Labor Supply, Criminal Behavior and Income Redistribution*

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Abstract

This paper develops an overlapping generations model of criminal behavior, which extends prior research on crime by taking into account individuals' labor supply decisions and the stigma effect that affects convicted offenders, lowering their likelihood of employment. I use the model to guide a quantitative assessment of the determinants of crime and of a counterfactual experiment in which an income redistribution policy is thought of as an alternative to greater law enforcement. The model economy considered in this paper is populated by heterogeneous agents who live for a realistic number of periods, have preferences over consumption and leisure, and differ in terms of their age, their skills as well as their employment shocks. In addition, savings may be precautionary and allow partial insurance against the labor income shocks. Because of the lack of full insurance, this model generates an endogenous distribution of wealth across consumers, enabling us to assess the welfare implications of the redistribution policy experiment. I calibrated the model using the U.S. data for 1980 and then used the model to investigate the changes in criminality between 1980 and 1996. The main results of this study are: 1) Law enforcement policy was the the most important factor behind the fall in criminality in the period, while the increase in inequality was the most important single factor promoting crime; 2) Stigmatization is not a free-cost crime control policy; 3) Income redistribution can be a powerful alternative policy to fight crime.

Keywords: Criminal Behavior, Labor Supply, Income Redistribution.

JEL Codes: K42, I28.

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1. Introduction

The research agenda in the economics of crime has recently sought to resume a long tradition started by Becker (1968), Stigler (1970) and Ehrlich (1973) which consists of the use of structural models to guide the quantitative assessment of the economic determinants of criminal behavior. Among the most relevant references are Imrohoroglu et al. (2000, 2004), Lochner (2004), Mocan et al. (2005), Engelhardt et al. (2008), and Gallipoli and Fella (2006). These papers keep many of the features of existing models and embed Becker's paradigm in a dynamic equilibrium framework. These extensions have contributed to bringing the research in the field into two important dimensions. First, the dynamic nature of these models allows one to assess individuals' decisions to engage in criminal activities over their life cycle (Merlo, 2003); second, by using an equilibrium approach rather than a partial one, we can investigate the response of the aggregate crime rate to a variety of factors without leaving aside potentially important general equilibrium effects.

The papers of Lochner (2004), Mocan et al. (2005) and Gallipoli and Fella (2006) focus on the relation between human capital accumulation and crime. Using dynamic models in which educational choices and criminal behavior are endogenous, they find that educational policy intervention could be thought of as a cost-effective alternative to greater police protection expenditures. Engelhardt et al. (2008) argue that the allocation of time towards criminal activities is determined by the same factors that influence legal labor supply. As a consequence, the authors investigate how labor market policies may affect crime.

Imrohoroglu et al. (2004) propose a broader assessment of the determinants of crime. In fact, besides considering the effect of human capital, law enforcement and labor market conditions, the authors also take into account the changes in the age distribution of population, economic growth and inequality. They calibrate a dynamic general equilibrium model using data for the U.S. and carry out a decomposition of the determinants of crime. An important result of their assessment is that greater law enforcement policy was the most important factor behind the large fall in criminality in the U.S. in the 1980s and 1990s. The authors also underscore that inequality is an important factor promoting crime. In fact, they argue that the decrease in the crime rate would have been much bigger if income inequality had not increased. According to their simulations, the increase in inequality alone would have caused the crime rate to go up by nearly 59%.

Nevertheless, in addition to contributing to the decrease in the crime rate, the change in law enforcement in the U.S. brought with it a large increase in the prison population, which has more than doubled over the same period and now remains at more than two million inmates. The problem lies in the fact that the cost associated with incarceration is enormous, posing a sizeable burden on government's finances and on society. These costs are not limited to food and medical related expenditures to keep convicted individuals in prison; they also include capital outlays, the costs of the criminal justice system, the loss of potentially productive

citizens, as well as costs of crime to victims. The depreciation of legal human capital and the informal training for illegitimate activities that prisoners receive from associating with other convicts could also be included as a cost of imprisonment (Mocan et al., 2005).

In light of these considerations and given the potentially big effect that inequality may have on crime, in this paper I propose a dynamic general equilibrium model with endogenous criminal behavior to investigate whether an income redistribution policy can be thought of as an alternative to further police protection expenditures. The motivation for this assessment is that, given the large cost associated with incarceration, a redistribution policy that has even marginal success in making crime less attractive and legitimate work more rewarding is likely to have a sizeable social payoff. In order to attack this problem, the model economy considered in this paper is populated by heterogeneous agents who live for a realistic number of periods, have preferences over consumption and leisure, and differ in terms of their age, their skills as well as their employment shocks. In addition, agents can accumulate a single risk-free asset, which, following Aiyagari (1994), takes the form of capital. Savings may be precautionary and allow partial insurance against labor income shocks. Because of the lack of full insurance, this model generates an endogenous distribution of wealth across consumers, enabling us to assess the welfare implications of the redistribution policy experiment.

The redistribution policy considered in this paper is such that it taxes labor income and transfers the revenue to individuals in a lump-sum fashion. In order to assess the welfare implications of this policy experiment, I take a stand on a specific social welfare function, which is based on a utilitarian social welfare function among all generations currently alive in the steady state. Under this criterion, well-being of the heterogeneous population is aggregated by the weighted sum of individual utilities. The usage of this social welfare function is desirable in our context because its curvature, which in our context is determined by the curvature of the individuals' utility function, reflects the marginal social value of equality - the extent to which a dollar is deemed to be worth more to a poorer individual than to a richer one.¹ Thus, we can assess the performance of our policy experiment considering different levels of society's aversion to inequality.

The model used to guide the quantitative assessment in this paper is related to Imrohoroglu et al. (2004), Mocan et al. (2005) and Gallipoli and Fella (2006). However, differently from these papers, which assume that labor is exogenous, I explicitly model individuals' labor supply decisions. This seems to be a natural extension in the current context since there are potentially important general equilibrium effects associated with the redistribution policy acting through changes in labor, which may be crucial to correctly evaluate the implications of the policy change. Moreover, the presence of endogenous labor in an uncertain environment is important because individuals have an additional element, along with asset

¹See, for example, Atkinson (1970, 1973) and Atkinson and Stiglitz (1980).

holdings, to insure themselves against idiosyncratic shocks.

Another important contribution I make to the previous literature is the inclusion of the social stigma resulting from conviction. As far as I know, the model developed in Imrohoroglu et al. (2004) is the only one that explicitly takes into account the stigma effect. In their model, stigma only decreases individuals' wage and does not affect their likelihood of employment. Nevertheless, according to the empirical evidence in Freeman (1991), Grogger (1992) and Nagin and Waldfogel (1995), stigma tends to be much more important in increasing unemployment duration than in decreasing wages. Thus, in this paper, I follow this evidence, and the stigma effect appears as a lower probability of ex-convicts finding a job. The importance of introducing the stigma effect into the model relies upon the fact that it might affect the analysis of the determinants of criminal behavior. In particular, the sensitivity of crime to changes in law enforcement and labor market conditions tends to be higher since the possibility of being stigmatized increases the expected cost of engaging in criminal activities.

