

# What Accounts for the Decline in Crime?

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## Abstract

In this paper we analyze recent trends in aggregate property crime rates in the United States. We propose a dynamic equilibrium model which guides our quantitative investigation of the major determinants of observed patterns of crime. Our main findings can be summarized as follows. First, the model is capable of reproducing the drop in crime between 1980 and 1996. Second, the most important factors that account for the observed decline in property crime are the higher apprehension probability, the stronger economy, and the aging of the population. Third, the effect of unemployment on crime is negligible. Fourth, the increased inequality prevented an even larger decline in crime. Overall, our analysis can account for the behavior of the time series of property crime rates over the past quarter century.

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## 1. Introduction

An important phenomenon of this decade has been the sharp and steady decline in crime. In the United States, the crime rate per 100 inhabitants was equal to 5.95 in 1980 and dropped to 5.09 in 1996. While this general trend has been observed for most categories of crime, the most noticeable decline has been observed for property crimes, which account for over 90% of all crimes. The property crime rate per 100 inhabitants in the United States went down 17% from 5.60 in 1980 to 4.65 in 1996.<sup>1</sup>

What accounts for this decline? Both the popular press and the academic literature have been searching for answers to this important question.<sup>2</sup> Several main factors have been identified as possible explanations for this phenomenon. The first factor is related to demographics. It is well documented that most crimes are committed by youths.<sup>3</sup> The fraction of youths in the population has been declining in the 1990s.<sup>4</sup> For instance, the fraction of people between the ages of 15 and 25 was equal to 20.5% in 1980 and went down to 15.1% in 1996.

Another key factor is related to law enforcement. Expenditures on police protection have increased from 0.6% of GDP in 1980 to 0.7% of GDP in 1996. Also, many initiatives to change the “style of policing” have been implemented in many U.S. cities. As a result, the clearance rate (i.e., the fraction of crimes cleared by arrest) has been increasing.<sup>5</sup> For example, in 1980

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<sup>1</sup>These numbers come from the Sourcebook of Criminal Justice Statistics, Bureau of Justice Statistics. The categories of crimes we include in our definition of property crime are burglary, larceny, robbery, and motor vehicle theft. This definition differs slightly from the one used by the Federal Bureau of Investigation, which does not include robbery and does include arson.

<sup>2</sup>See for example the article “Crime in America: Defeating the bad guys” in *The Economist* (October 3, 1998) and the collection of articles in the 1998 Summer issue (Volume 88) of the *Journal of Criminal Law and Criminology*.

<sup>3</sup>See, e.g., Freeman (1996) and Levitt (1998).

<sup>4</sup>Donohue and Levitt (2000) argue that the legalization of abortion not only reduced the number of births, but also improved the composition of the youth cohort of the 1990s by eliminating unwanted children who supposedly would be the population group most likely to engage in criminal activities.

<sup>5</sup>At the same time, the “severity” of punishment has remained pretty much constant. For example, the expected punishment for property crimes (measured by the average length of prison sentences multiplied

the clearance rate for property crimes was equal to 16.8. In 1996, it increased to 18.5.<sup>6</sup>

There are also other important phenomena that have been taking place in the 1990s that must be taken into consideration when trying to account for what is happening to crime. In particular, changes in the structure of earnings, employment opportunities, and the skill composition of the work force are likely to be intimately related to changes in the level of criminal activity.

The following observations all seem to point to a reduction in crime. Real earnings have been increasing. Average real earnings increased by approximately 10% between 1980 and 1996. At the same time, aggregate unemployment has been decreasing and so has the fraction of unskilled individuals in the labor force. For example, the fraction of individuals in the labor force with less than a high school degree has declined substantially between 1980 and 1996.

Other observations, however, point in the direction of an increase in crime. Income inequality has been increasing. By virtually any measure, the distribution of real earnings has become substantially more unequal over the past twenty years. In addition, youth unemployment has been increasing. For example, the unemployment rate for people between the ages of 15 and 19 was equal to 17.1 in 1980 and rose to 17.8 in 1996.<sup>7</sup>

The goal of this paper is to quantify the relative contribution of the above listed factors to explain the observed decline in property crime evidenced between 1980 and 1996. Unlike violent crimes, property crimes are typically motivated by the prospect of direct pecuniary gain. Economic considerations are therefore most likely to guide individual decisions of engaging in this type of criminal activities.

To guide our quantitative investigation of the major determinants of observed patterns 

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by the fraction of offenders sentenced to prison) was equal to 12.5 and 12.3 months in 1980 and 1995, respectively.

