market increases, participation increases as well.

Of course, if $b$, $\gamma$ and $x$ are proportional to $y$ then an increase in productivity would be qualitatively equivalent to a decrease in $p$. In this case the unemployment rate is unchanged, participation increases and workers out of the labor force commit more crimes.

There is considerable evidence that the increases in productivity observed over the past few decades have not affected individuals equally. This has been labeled skill-biased technological progress. Hornstein, Krusell, and Violante (2005) write that “the average and median wage have remained constant in real terms since the mid-1970’s,” while “the 90-10 weekly wage ratio rose by 35 percent for both males and females in the period 1965-1995: from 1.20 to 1.55 for males, and from 1.05 to 1.40 for females. The increase in inequality took place everywhere in the wage distribution: both the 90-50 differential and the 50-10 differential rose by comparable amounts.” Evidently, wage inequality for women has increased more than it has for men. We investigate the effect of such changes on the crime behavior of females.

In our model, workers are homogeneous in terms of their productivity in the market. To study skill-biased technological progress we follow Mortensen and Pissarides (1999) in assuming that workers have different productivities, $y$, corresponding to different skill levels. Assuming that labor markets are segmented by skills, we can solve for the equilibrium for each submarket separately. However, we impose that each submarket is subject to the same matching frictions and the same separation rate. The experiment we perform allows for five groups representing the three quantiles ($25^{th}$, $50^{th}$ and $75^{th}$) and the first and last deciles ($10^{th}$ and $90^{th}$).

\textsuperscript{24}In 1960, for those 25 years and older, about 6 percent of women had four or more years of college; by 2000, that number had risen to nearly 25 percent. U.S. Census Bureau, Table A-1.
To begin the illustration, we use information on income inequality in the U.S. for the years 1960 and 2000 taken from Katz and Autor (1999). Next, we choose wages for each group (five for each year) that will generate the same inequality measure found in the data. Table 4 displays the chosen values for each group by year. Table 5 illustrates how the inequality found in the data matches the inequality produced from Table 4. We label the wage distributions that approximate the years 1960 and 2000 as $D_{1960}$ and $D_{2000}$, respectively. Note that for $D_{2000}$, the wages have been normalized so the median wage is equal to 1, and that the median in each year stays constant. Table 4 shows, for example, that the wage of the lowest decile declined from 0.6 in $D_{1960}$ to 0.5 in $D_{2000}$. Wages at the 90th percentile increased from 1.7 in $D_{1960}$ to 2.0 in $D_{2000}$.

Table 4: Simulated Wage Distribution

<table>
<thead>
<tr>
<th>Distribution</th>
<th>$D_{1960}$</th>
<th>$D_{2000}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>10%</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>25%</td>
<td>0.8</td>
<td>0.65</td>
</tr>
<tr>
<td>50%</td>
<td>1.0</td>
<td>1.0</td>
</tr>
<tr>
<td>75%</td>
<td>1.2</td>
<td>1.35</td>
</tr>
<tr>
<td>90%</td>
<td>1.7</td>
<td>2.0</td>
</tr>
</tbody>
</table>

Table 5: Female Inequality, Log Wages

<table>
<thead>
<tr>
<th>Data Inequality Measure</th>
<th>1960</th>
<th>2000</th>
</tr>
</thead>
<tbody>
<tr>
<td>90-10 Ratio</td>
<td>1.04</td>
<td>1.38</td>
</tr>
<tr>
<td>50-10 Ratio</td>
<td>0.50</td>
<td>0.68</td>
</tr>
<tr>
<td>90-50 Ratio</td>
<td>0.54</td>
<td>0.70</td>
</tr>
<tr>
<td>Standard Dev.</td>
<td>0.41</td>
<td>0.55</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model Inequality Measure</th>
<th>$D_{1960}$</th>
<th>$D_{2000}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>90-10 Ratio</td>
<td>1.04</td>
<td>1.39</td>
</tr>
<tr>
<td>50-10 Ratio</td>
<td>0.51</td>
<td>0.69</td>
</tr>
<tr>
<td>90-50 Ratio</td>
<td>0.53</td>
<td>0.69</td>
</tr>
<tr>
<td>Standard Dev.</td>
<td>0.40</td>
<td>0.56</td>
</tr>
</tbody>
</table>

The goal of this exercise is to illustrate how income inequality might affect the level of crime. It is possible to reformulate the parameters by skill group. As an illustration, we take a simplified approach by holding all the parameters constant except the arrival rates of crime and the benefits when unemployed. The arrival rates are chosen such that the overall crime rate in 2000 matches

---

25 The difference between worker productivity and the wage is the upfront cost $\phi$. If $\phi$ is paid through a competitive capital market during the course of employment then $0.98y = w$. Therefore nothing would change if we used $w$ instead of $y$. 