Imrohoroglu et al. (2000) have also analyzed the relative desirability of income redistribution vis-à-vis law enforcement policies.² The authors find that, if the government is not able to prevent unpunished criminals from receiving transfers, then the redistribution policy may end up raising criminality. This result is due to their assumption that individuals can specialize either in legal market activities or in crime. In this case, higher income transfers do not increase the opportunity cost of crime, while the tax required to finance those transfers reduces the legal workers' wages. However, the assumption of specialization does not seem to be supported by the empirical evidence. As a matter of fact, various surveys on prison inmates show that crime and legal work are not mutually exclusive. For example, according to the Bureau of Justice Statistics (1986), 71 percent of all state prisoners were employed before their conviction.³

The rest of this paper is organized as follows: Section 2 describes the economic environment; Section 3 presents the calibration of the model; Section 4 presents and discusses the results of the numerical simulations; and, finally, Section 5 concludes the study.

2. The Model

The dynamic general equilibrium model that will be used to guide the quantitative assessment of the questions proposed in this paper has an overlapping generation structure. In what follows, I develop this model and present a definition of a competitive equilibrium for the economy under consideration.

²Other papers that analyze similar issues are Benoit and Osborne (1995), Merlo (2003) and Cassone and Marchese (2006).

³Further evidence can be found in Lochner and Moretti (2004).

2.1 Demographics and preferences

The model economy is populated by a continuum of mass one individuals. In each time period, a new generation is born with probability one. These individuals survive for a finite number of periods T , which is deterministic. The share of age- t individuals in the economy is denoted by γ_t . In addition, at each age t , individuals are heterogeneous with respect to their educational attainment $i = 1, \dots, I$. Let μ_i denote the share of individuals with education level i in the population. Both the age, $\{\gamma_t\}_{t=1}^T$, and education, $\{\mu_i\}_{i=1}^I$, distributions are exogenous and satisfy $\sum_{t=1}^T \gamma_t = 1$ and $\sum_{i=1}^I \mu_i = 1$.

In each period of life individuals are endowed with one unit of time, which can be used for labor or leisure. They enjoy utility from consumption, c_t , and leisure, l_t , over their life cycle according to:

$$E_0 \left(\sum_{t=1}^T \beta^{t-1} u(c_t, l_t) \right) \quad (1)$$

where β is the subjective discount factor, and E is the expectations operator conditional on information at birth. The utility function of each period is assumed to take the form:

$$u(c_t, 1 - h_t) = \frac{(c_t^{1-\rho} l_t^\rho)^{1-\gamma}}{1-\gamma} \quad (2)$$

where γ denotes the risk aversion parameter and ρ denotes the share of leisure in the utility.

2.2 Budget constraints

In the economy considered in this paper, individuals make decisions about labor supply, savings and whether or not to engage in criminal activities. At the beginning of each period $t = 1, \dots, T$, individuals receive a stochastic employment shock $s \in S = \{e, u\}$, where e and u denote employment and unemployment. The labor income of an employed agent aged t with education i depends on the wage rate, w , on the number of hours she spends working, $h_{i,t}$, and on an age-education efficiency index $\varepsilon_{i,t}$, where $\varepsilon_{i,t}$ is exogenously given and intended to capture the heterogeneity of individuals' earnings over their life cycle and in terms of education attainment as well. Let $y_{e,i,t} = (1 - \tau)wh_{i,t}\varepsilon_{i,t}$ denote individuals' after-tax income when $s = e$, where τ denotes the labor income tax rate. On the contrary, unemployed individuals ($s = u$) do not work at all (ie, $h_{i,t} = 0$) and receive unemployment insurance benefits, which amount to a fraction θ of the employed income, that is, $y_{u,i,t} = \theta wh_{i,t}\varepsilon_{i,t}$.

Moreover, regardless of their employment status, agents can choose to engage in criminal activities.⁴ The types of crimes considered in this paper are those under the general category of property crime, consisting of burglary, robbery, theft, motor-vehicle theft, and larceny. This is so because these crimes are more probably motivated by the prospect of monetary gain.⁵ For simplicity, I assume that criminals do not have information about their victim's income, which implies that they do not have the ability to target their victims based on that variable. Instead, criminals choose their victims randomly within the population. If they succeed, which occurs with probability π_a , a fraction α of the victim's income is stolen. As a consequence, the expected payoff of getting involved in a successful criminal activity is $\alpha\bar{y}$, where $\bar{y}$ denotes the average income of the economy.

However, if they fail, which occurs with probability $1 - \pi_a$, they are arrested and held in jail during an entire period.⁶ In this case, they do not make any decisions and receive a subsistence consumption level denoted by $\underline{c}$. The income of individuals who are convicted of a crime and sent to prison is confiscated and distributed in a lump-sum fashion among all the individuals who are not in jail.⁷ In addition, a convicted criminal keeps her assets, but she cannot access them while in jail. After a crime sentence ends, individuals are released, and they resume making work, savings and crime decisions. Criminal choice in the model is discrete and I assume that criminals can commit only one crime per period. This assumption is used here for computational reasons and it is not crucial for our assessment of the factors leading individuals to become criminals.⁸

The probability of being caught is endogenous, which allows the model to capture some equilibrium effects on crime acting through changes in the output

⁴In other words, crime and legal work are not mutually exclusive. This assumption is supported by various surveys on prison inmates. For example, according to the Bureau of Justice Statistics (1986), 71 percent of all state prisoners were employed before their conviction.

⁵Following Imrohoroglu et al. (2000, 2004) and Gallipoli and Fella (2006), I consider robbery as a property crime, even though the FBI classifies it as a violent crime. For the proposal of this paper, that seems to be reasonable since many crimes in that category are motivated by the prospect of monetary gains.

⁶Later, I will specify a model period that corresponds to one year. Given that the average sentence length is around one year for property crimes and has not changed during the 1980s and 1990s (Sourcebook of Criminal Justice Statistics, Bureau of Justice Statistics, 1995), this assumption keeps us close to the reality and, at the same time, it helps simplify the model.

⁷This assumption slightly differs from the one used in Imrohoroglu et al. (2004), who use the convicted criminals' income to finance the consumption of prisoners. Even though this is a strong assumption, it helps keep the model tractable, without significantly affecting the results. An alternative could be to give the proceeds of crime back to the victims, but it would require another state variable to identify the victims, leading us to face the curse of dimensionality.