<sup>6</sup>The population numbers come from the Bureau of the Census, P25 917. Expenditures on police protection and clearance rates come from the Sourcebook of Criminal Justice Statistics. Data on GDP was taken from the Statistical Abstract of the U.S., 1999.

<sup>7</sup>Unemployment rates and real earnings are obtained from the CPS. Such trends are also found, for example, in Juhn, Murphy and Pierce (1993).

of property crime, we specify a dynamic equilibrium model with heterogeneous agents. The agents in our model differ *ex ante* with respect to their income earning abilities. In each period of their finite life, agents receive a stochastic employment opportunity. After knowing their employment status, they decide how much to save and whether to engage in criminal activities in that period. Criminal activities amount to stealing from other agents in the economy. If agents choose to commit a crime, they may be apprehended and punished.

There is a long tradition of economic models of crime initiated by Becker (1968).<sup>8</sup> Our model shares many of the features of existing models and embeds Becker's paradigm in a dynamic equilibrium framework. The dynamic nature of our model allows us to investigate individual decisions to engage in criminal activities over the life cycle.<sup>9</sup> The equilibrium aspect of our model allows us to investigate the response of the aggregate crime rate to a variety of factors.<sup>10</sup>

We calibrate our model using U.S. data for 1980 so as to reproduce the observed property crime rate. We then use 1996 data to evaluate the effect of changes in demographics, police activities, the distribution of wages, employment opportunities, and the skill composition of the work force on crime. Our main findings can be summarized as follows. First, the model is capable of reproducing the drop in crime between 1980 and 1996. Second, the most important factors that account for the observed decline in property crime are (in order of importance): the higher apprehension probability, the stronger economy, and the aging of the population. Third, the effect of unemployment on crime is negligible. Fourth, the increased inequality prevented an even larger decline in property crime. In fact, holding everything else constant, the increase in income inequality between 1980 and 1996 would have caused a substantial increase in property crime.<sup>11</sup>

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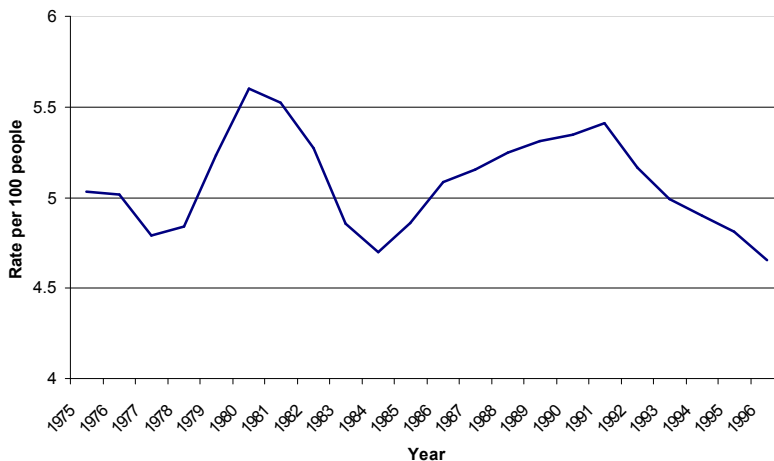
<sup>8</sup>See, e.g., Harris (1970), Stigler (1970), Ehrlich (1973), and Polinsky and Shavell (1984). Ehrlich (1996) provides a survey of recent contributions.

<sup>9</sup>Lochner (1999) also studies a dynamic model of criminal behavior which incorporates individual decisions to invest in human capital.

<sup>10</sup>Other general equilibrium models of crime include Ehrlich (1981), Furlong (1987), Burdett, Lagos and Wright (1999), and Imrohoroglu, Merlo and Rupert (2000).

<sup>11</sup>There is a huge empirical literature on estimating the economic model of crime that is somehow related to our work. Ehrlich (1973), Witte (1980), Tauchen, Witte and Griesinger (1994) and Levitt (1997), among

Figure 1: Property Crime Rate



Over the past quarter century the property crime rate in the United States has displayed some interesting patterns, as illustrated in Figure 1. In fact, the decline during the 1990s is only one of the interesting features of this time series. Property crime peaked in 1980, fell sharply during the first half of the 1980s, rose again during the second half of the 1980s (although not back to its 1980 level), and is currently at its lowest level in a quarter of a century. Can our analysis account for these patterns? To answer this question, we use data for 1975, 1985, and 1990 and compare the time series of property crime rates generated by the model to the observed series. We find that the model is capable of reproducing the behavior of the time series of property crime rates between 1975 and 1996.

## 2. The Model

We consider a dynamic equilibrium model with heterogeneous agents. Below, we describe the various components of our framework.