22
the benchmark. We normalize the $\lambda_i$'s by a factor of 1.684, therefore $\lambda_e = 2.044$, $\lambda_u = 10.802$, and $\lambda_o = 4.291$. The unemployment benefit is kept at a constant fraction of the wage, or $b = 0.4y$.\footnote{We have tested the model using a constant $b = 0.4$. The results in Table 6, which are calculated for $b = 0.4w$, change only slightly. For instance, the change in the crime rate becomes 29% as opposed to 28% as found in Table 6.}

To reiterate, we take the simplified approach in leaving all the other parameters the same as the original calibration. For example, $A$ and $\gamma$ are unchanged. On the other hand, the different wages affect the endogenous variables when calculating the equilibrium. For instance market tightness and the job finding rate ($\theta$ and $\theta_q(\theta)$) change as $y$ changes.

We find the overall crime rate, labor force participation rate, and employment status shown in Table 6 by taking the weighted averages (using equal weights of 0.2 for each group) of the five separate groups found in each year. The breakdown of each group by year is in Table 7. Crime in the model rises by roughly 30%. The mechanism through which crime increases is intuitive. Skilled workers tend to commit fewer crimes since their relative wage increases while unskilled workers commit more crimes due to a lower relative wage. Whether total crime increases or decreases depends on the distribution of the crime values. With our calibration it turns out that high value crimes are much less likely than low value ones. As a consequence, the decrease in the crime rate of skilled workers is less than the increase in the crime rate of unskilled workers.\footnote{It should be noted that if one adopts a uniform distribution for crime values, the increase in the dispersion of workers’ productivities has almost no effect on total crime.}

<table>
<thead>
<tr>
<th></th>
<th>$D_{1960}$</th>
<th>$D_{2000}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Crime</td>
<td>12.24</td>
<td>15.68</td>
</tr>
<tr>
<td>Employment</td>
<td>0.54</td>
<td>0.54</td>
</tr>
<tr>
<td>NILF</td>
<td>0.41</td>
<td>0.41</td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.05</td>
<td>0.05</td>
</tr>
</tbody>
</table>

6 Conclusion

This paper has proposed a simple model of the labor market and female crime. Our description of the labor market follows the canonical model of Pissarides (2000) extended to have a participation decision. Criminal activities are described as the result of rational decisions to undertake crime opportunities that occur randomly. The outcome of the labor market and the extent of criminal
Table 7: Effects of Changes in the Wage Distribution by Percentile

<table>
<thead>
<tr>
<th>Percentiles</th>
<th>10%</th>
<th>25%</th>
<th>50%</th>
<th>75%</th>
<th>90%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Prob(Commit Crime in $D_{1960}$</td>
<td>E)</td>
<td>0.054</td>
<td>0.027</td>
<td>0.015</td>
<td>0.009</td>
</tr>
<tr>
<td>Prob(Commit Crime in $D_{2000}$</td>
<td>E)</td>
<td>0.081</td>
<td>0.045</td>
<td>0.015</td>
<td>0.006</td>
</tr>
<tr>
<td>Prob(Commit Crime in $D_{1960}$</td>
<td>U)</td>
<td>0.376</td>
<td>0.189</td>
<td>0.105</td>
<td>0.062</td>
</tr>
<tr>
<td>Prob(Commit Crime in $D_{2000}$</td>
<td>U)</td>
<td>0.558</td>
<td>0.313</td>
<td>0.105</td>
<td>0.044</td>
</tr>
<tr>
<td>Prob(Commit Crime in $D_{1960}$</td>
<td>O)</td>
<td>0.034</td>
<td>0.019</td>
<td>0.012</td>
<td>0.008</td>
</tr>
<tr>
<td>Prob(Commit Crime in $D_{2000}$</td>
<td>O)</td>
<td>0.047</td>
<td>0.029</td>
<td>0.012</td>
<td>0.006</td>
</tr>
<tr>
<td>Employed in $D_{1960}$</td>
<td>0.37</td>
<td>0.47</td>
<td>0.54</td>
<td>0.61</td>
<td>0.73</td>
</tr>
<tr>
<td>Employed in $D_{2000}$</td>
<td>0.32</td>
<td>0.4</td>
<td>0.54</td>
<td>0.65</td>
<td>0.78</td>
</tr>
<tr>
<td>Unemployed in $D_{1960}$</td>
<td>0.04</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>Unemployed in $D_{2000}$</td>
<td>0.04</td>
<td>0.04</td>
<td>0.05</td>
<td>0.05</td>
<td>0.06</td>
</tr>
<tr>
<td>NILF in $D_{1960}$</td>
<td>0.59</td>
<td>0.49</td>
<td>0.41</td>
<td>0.34</td>
<td>0.21</td>
</tr>
<tr>
<td>NILF in $D_{2000}$</td>
<td>0.64</td>
<td>0.56</td>
<td>0.41</td>
<td>0.3</td>
<td>0.16</td>
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</table>