⁸An alternative approach is used in Lochner (2004) and Mocan et al. (2005), who model criminal choice as continuous (time spent committing crimes), but they do not take into account life-cycle savings. In the current setup, besides asset holdings, agents choose leisure, so that modeling criminal behavior also as a continuous variable would make the solution of the model a significantly more time-consuming task since we would have to solve one more choice variable for each agent in every period.

of economy. Following Imrohoroglu et al. (2000), the apprehension technology of the police is described by:

$$\pi_a = 1 - (1 - pY)^{\frac{1}{\sigma}} \quad (3)$$

where $\sigma > 0$ and Y is the output of economy and p is the share of output spent on public safety. Thus, p summarizes the law-enforcement policy in the model.

The function (3) is convenient because it is concave and depends on only one parameter, which is easier to calibrate. However, the literature is silent about the most appropriate way to model the probability of arrest. Thus, I also provide results of simulations in which π_a is exogenously determined.

I assume that employment shocks are correlated across time in such a way that the probability of receiving a realization s' in the next period depends on the individual's current employment status s . Let $\pi_{ss',t+1}$ denote such a probability. These transition probabilities also depend on individuals' criminal record. In fact, there is substantial body of empirical evidence showing that after a conviction individuals face lower probability of finding a job than if they had not been convicted.⁹ The higher duration of unemployment for ex-prisoners is due to the stigma of incarceration, which appears as a societal outcome. Thus, even though this stigma effect is not legislated, it constitutes an additional component of punishment. Let ch denote individuals' criminal record. In particular, employment shock s is a two-state, first-order Markov process with the transition probability matrix given by:¹⁰

$$P_{t+1} = \begin{cases} \begin{pmatrix} \pi_{ee,t+1} & \pi_{eu,t+1} \\ \pi_{ue,t+1} & \pi_{uu,t+1} \end{pmatrix} & \text{if } ch = 0 \\ \begin{pmatrix} \pi_{ee,t+1} & \pi_{eu,t+1} \\ \phi\pi_{ue,t+1} & 1 - \phi\pi_{ue,t+1} \end{pmatrix} & \text{otherwise} \end{cases} \quad (4)$$

where $\phi \in [0, 1]$ captures the extent to which the stigma reduces the probability of finding a job for an ex-convict.

In this economy, individuals are allowed to save in a risk-free asset which pays an interest rate r . Let c_t and a_t denote, respectively, consumption and ordinary asset holdings of an agent at age t . Thus, we can write the budget constraint of an individual with employment status s who chooses not to become a criminal as:

$$a_{t+1} = \begin{cases} (1+r)a_t + y_{s,i,t} + \zeta - c_t, & \text{with probability } 1 - \pi_v \\ (1+r)a_t + (1-\alpha)y_{s,i,t} + \zeta - c_t, & \text{with probability } \pi_v \end{cases} \quad (5)$$

⁹See, for example, Freeman (1991), Grogger (1992), Nagin and Waldfogel (1995) and Nagin (1998).

¹⁰By allowing for the probability matrix to depend on age, the model is able to take into account the pattern of unemployment duration over the life cycle. However, in order to keep the model treatable, the transition probabilities do not vary with individuals' education since it would make the computer code too computationally burdensome.

On the other hand, the budget constraint of a criminal agent is given by:

$$a_{t+1} = \begin{cases} (1+r)a_t + y_{s,i,t} + \zeta + \alpha\bar{y} - c_t, & \text{with probability } (1-\pi_a)(1-\pi_v) \\ (1+r)a_t + (1-\alpha)y_{s,i,t} + \zeta + \alpha\bar{y} - c_t, & \text{with probability } (1-\pi_a)\pi_v \\ (1+r)a_t, \text{ and } c_t = \underline{c}, & \text{with probability } \pi_a \end{cases} \quad (6)$$

where ζ denotes a lump-sum transfer.

Additionally, agents cannot have negative assets at any age, so that the amount of assets carried over from age t to $t+1$ is such that $a_{t+1} \geq 0$. Also, given that there is no altruistic bequest motive and death is certain at the age $T+1$, agents consume all their assets at this age T , that is, $a_{T+1} = 0$.

2.3 Recursive formulation of individuals' maximization problems

Let ω_t denote the state space of an individual at age t . It is fully characterized by the amount of asset holdings a at the beginning of the period, by the employment status s , by education i and by individual's criminal history ch , that is $\omega_t = (a_t, s_t, i, ch_t)$. Let $V_t^{nc}(\omega_t)$ denote the value function of an agent at age t who does not engage in illegal activities and $V_t^c(\omega_t)$ the value function of an agent that chooses to commit a crime. Thus, the criminal decision is such that an individual in the state ω_t becomes a criminal if $V_t^c(\omega_t) > V_t^{nc}(\omega_t)$. The value functions $V_t^{nc}(\omega_t)$ and $V_t^c(\omega_t)$ are defined by the following dynamic programs:

If not criminal :

$$V_t^{nc}(\omega_t) = \underset{\eta_t}{Max} \left\{ \begin{array}{l} (1-\pi_v)[u(c_{t,nv}, 1-h_t) + \\ \beta \sum_{s_{t+1}} P_{t+1}(s_{t+1}, \omega_t) V_{t+1}(\omega_{t+1})] \\ + \pi_v[u(c_{t,v}, 1-h_t) + \\ \beta \sum_{s_{t+1}} P_{t+1}(s_{t+1}, \omega_t) V_{t+1}(\omega_{t+1})] \end{array} \right. \quad (7)$$

subject to (5)

If criminal :

$$V_t^c(\omega_t) = \underset{\eta_t}{Max} \left\{ \begin{array}{l} (1 - \pi_v)(1 - \pi_a)[u(c_{t,nv}, 1 - h_t) \\ + \beta \sum_{s_{t+1}} P_{t+1}(s_{t+1}, \omega_t) V_{t+1}(\omega_{t+1})] \\ + \pi_v(1 - \pi_a)[u(c_{t,v}, 1 - h_t) \\ + \beta \sum_{s_{t+1}} P_{t+1}(s_{t+1}, \omega_t) V_{t+1}(\omega_{t+1})] \\ + \pi_a[u(\underline{c}, 1) \\ + \beta \sum_{s_{t+1}} P_{t+1}(s_{t+1}, \omega_t) V_{t+1}(\omega_{t+1})] \end{array} \right. \quad (8)$$

subject to (6)

where $\eta_t = (a_{t+1,nv}, a_{t+1,v}, h_t) \geq 0$, with also $h_t \leq 1$, denotes the set of choice variables at age t and $V_{t+1}(\omega_{t+1}) = \max\{V_{t+1}^c(\omega_{t+1}), V_{t+1}^{nc}(\omega_{t+1})\}$.