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others, document the deterrent effects of the apprehension probability and market wages on crime. The existence of a strong positive correlation between income inequality and crime and a weak positive correlation between unemployment and crime are also well documented (see, e.g., Ehrlich (1973) and Freeman (1995)).

## 2.1. Preferences

The economy is populated by a large number of individuals who are *ex ante* heterogeneous with respect to their income earning abilities. Each individual maximizes the expected, discounted lifetime utility

$$E \sum_{j=1}^J \beta^{j-1} U(c_j^i), \quad (1)$$

where  $\beta$  is the subjective discount factor, and  $c_j^i$  is consumption of a type- $i$  individual of age  $j$ . The share of age- $j$  individuals in the population is given by the fraction  $\mu_j$ ,  $j = 1, \dots, J$ ,  $\sum_{j=1}^J \mu_j = 1$ , where  $J$  is the maximum possible lifetime. The share of type- $i$  individuals in the population is given by the fraction  $\gamma_i$ ,  $\sum_{i=1}^I \gamma_i = 1$ , where  $I$  is the number of skill types.

## 2.2. Opportunities

In each period of their life, individuals face a stochastic employment opportunity. Let  $s \in S = \{e, u\}$  denote the employment opportunities state. If  $s = e$ , the agent is given the opportunity to work. If  $s = u$ , the agent is unemployed. Agents in this economy supply labor inelastically whenever they are given an opportunity to work. In addition, regardless of their employment status, agents can choose to engage in criminal activities.

Let  $w$  denote the wage rate,  $h$  denote the number of hours spent working, and  $\varepsilon_j^i$  denote the efficiency index of a type- $i$  agent of age  $j$ . Then, the labor income of an agent who is given an opportunity to work is equal to  $wh\varepsilon_j^i$ . If an individual is unemployed, he receives unemployment insurance benefits equal to a fraction  $\theta$  of the employed wage,  $\theta wh\varepsilon_j^i$ . The only role of government in this economy is to administer the unemployment insurance program.<sup>12</sup> Given unemployment insurance, the government chooses the tax rate  $\tau$  so that its budget is balanced. Hence, the disposable income from legitimate activities of a type- $i$  individual of age  $j$  is given by

$$y_j^i = \begin{cases} (1 - \tau)wh\varepsilon_j^i, & \text{if } s = e \\ \theta wh\varepsilon_j^i, & \text{if } s = u. \end{cases} \quad (2)$$

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<sup>12</sup>The government may also use tax revenue to finance a technology used to apprehend or deter criminals. In this paper we abstract from this using an exogenous probability of apprehension. For a model where expenditures on police are determined endogenously see Imrohorglu, Merlo, and Rupert (2000).

We assume that the employment opportunities state follows a Markov process with transition probabilities matrices  $\Pi_j = [\pi_j(l, k)]$ ,  $l, k = e, u$ , where  $\pi_j(l, k) = \Pr(s_{j+1} = k | s_j = l)$ ,  $j = 1, \dots, J - 1$ . We allow for the unemployment rate to vary with age.

In this economy, criminal activities amount to theft. Each individual faces an equal probability  $\pi_v$  of being the victim of a crime, where  $\pi_v$  is equal to the (endogenous) fraction of criminals in the population. If victimized, an individual loses a fraction  $\alpha$  of his disposable income from legitimate activities. For simplicity, we assume that criminals do not have the ability to target their victims based on their income and each criminal steals a fraction  $\alpha$  of average disposable income from legitimate activities,  $\bar{y}$ . Criminals face a probability  $\pi_a$  of being apprehended. A criminal who is apprehended for a crime goes to jail. To simplify exposition we assume that an apprehended criminal goes to jail for one period. Our analysis is, however, general and allows the prison term to be either longer or shorter than one model period (including fractions of a period).<sup>13</sup>

Given these assumptions, the budget constraint facing an individual who chooses not to be a criminal can be written as

$$a_{j+1}^i = \begin{cases} (1+r)a_j^i + y_j^i - c_j^i + T, & \text{with probability } 1 - \pi_v \\ (1+r)a_j^i + (1-\alpha)y_j^i - c_j^i + T, & \text{with probability } \pi_v \end{cases} \quad (3)$$

where  $a_j^i$  is the end-of-period asset holdings of a type- $i$  agent of age  $j$ ,  $r$  is the rate of return on asset holdings, and  $T$  denotes a lump-sum transfer. Similarly, the budget constraint facing an individual who chooses to be a criminal can be written as

$$a_{j+1}^i = \begin{cases} (1+r)a_j^i + y_j^i + \alpha\bar{y} - c_j^i + T, & \text{with probability } (1-\pi_v)(1-\pi_a) \\ (1+r)a_j^i + (1-\alpha)y_j^i + \alpha\bar{y} - c_j^i + T, & \text{with probability } \pi_v(1-\pi_a) \\ (1+r)a_j^i \text{ and } c_j^i = \bar{c}, & \text{with probability } \pi_a, \end{cases} \quad (4)$$

where  $\bar{c}$  is the level of consumption of a convicted criminal. Note that we assume that apprehended criminals cannot access their assets to finance their consumption while they are in jail.