activities are determined jointly. The model generates crime rates that differ according to labor force status - the unemployed have the highest propensity to commit crime compared to being employed or out of the labor force - a feature that is present in the data. The model has been calibrated to the US data (using data on females where possible) and various explanations for the increase in female crime have been investigated. For instance, technological progress in the home sector can generate a rise in crime along with a rise in labor market participation.
References


7 Appendix 1: Home sector

In this appendix, we provide foundations for the utility that individuals get in the home sector. The home sector is similar in spirit to the one in Greenwood et al. (2005). There exists a technology that allows to produce the final good outside of the market from labor and an intermediate input. The home-technology is \( F(\kappa \ell_o, k) \) where \( \ell_o \in \{0, 1\} \) is the time devoted to home production, \( \kappa \) is the specific productivity of an individual, and \( k \) is the quantity of the intermediate input. Individuals who do not spend any time at home (\( \ell_o = 0 \)) can still use the home technology with intermediate goods only. The price of the intermediate good in terms of the final good is \( p \).

Denote \( z(\kappa \ell_o, p) = \max_k [-pk + F(\kappa \ell_o, k)] \) the net return of the home technology. We assume that the technology is such that the demand for intermediate goods is decreasing with \( \ell_o \). Consequently, \( z(\kappa, p) - z(0, p) \) is increasing with \( p \). As the price of the intermediate good rises individuals have higher incentives to use their time in the home technology. The above description of the home sector captures some of the features of the model in Greenwood et al. (2005). That is, on pg. 129 they argue

“If the rental price of durables drops, then the household will demand more of them. When durables and housework are substitutes in the Edgeworth–Pareto sense, an increase in durables decreases the marginal product of housework denominated in utility terms (i.e. the marginal product of housework multiplied by marginal utility of home goods). Hence, housework falls. Thus, market work increases.”

Consider the specification \( F(\kappa \ell_o, k) = B [\kappa \ell_o + k]^a \) with \( B > 0, \ a < 1 \). Then, \( z(\kappa \ell_h, p) = \max_k [-pk + B(\kappa \ell_h + k)^a] \). Assuming an interior solution, \( k = \left( \frac{ab}{p} \right)^{\frac{1}{1-a}} - \kappa \ell_h \) and

\[
z(\kappa \ell_h, p) = -p \left[ \left( \frac{ab}{p} \right)^{\frac{1}{1-a}} - \kappa \ell_h \right] + B \left( \frac{ab}{p} \right)^{\frac{a}{1-a}}.
\]

Consequently, the return from staying at home is \( z(\kappa, p) - z(0, p) = p \kappa \) as in our current formulation. In order to guarantee that the choice for \( k \) be interior, \( \left( \frac{ab}{p} \right)^{\frac{1}{1-a}} \) must be larger than \( \kappa \).
8 Appendix 2