Suppose $A \subset R_+$, $S = \{e = 1, u = 2\}$ and $I \subset R_+$, are the sets of possible values that a , s and i can take, so that we can define the state space as $\Omega = A \times S \times I$. Let $g_{a,t} : \Omega \rightarrow R_+$, $g_{c,t} : \Omega \rightarrow R_+$ and $g_{h,t} : \Omega \rightarrow [0, 1]$ be the policy functions associated with asset holdings, consumption and hours worked, respectively, in the dynamic programs (7) and (8). Finally, let $\varphi_t : \Omega \rightarrow \{0, 1\}$ be the decision rule of crime, defined as follows:

$$\varphi_t(\Omega) = \begin{cases} 1 & \text{if } V_t^c(\Omega) > V_t^{nc}(\Omega) \\ 0 & \text{otherwise} \end{cases}$$

2.4 Technology

The technology in this economy is given by a Cobb-Douglas production function with constant returns to scale: $Y_t = BK_t^\alpha N_t^{1-\alpha}$ where $\alpha \in (0, 1)$ is the output share of capital income, and Y , K and N denote aggregate output, capital and labor, respectively, and $B > 0$ is a constant scale parameter. The problem of the firms is standard. They pick capital and labor optimally and the first-order conditions are given by:

$$r = \alpha B \left(\frac{K}{AN} \right)^{\alpha-1} - \delta \quad (9)$$

$$w = (1 - \alpha) B \left(\frac{K}{AN} \right)^\alpha \quad (10)$$

where r denotes the net rate of return on capital, w the wage rate and δ the depreciation rate of capital.

2.4.1 Recursive competitive equilibrium

At each point of time, agents are heterogeneous in regard to age t and to state $\omega \in \Omega$. The agents' distribution at age t across the states ω is represented by a measure of probability λ_t defined in the subsets of the state space Ω . Let $(\Omega, B(\Omega), \lambda_t)$ be a probability space, where $B(\Omega)$ is the Borel σ -algebra on Ω . Thus, for each $b \subset B(\Omega)$, we have that $\lambda_t(b)$ denotes the fraction of agents at age t that are in b . Let $Q_t(\omega, b)$ be the transition function from age t to age $t + 1$, which depends on the decision rule $g_t(\omega)$ and on the transition probability matrix P_{t+1} . The function $Q_t(\omega, b)$ gives the probability of an agent at age t and state ω transiting to set b at age $t + 1$. A recursive competitive equilibrium for this economy can be defined as follows:

Definition 1 *Given the policy parameters, a recursive competitive equilibrium for this economy is a collection of value functions $\{V_t^{nc}(\omega_t), V_t^c(\omega_t)\}$, decision rules for individual asset holdings $g_{a,t}(\omega_t)$, for consumption $g_{c,t}(\omega_t)$, for labor supply $g_{h,t}(\omega_t)$ and for crime $\varphi_t(\omega_t)$, prices $\{w, r\}$, age dependent but time-invariant measures of agents $\lambda_t(\omega_t)$, transfers ζ , victimization rate π_v , crime rate π_c , probability of being caught π_a , average income of economy $\bar{y}$ and a tax rate τ such that:*

- 1) $g_{a,t}(\omega_t)$, $g_{c,t}(\omega_t)$, $g_{h,t}(\omega_t)$ and $\varphi_t(\omega_t)$ solve the dynamic problems (7) and (8);
- 2) The individual and aggregate behaviors are consistent, that is:

$$\begin{aligned} K &= \sum_{t=1}^T \mu_t \int_{\Omega} g_{a,t}(\omega_t) d\lambda_t \\ N &= \sum_{t=1}^T \mu_t \int_{\Omega} g_{h,t}(\omega_t) \varepsilon_{i,t} d\lambda_t \end{aligned}$$

- 3) $\{w, r\}$ are such that they satisfy the optimal conditions (9) and (10);
- 4) The final good market clears, that is:

$$\sum_{t=1}^T \mu_t \int_{\Omega} \{g_{c,t}(\omega_t) + [g_{a,t}(\omega_t) - (1 - \delta)g_{a,t-1}(\omega_t)]\} = BK^{\alpha} N^{1-\alpha}$$

- 5) Given the decision rule $g_{a,t}(s)$, $\lambda_t(b)$ satisfies the following law of motion:

$$\lambda_{t+1}(b) = \int_{\Omega} Q_t(\omega, b) d\lambda_t \quad \forall b \subset B(\Omega)$$

6) The victimization and crime rates are given by;

$$\pi_v = \sum_{t=1}^T \mu_t \int_{\Omega} \varphi_t(\omega_t) d\lambda_t$$

$$\pi_c = \varphi \pi_v$$

where φ is a scale parameter that, for example, can be used to account for reporting bias.¹¹

7) The unemployment insurance benefits program is self-financing:

$$\tau = \frac{\sum_{t=1}^T \mu_t \int_{\Omega} y_{u,i,t} d\lambda_t + c \pi_c \pi_a}{\sum_{t=1}^T \mu_t \int_{\Omega} y_{e,i,t} d\lambda_t}$$

8) The lump-sum transfers ζ are given by:

$$\zeta = \frac{\pi_a \sum_{t=1}^T \mu_t \int_{\Omega} \varphi_t(\omega_t) [d(s_t) y_{e,i,t} + (1 - d(s_t)) y_{u,i,t} + \alpha \bar{y}] d\lambda_t}{1 - \pi_a \pi_c}$$

where $d(s_t) = 1$ if $s_t = e$ and $d(s_t) = 0$ otherwise.

9) The average income of economy satisfies:

$$\bar{y} = \sum_{t=1}^T \mu_t \int_{\Omega} [d(s_t) y_{e,i,t} + (1 - d(s_t)) y_{u,i,t}] d\lambda_t$$

In short, the time line of the events in the model economy is as follows:

- i) At the beginning of each period, individuals find out their employment status;
- ii) Given s_t , they solve the dynamic programs in (7) and (8) in order to determine $V_t(\omega_t)$;
- iii) crimes are committed and the uncertainty with regard to victimization is revealed;
- iv) captured criminals go to prison;
- v) savings are carried out.

¹¹See discussion below.

3. Data and calibration

In order to obtain numerical solutions to the model and examine the determinants of criminal behavior, we need to choose particular values for the structural parameters of the economy under consideration. These values are chosen with the objective to build a numerical counterpart of the model which is able to reproduce selected features of the U.S. economy.¹² Cooley and Prescott (1995) describe how to calibrate a specific representative agent, based on an infinite-horizon model in the real-business-cycle literature, while Auerbach and Kotlikoff (1987) undertake a similar task for overlapping generations models. The calibration procedures described below follow these studies.

Initially, the model is calibrated taking into account 1980 data, which are set as a benchmark. Afterwards, we introduce the changes observed in the economic environment between 1980 and 1996 into the model and investigate whether or not our model is able to replicate the changes in criminality. Finally, we isolate the effect of the law enforcement, of aging population, of income inequality, of economic growth and of education, and investigate the relative importance of each factor to the changes in the crime rate in the period.

3.1 Demographics

We calibrate our model under the assumption that the model period is one year. In this economy, I examine individuals who start their economically meaningful lives at the age of 15 and live until the age of 65. Thus, the extension of individuals' lifetime in the model is 51 periods ($T = 51$). The age population distribution, $\{\gamma_t\}_{t=1}^T$, is obtained from the U.S. Census Bureau, Statistical Abstract. Figure 1 shows the population distribution by age for 1980 and 1996. It can be seen in the Figure that there was an aging population in the period, with a substantial fall in the share of young individuals (ages 15-30) and a corresponding increase in the share of experienced ones (ages 30-50). As it will turn out, these demographic changes may strongly affect criminality since most criminals are aged 15-30.

¹²I use data from the U.S. to calibrate the model because there is a shortage of panel data on crime in Brazil, which is a hindrance to any assessment of changes in the crime rate over time. This problem has been pointed out by many researchers such as Fajnzylber et al. (2001) and Cerqueira and Lobao (2004). Nevertheless, it should be stressed that the model developed in this paper is general and can be applied to the patterns of criminality in different datasets.

Figure 1: Population distribution by age (%)

The education levels considered in this paper are: less than high school ($i = 1$), high school ($i = 2$), college ($i = 3$) and more than college ($i = 4$). The distribution of human capital $\{\mu_i\}_{i=1}^4$ is also obtained from the U.S. Census Bureau and is shown in Table 2. Note that the share of individuals with less than college decreased between 1980 and 1996, going from 75 to 70%. At the same time, the number of individuals with higher education increased by 4 percentage points for those with just a college degree and by 1 percentage point for those with a post-college degree.

Table 1: Distribution of human capital

	μ_1	μ_2	μ_3	μ_4
1980	0.11	0.64	0.19	0.06
1996	0.09	0.61	0.23	0.07

3.2 Preferences and technology

The values of the parameters related to the individual preferences (β, γ, ρ) are summarized in Table 1. The value of the relative risk aversion parameter γ along with the share of leisure in the utility ρ determine the elasticity of intertemporal substitution of consumption, which is given by $1/[1 - (1 - \rho)(1 - \gamma)]$. Using the values for (γ, ρ) reported in Table 1, we obtain a value of 0.71 for the intertem-

poral substitution of consumption, which is in the range of the estimates of the microeconomic studies reviewed by Auerbach and Kotlikoff (1987).

In representative agent models, given the capital income share and the depreciation rate, there is a one to one relationship between the parameter ρ and the fraction of time that individuals spend working in the stationary state. In overlapping generations models, however, such relation is more complicated because of heterogeneity among agents. In this case, the procedure used to choose ρ is such that the average fraction of time that individuals in our model spend working is consistent with the empirical evidence, which suggests a value near 33%.¹³

Table 2: Preferences and technological parameters

β	γ	ρ	B	α	δ
0.989	2.00	0.61	0.90	0.36	0.07

The discount factor β has traditionally been calibrated using the capital-output ratio observed in the data. I follow this procedure here and choose a value for β such that the model delivers a capital-output ratio of 2.76, which is close to the estimated value for K/Y in the U.S. economy.

The values of technological parameters (B, α, δ) are also summarized in Table 1. I chose a value for α based on U.S. time series data from the National Income and Product Accounts (NIPA).

Following the real-business-cycle literature, the depreciation rate shown in Table 1 is obtained using the law of motion for the capital stock in steady state, an empirical investment-capital ratio of 0.072 and an economic growth rate of 3%.

Finally, I follow Huggett (1996) and choose the total factor productivity parameter B in such a manner that the benchmark economy delivers a wage rate w equal to 1. Thus, given a capital-output ratio of 2.76 and $\alpha = 0.36$, the value of B is 0.9.

3.3 Age-education efficiency profile

The age-education earnings profiles, $\varepsilon_{i,t}$, used in the simulations are estimated in Imrohoroglu et al. (2004).¹⁴ They use data from the Current Population Survey for each year to regress the log of real weekly earnings on age, age squared, and dummy variables for different human capital types. Figure 2 presents the estimated earnings profiles for the benchmark year. An important change that can be observed in the data is that earnings of individuals with less than a high school education have shown a relative decline between 1980 and 1996. On the contrary, the earnings of those with a college degree or more have increased relative to their counterparts. Thus, as one can see in Table 3, which shows some

¹³See, for instance, Juster and Stafford (1991).

¹⁴I would like to thank Peter Rupert for providing the data.

descriptive statistics of the earnings distribution, even though the labor income has grown, inequality, measured by the standard deviation of the earnings, increased substantially over the period.¹⁵

Figure 2: Earnings profiles - Benchmark economy

Table 3: Descriptive statistics

	average earnings	standard deviation
1980	1.000	1.095
1996	0.397	0.476

3.4 Transition probability matrix

Figure 3 shows the unemployment rate by age for 1980 and 1996. The data are from the Current Population Survey (CPS), Bureau of Labor Statistics. Given that the CPS only provides data for fixed intervals of age, linear interpolations were used to obtain the unemployment profile for all possible ages. As can be seen in the table, a marked change in the labor market in the period was the increase of unemployment among young individuals. This, in fact, took place at the same time that the aggregate employment was growing.

¹⁵I have normalized the distribution of earnings in such a way that the average earnings in the benchmark economy are equal to 1. The descriptive statistics shown in Table 3 correspond to the normalized data.