Proof of Lemma 2 The slope of CS in the \((\varepsilon_u, \theta)\) space is
\[
\left. \frac{d\theta}{d\varepsilon_u} \right|_{CS} = (1 - \beta) \frac{r + \delta + \lambda_u \pi [1 - G(\varepsilon_u)]}{\pi \beta \gamma}.
\]
The slope of JC in the \((\varepsilon_u, \theta)\) space is
\[
\left. \frac{d\theta}{d\varepsilon_u} \right|_{JC} = (1 - \beta) \frac{\lambda_u [1 - G(\varepsilon_u)] - \lambda_e [1 - G(\varepsilon_e)]}{\beta \gamma - \{(r + s) \gamma + \lambda_e \pi \gamma [1 - G(\varepsilon_e)]\} \frac{q'(\theta)}{[q(\theta)]^2}}.
\]
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
\[
\beta \gamma \leq \{(r + s) \gamma + \lambda_e \pi \gamma [1 - G(\varepsilon_e)]\} \frac{-q'(\theta)}{[q(\theta)]^2} + \beta \gamma,
\]
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 3 Summing (12) and (18) one obtains
\[
\frac{(r + s) \gamma}{(1 - \beta) q(\theta)} + \left( \frac{r + \delta}{\pi} \right) \varepsilon_u = y - x + \lambda_e \int_{\varepsilon_u + \frac{\pi \gamma \theta}{1 - \beta \gamma \theta}}^\varepsilon [1 - G(\varepsilon)] d\varepsilon.
\]
From (36), it can be checked that \(\theta\) is a strictly decreasing function of \(\varepsilon_u\). So if a solution to (12) and (36) exists then it is unique. Denote \(\varepsilon_u(\theta)\) the solution \(\varepsilon_u\) to the equation (12). Since \(b - x - \tau > 0\) then \(\varepsilon_u(\theta) > 0\). Furthermore, \(\varepsilon_u(\theta)\) is non-decreasing in \(\theta\). Define \(\Gamma(\theta)\) as
\[
\Gamma(\theta) = y - x + \lambda_e \int_{\varepsilon_u(\theta) + \frac{\pi \gamma \theta}{1 - \beta \gamma \theta}}^\varepsilon [1 - G(\varepsilon)] d\varepsilon - \frac{(r + s) \gamma}{(1 - \beta) q(\theta)} - \left( \frac{r + \delta}{\pi} \right) \varepsilon_u(\theta).
\]
An equilibrium is then a \(\theta\) that solves \(\Gamma(\theta) = 0\). Using the expression for \(\left( \frac{r + \delta}{\pi} \right) \varepsilon_u(\theta)\) given by (12), we have
\[
\Gamma(0) = y - b + (\lambda_e - \lambda_u) \int_{\varepsilon_u(0)}^\varepsilon [1 - G(\varepsilon)] d\varepsilon.
\]
So if (28) holds then \(\Gamma(0) > 0\). Furthermore, \(\Gamma(\infty) = -\infty\). Therefore, a solution exists and it is such that \(\theta > 0\).
Proof of Proposition 7 The pair $(\varepsilon_u, \theta)$ are determined by (12) and (36). Differentiating these two equations one can establish that $d\theta/d\beta < 0$. In order to determine the effects on $\varepsilon_u$ we adopt the following change of variable: $\tilde{\gamma} = \gamma / [(1 - \beta)q(\theta)]$. Equations (12) and (36) can now be rewritten as

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

(37)

$$(r + s) \tilde{\gamma} + \left(\frac{r + \delta}{\pi}\right) \varepsilon_u = y - x + \lambda \int_{\varepsilon_u}^{\varepsilon} [1 - G(\varepsilon)] d\varepsilon.
$$

(38)

Equations (37) and (38) determine $\varepsilon_u$ and $\tilde{\gamma}$. The term $\frac{\beta}{1 - \beta} q^{-1} \left[\frac{\gamma}{(1 - \beta)\tilde{\gamma}}\right]$ on the RHS of (37) increases in $\beta$ if $\beta < \eta(\theta)$. Differentiating (37) and (38) 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 $\beta$ on $\varepsilon_e$ we use (13) which can be reexpressed as

$$
\left(\frac{r + \delta}{\pi}\right) \varepsilon_e = y - x + (\delta - s) \tilde{\gamma} + \lambda \int_{\varepsilon_e}^{\varepsilon} [1 - G(\varepsilon)] d\varepsilon.
$$

(39)

From (38) there is a negative relationship between $\varepsilon_u$ and $\tilde{\gamma}$. Therefore, $\text{sign}(d\varepsilon_e/d\beta) = \text{sign}[(s - \delta)d\varepsilon_u/d\beta]$. It is also possible to show that $\kappa_u$ increases with $\varepsilon_u$.

Proof of Proposition 8 Equation (12) is independent of $y$ or $s$. Therefore, it is easy to show from (12) and (36) that both $\theta$ and $\varepsilon_u$ increase following an increase in $y$ or a decrease in $s$. From (15) one can show that

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

Similarly, $\frac{d\varepsilon_e}{ds} < 0$. One can establish that $\gamma'$ and $\kappa_u$ increase with $y$ or $1/s$.  

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