Figure 3: Unemployment rate by age (%)

The stochastic matrix P_t describing the transitions of the Markov chain for the employment shocks is constructed using the data shown in Figure 3. In particular, the entries of the matrix are chosen in such a way that the invariant distribution of employment associated with P_t matches the employment conditions observed in the data. Thus, for instance, given an unemployment rate of 13.59% for individuals aged 20, we have that the transition probabilities are such that:¹⁶

$$\begin{pmatrix} 0.8518 & 0.1482 \\ 0.9418 & 0.0582 \end{pmatrix} = \begin{pmatrix} 0.1359 & -0.5 \\ 0.8641 & -0.5 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & -0.09 \end{pmatrix} \begin{pmatrix} 0.1359 & -0.5 \\ 0.8641 & -0.5 \end{pmatrix}^{-1}$$

It is straightforward to show that the stochastic matrix above satisfies:

$$\begin{pmatrix} 0.8518 & 0.1482 \\ 0.9418 & 0.0582 \end{pmatrix}^{1000} = \begin{pmatrix} 0.8641 & 0.1359 \\ 0.8641 & 0.1359 \end{pmatrix}$$

3.5 Crime data and law enforcement parameters

The major source of nationwide crime statistics in the U.S. is the Uniform Crime Reports (UCR), which is based on the number of crimes reported to the

¹⁶More formally, we have that $A = PDP^{-1}$ where D is the diagonal matrix of the eigenvalues of A , and P is the matrix of the eigenvectors of A .

police. The UCR contains information from most jurisdictions and accounts for broader range of crime categories. Additionally, it has more tradition and prestige because of the FBI's involvement in the data collection and reporting process (Gove et al., 1985). However, a major criticism that has been made to the UCR is that not all crimes are reported to the police. This can happen, for example, because victims feel that the police will do nothing about the crime, because of the embarrassment of talking about the crime (a man who was robbed by a prostitute) or because they are afraid of retaliation.¹⁷

The second most important source of crime data is the National Crime Victimization Surveys (NCVS), whose main purpose is to uncover crimes that have not been reported. Thus, the survey is based on the premise that citizens may report to the NCVS interviewers the crime that they did not report to the police. However, the NCVS has also faced many criticisms, which focus primarily upon the lack of seriousness of crimes reported to the NCVS as interviewees report trivial incidents as crime, as well as lack of respondents' accuracy (Vito et al., 2007). In fact, respondents are not always reliable because the NCVS asks them to recall events from a specific time period; therefore, forgetting and telescoping (moving a crime event from the past forward or pushing a victimization backward) is a problem.

There is, however, empirical evidence showing that both statistics of criminality are highly correlated, mainly for property crimes, and, as a consequence, they measure the same phenomenon.¹⁸ The validity of these measures of crime is also supported by different research strategies. Indeed, Penick and Owens (1976) carry out a survey in which NCVS respondents are asked whether or not they have reported crimes to the police which they reported to the interviewer. The authors find that the average percentage of victimizations reported to the police is about 70% for property crimes. Thus, they conclude that property crime rates for UCR and NCVS measures show a high level of agreement.

Therefore, given this evidence supporting the UCR as valid indicator of criminal activity, especially with regard to property crimes, UCR is used in this paper mainly because it is a more comprehensive source of crime statistics.¹⁹ However, to account for the difference between the victimization rate measured by the NCVS and the number of crimes reported to the police, I define crime rate in the model as: $\pi_c = \varphi \pi_v$, where φ captures the level of underreporting observed in the UCR data. According to the evidence above, I set $\varphi = 0.70$. Table 4 shows the crime

¹⁷Another criticism made to the UCR is that crime reporting behavior is affected by the size of police force and, as a consequence, the usage of this dataset to assess the effectiveness of increasing public safety expending should be avoided. Nevertheless, Levitt (1998) shows that, despite the existence of reporting bias, it is too small to compromise the evaluation of crime control policies based on UCR.

¹⁸See, for example, O'Brien et al. (1980) and Vito et al. (2007) and the evidence they cite.

¹⁹Other papers related to mine, such as Imrohoroglu et al. (2000, 2004), Gallipoli and Fella (2006), Mocan et al. (2005) and Merlo (2003), have also used the UCR data.

rate per 100 inhabitants in the U.S. for different years.

Table 4: Crime rate (%) – UCR data

1975	1980	1986	1996
5.02	5.60	5.05	4.6

The parameter α , which characterizes criminal earnings from property crimes, in addition to the costs of property crime to victims, is set to be 0.15 (Imrohoroglu et al., 2000). While in prison, the arrested criminal receives a subsistence–consumption level denoted by $\underline{c}$, which is calibrated appropriately for the model to match the observed crime rate in the benchmark economy. Given that the property crime rate per 100 inhabitants in the U.S. in 1980 was 5.60%, a value for $\underline{c}$ of 0.0474 was obtained. This value corresponds to about \$1,300 (in 1990 dollars), which is close to the per inmate annual expenditure on food.²⁰

The apprehension technology of the police is characterized by the parameter σ . To calibrate this parameter, pY is first set equal to 0.6% of the output of the benchmark economy, which corresponds to the amount spent by the U.S. on law enforcement in 1980. Given this value for pY , σ is then chosen in order for the model to match the probability of apprehension observed in the data for 1980. The closest empirical counterpart of the probability of apprehension π_a is the clearance rate. This rate corresponds to the share of crimes for which the police have obtained enough evidence to arrest a person for the particular offense with reference to the number of offenses.²¹ After decreasing from 18.9 to 16.8% between 1975 and 1980, the clearance rate has steadily increased through the 1980s and 1990s, reaching 18.6% in 1996. As it will turn out, this increase is largely due to a marked expansion in the public safety spending observed in the period, which went from 0.6% of the GDP in 1980 to 0.71% in 1996. Thus, by choosing a value of 0.1390 for σ , the model generates a π_a equal to 0.1685 under the baseline calibration.

Finally, the parameter ϕ , which captures the extent to which social stigma reduces the likelihood of employment for ex-convicts, is calibrated based on the empirical evidence in Freeman (1991). Exploiting the panel data for a sample of young U.S. men in the 1980s, he finds that incarceration reduces the probability of work by 15 to 30 percentage points. Thus, I set $\phi = 0.80$ for the benchmark economy.

²⁰In fact, according to Imrohoroglu et al. (2000), who use data from the U.S. Bureau of Prisons, Office of Research and Evaluation, the average expenditure on food in the U.S. prisons was about \$1,600 in 1990. Also, I do not include the expenditures on food in the public safety spending because the latter is treated as a policy parameter in the model.

²¹It should be stressed that, even though the probability of punishment, which is related to the number of convictions, may differ from the clearance rate, they are correlated because an offense could not be considered “cleared” unless there was a reasonable chance that a conviction would result.

4. Results

Table 5 characterizes the profile of criminals in the model under the baseline calibration by presenting the crime rate among different groups in the population. As one can see in the table, while the aggregate crime in the model is 5.65% in the benchmark year, the crime rate is 18.73% among unemployed individuals, 27.92% among individuals younger than 19 years old and 24.30% among those without a high school diploma. Given that these findings are close to the values observed in the data, which are also shown in Table 5, the model is able to replicate a stylized fact that being unemployed, young and uneducated is largely associated with criminal behavior.²² The reason why the model yields these results is that these features are highly correlated with low levels of income and, as a consequence, with a high marginal utility of income. Considering that the marginal utility of income measures the extent to which individuals value an extra unit of money, we have that the higher the marginal utility of income, the higher their inclination to engage in criminal activities.

Table 5: Crime rate among different groups (%) – Benchmark

	Model	Data
All economy	5.65	5.60
Unemployed individuals	18.73	23.10
Individuals Younger than 19	27.92	24.35
Individuals without HS diploma	24.30	26.83

Table 6 shows the decomposition of the change in the crime rate between 1980 and 1996. The exercise behind the results shown in Table 6 consists in taking the calibrated model for the benchmark year, replacing the 1980 data with data relative to unemployment, age-efficiency profiles, age distribution of the population, human capital distribution, and law enforcement for 1996, and then computing the new stationary equilibrium. Note that besides the case in which π_a is given by (3), I also present the results for the case in which π_a is exogenous.²³ It can be seen in the table that the crime rate is more sensitive to changes in the economic environment when π_a is endogenous. This should be expected because, in this case, changes in the labor market conditions or in law enforcement that affect individuals' decisions about labor supply and asset holdings also affect the output of economy. Considering that police protection expenditures are proportional to the output, pY , they entail an increase in public safety spending and thereby an increase in the probability of apprehension, which amplifies the change in the crime rate.

Overall, the model is able to replicate the change in the crime rate in the period

²²See, for example, Buonanno and Montolio (2008).

²³I do that because of the lack of consensus among criminologists and economists about the best functional form for the technology of apprehension.

under consideration, regardless of whether π_a is endogenous or not. According to Table 6, greater law enforcement policy was the most important factor behind the decline in crime between 1980 and 1996, followed by labor income growth.²⁴ The channel through which both variables affect criminality is straightforward. First, an increase in the probability of apprehension increases the expected cost of crime, leading criminals to find optimal not to engage in criminal activities any longer. Second, the increase in labor income decreases the individuals' marginal utility of income, thereby reducing their willingness to take the risk associated with crime.

In order to investigate the isolated effect of inequality on crime, I have fed the model with data about the earnings profiles for 1996, keeping the average earnings normalized to its value in the benchmark case. As a consequence, in this experiment the only difference between the disturbed and benchmark economies is the dispersion of labor income. Table 6 shows that the increase in inequality constitutes the most important single factor promoting crime in the period. The model predicts that one percent of increase in inequality, measured by the standard deviation of earnings, is associated with an increase of 5.17 (2.92 with π_a constant) percentage points in the crime rate. To understand the channel through which inequality affects criminality in the model, one should recall that the change in the earnings profiles observed in the period made disadvantaged individuals even poorer in relation to those at the top of the income distribution, thereby increasing their inclination to engage in criminal activities.

This result is consistent with the empirical evidence in Demombynes and Ozler (2005) and Fajnzylber et al. (2002), which shows that the level of criminality is more correlated with the distribution than with the level of income in a particular economy. The intuition is that when everyone is poor in a given region, the average income and hence the expected return of crime are low, offsetting the higher inclination to commit crime. On the other hand, the larger the number of rich people, the higher the expected return of crime and more prone to commit crime poor people will be.

²⁴In Table 6, the change in law enforcement in the second column takes the form of an increase in public safety spending as a share of output, p , from 0.006 to 0.0071, while in the third column it consists of an increase of π_a from 0.168 to 0.186.

Table 6: Decomposition of the change in the crime rate

	π_a endogenous	π_a exogenous
Model benchmark year	5.61	5.66
Police protection ¹	2.74	3.36
Age profile	4.29	5.95
Human capital	5.25	5.38
Average Income	3.78	4.23
Inequality	10.78	8.62
Unemployment	5.69	5.62
Model 1996	4.48	4.86
Data 1996	4.60	4.60

¹In the second column, p is increased to 0.0071, while in the third one I raise the

¹probability of apprehension to 0.186.

Another interesting result seen in Table 6 is that the effect of the change in the age distribution of population depends on whether π_a is endogenous or constant. In fact, if π_a is endogenous (constant) we have that the aging population decreases (increases) criminality. To understand this result, note that, with endogenous labor supply, the aging of the population has a twofold effect on crime. On the one hand, it has a negative effect (i.e., it diminishes crime) due to the reduction in the percentage of young who, according to Table 5, are more likely to engage in criminal activities than mature individuals. On the other hand, the larger number of experienced individuals entails a higher level of employment and income, as the average hours worked and earnings of these individuals are higher (see Figure 4), which increases the expected return of crime, thereby generating a positive effect on crime. In the model with exogenous π_a , the second effect tends to dominate, while the opposite is true when π_a is endogenous. This is so because in the latter case the increase in the income due to a larger share of experienced agents in the economy raises police protection expenditures, which reinforces the effect of the demographic change on crime.

This result is at odds with the one obtained in Imrohoroglu et al. (2004), in whose paper labor and π_a are constants. The difference can be explained by the fact that the authors abstract from the general equilibrium effects associated with the behavior of the aggregate labor along the life cycle and, as a consequence, the second effect of the demographic change mentioned above tends to dominate.

Figure 4: Average Hours Worked over the Life-Cycle

4.1 The impact of income redistribution

When one has to evaluate the welfare implications of policy interventions across agents, there is still some disagreement about the method to be used. In this subsection, I take a stand on a specific social welfare function in order to assess the welfare implications of an income redistribution policy, which progressively taxes labor income to finance lump-sum transfers to all individuals in the economy that are out of jail. The idea of this experiment is to investigate whether such a policy can be thought of as an alternative to further police protection expenditures. The function used is based on a utilitarian social welfare function among all generations currently alive in the steady state. Under this criterion, the well-being of the heterogeneous population is aggregated by the weighted sum of individual utilities. In particular, given the decision rules $g_{a,t}(\omega_t)$ and $g_{h,t}(\omega_t)$ and the invariant cross-sectional distribution $\lambda_t(\omega_t)$ of the generation t across the states ω_t , the average steady-state utility for a policy arrangement Δ can be written as:

$$SWF(\Delta) = \sum_{t=1}^T \beta^{t-1} \int_{\Omega} u(c_t(g_{a,t}(\omega_t), g_{h,t}(\omega_t)), 1 - g_{h,t}(\omega_t)) d\lambda_t(\omega_t) \quad (11)$$

Table 7 shows the main results of the counterfactual experiment. For the sake of easier comparison, the third column of the table shows the results associated

with an increase in police protection expenditures by 0.1%, which was one of the experiments carried out in the last subsection, and in the second column, I increase the lump-sum transfers until the crime rate gets close to that obtained through greater police protection.²⁵ It can be seen that, even though the income redistribution policy entails bigger losses in terms of aggregate labor and average income, it increases social welfare by more than four times as much as the change in the law enforcement policy (4.3% as opposed to 1.1%).

Table 7: Impacts of income redistribution vis-à-vis law enforcement

	Income redistribution	Police protection
Crime rate	2.82%	2.74%
Aggregate labor	-0.61%	-0.29%
Average income	-0.42%	-0.21%
Welfare (SWF)	104.3	101.1

To understand the latter result, one should consider that more public safety spending reduces criminality by increasing the expected cost of engaging in criminal activities, whereas the redistribution policy, according to the model, can reach approximately the same result by enhancing the situation of low-income individuals. However, the concavity of the social welfare function, which measures the extent to which a dollar is deemed to be worth more to a poorer individual than to a richer one, means that changes in consumption and labor for low-income agents have a larger impact on social welfare than for high-income individuals. Therefore, a policy intervention that makes poor agents better off will have a much larger impact on $SWF(\Delta)$ in comparison to one that does not affect low-income individuals' welfare.

It is worthwhile to note that the risk aversion parameter γ governs the concavity of individuals' utility and, as a consequence, this parameter also governs the society's aversion to inequality.²⁶ Therefore, it is intuitive that the larger γ , the greater the welfare gains associated with the income redistribution policy tend to be. This happens not only because a higher aversion to inequality entails that the aggregate welfare is even more sensitive to changes in the allocation of poorer individuals, but also because a larger risk aversion parameter undermines individuals' willingness to engage in criminal activities, which lowers the cost due to the transfers required to bring the crime rate down. Table 8 shows the welfare implications of the redistribution policy and greater police force for alternative values of γ .

²⁵In both cases, higher expenditures are financed by progressive taxation on labor income.

²⁶See Atkinson (1970, 1973) and Atkinson and Stiglitz (1980).

Table 8: Impacts of income redistribution for alternatives γ

	Income redistribution		Police protection	
	Crime rate	Welfare	Crime rate	Welfare
$\gamma = 2.25$	2.26%	108.8	2.19%	102.1
$\gamma = 2.50$	1.75%	113.6	1.66%	103.5

4.2 The stigma effect of crime

Recall that the stigma effect in the model, which has been kept constant at its benchmark level, is measured by ϕ . The lower ϕ , the lower the likelihood of employment for an ex-convict. Given that government can partly control the level of stigmatization by, for example, handing out criminal records to the employers or not, it can be seen as an alternative policy tool to fight crime. As a consequence, understanding how changes in the level of stigmatization affect the economy is important to guide the formulation of crime control policies.

Figure 5 shows the crime rate, recidivism and welfare for different values of ϕ . It can be seen that increases in the level of stigmatization have a twofold effect on the economy. On the one hand, they reduce crime by increasing the expected cost of incarceration. Indeed, the model predicts that without this informal type of punishment, that is $\phi = 1$, the crime rate would be nearly 6% as opposed to 5.65% obtained under the baseline calibration ($\phi = 0.8$), while a decrease of 50% ($\phi = 0.5$) in the likelihood of employment for an ex-convict is associated with a fall in the crime rate by as much as 8.84%. These results are in line with theoretical arguments as well as with a large body of empirical evidence suggesting that the formal (governmental) punishment that a convicted criminal is confronted with, constitutes only part of the whole penalty and that the occurrence of (informal) “punishment” in the labor market by stigmatization can play an important role in deterring crime.

On the other hand, even though stigma enhances deterrence of an unconvicted offender, it drives a stigmatized ex-convict towards recidivism as ex-prisoners face fewer opportunities in the labor market. According to the Figure, an increase in the stigma effect in relation to its benchmark value of 12.5% (from $\phi = 0.8$ to $\phi = 0.7$) entails an increase in recidivism of nearly 5.80%. When we assume no stigma ($\phi = 1$), the model predicts that 43% of ex-convicts end up committing crime again after leaving jail.

Figure 5: The effect of stigma on crime, recidivism and welfare

An interesting result observed in Figure 5 is that for lower levels of stigmatization, the aggregate welfare, measured by (11), increases as ϕ goes down, which is mainly due to the fall in criminality. However, as ϕ continues to decrease, thereby raising the number of recidivists, the aggregate welfare will eventually fall. To understand this finding, recall first that recidivism depresses the level of employment as ex-prisoners face lower probability of finding a job and thus imposes a cost on society. In addition, keep in mind that criminals are overall low-income individuals with a high marginal utility of income and, the bigger the stigma effect, the worse their situation because it changes the stochastic process that underlies the income paths of these individuals. Thus, given that the social welfare function defined in (11) is more sensitive to changes in the consumption-labor allocations of disadvantaged individuals than of richer ones, we have that high levels of stigmatization can adversely affect social welfare as it increases recidivism.

5. Conclusions

In this paper, I have studied a stochastic life-cycle economy in which individuals optimally pick labor, life-cycle savings or choose to engage in criminal activities. The model mimics selected features of the U.S. economy and takes special care in the assessment of the economic incentives driving agents towards criminality. Simulations were able to match very closely the changes in crime observed between 1980 and 1996.

The model replicates an important stylized fact that young, uneducated and unemployed individuals constitute at-risk populations, being the crime rate within these groups way above the average crime rate. The high incidence of crime among these individuals is due to their high marginal utility of income, which makes them more inclined to take the risk associated with illegal activities.

In addition, the model shows that greater police enforcement can account for the most part of the fall in crime observed in the period, while inequality was the most important factor promoting crime. This finding motivated a counterfactual experiment in which I compare the effects of an income redistribution policy to those obtained through more public safety spending. I found that lump-sum transfers, financed by progressive taxation of labor income, can reduce crime as much as greater police protection with much higher gains in terms of social welfare. Intuitively, this happens because redistribution diminishes crime by enhancing the situation of at-risk individuals as opposed to the law enforcement that increases the expected cost of crime.

I also investigated the effects of harsher stigmatization on crime and recidivism. The findings support existing empirical evidence showing that the higher the level of stigmatization, the lower the crime rate and the larger the number of recidivists. Moreover, I found that harsher stigmatization can be socially inefficient as it negatively affects the stochastic process that underlies the income paths of criminals.

There are some dimensions in which the theory of crime studied in this paper can be enriched, which is the goal of an ongoing research study. First, I want to investigate the consequences of allowing the households in our model economy to engage in activities such as human capital accumulation that change the labor income paths of individuals. Second, in line with Castaneda et al. (1999), we also aim to study the implications of altruism, which provides a reason for households to accumulate significantly larger amounts of wealth than those that are needed to maintain a high standard of living during the life cycle. This feature, along with the existence of uncertainty about longevity, introduces another dimension of heterogeneity that can be helpful to better assess the impacts of redistribution policies on crime.

It should be stressed that, even though the model developed in this paper is general and can be used to study the patterns of criminality in different datasets, I did not seek to understand the differences in crime rates across countries. In particular, I did not compare the patterns of crime in the U.S. with those observed in Brazil. This is so because, besides the limited availability of panel datasets about crime for the Brazilian economy, there are large differences in the way crime data are defined and collected as well as major differences in reporting practices across countries.

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