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<sup>13</sup>In our quantitative analysis, the length of a prison term is calibrated using data on prison sentences for property crimes as explained in Section 3 below.

For a type- $i$  individual of age  $j$ , we let  $\ell_j^i \in \{0, 1\}$  denote the individual's choice to engage in criminal activities or not. In particular,  $\ell_j^i = 1$  indicates an individual who commits a crime and  $\ell_j^i = 0$  indicates an individual who chooses not to do so.

Agents in this economy are not allowed to borrow and have no access to private insurance markets. They are able to accumulate assets to help smooth consumption across time. This liquidity constraint can be stated as

$$a_j^i \geq 0, j = 1, \dots, J, i = 1, \dots, I. \quad (5)$$

An implication of this assumption is that in period  $J$  all individuals will choose not to carry over any assets to the next period in the absence of a bequest motive:

$$a_J^i = 0, i = 1, \dots, I. \quad (6)$$

### 2.3. Technology

The production technology of the economy is given by a constant returns to scale Cobb-Douglas function

$$Q = f(K, N) \equiv BK^{1-\eta}N^\eta, \quad (7)$$

where  $B > 0$ ,  $\eta \in (0, 1)$  is the labor share of output, and  $K$  and  $N$  are aggregate capital and labor inputs, respectively. The aggregate capital stock is assumed to depreciate at the rate  $\delta$ .

The profit-maximizing behavior of the firm gives rise to first-order conditions which determine the net real return to capital

$$r = (1 - \eta)B \left( \frac{K}{N} \right)^{-\eta} - \delta \quad (8)$$

and the real wage

$$w = \eta B \left( \frac{K}{N} \right)^{1-\eta}. \quad (9)$$

### 2.4. Stationary Equilibrium

The concept of equilibrium we use in this paper follows Stokey and Lucas (1989) and starts with a recursive representation of the consumer's problem. Let  $A$  denote the discrete grid



of points on which asset holdings will be required to fall. For any beginning-of-period asset holdings and employment status  $(a, s) \in A \times S$  define the constraint set of a type- $i$  agent of age  $j$ ,  $\mathcal{C}_j^i(a, s) \in R_+^2 \times \{0, 1\}$ , as the set of all 3-tuples  $(c_j^i, a_j^i, \ell_j^i)$  such that for  $j = 1, \dots, J$ , and  $i = 1, \dots, I$ , equations (3) and (4) are satisfied,  $c_j^i \geq 0$ ,  $a_j^i \geq 0$ , and  $a_o^i$  is given.

We can represent the consumer's utility maximization problem as a finite-state, finite-horizon discounted dynamic program for which an optimal stationary Markov plan always exists. Let  $V_j^i(a, s)$  be the (maximized) value of the objective function of a type- $i$  agent of age  $j$  with beginning-of-period asset holdings and employment status  $(a, s)$ .  $V_j^i(a, s)$  is defined as the solution to the dynamic program.

In particular, the dynamic programming problem faced by an individual of a given skill-type  $i$  who may or may not have received an employment opportunity can be written as:

$$V^i(a, s) = \max \left\{ \begin{array}{l} (1 - \pi_v) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + y^i + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s') \right\} \\ + \pi_v \max_{a'} \left\{ U((1+r)a^i - a^{i'} + (1-\alpha)y^i + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s') \right\}, \\ (1 - \pi_v)(1 - \pi_a) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + y^i + \alpha\bar{y} + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s') \right\} \\ + \pi_v(1 - \pi_a) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + (1-\alpha)y^i + \alpha\bar{y} + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s') \right\} \\ + \pi_a (U(\bar{c}) + \beta \sum_{s'} \pi(s, s') V^i(a', s')) \end{array} \right\} \quad (10)$$

where  $i = 1, \dots, I$ ,  $y^i$  is equal to  $(1 - \tau)wh\varepsilon^i$  for  $s = e$  and  $\theta wh\varepsilon^i$  for  $s = u$ , and the maximization problem is subject to (3) and (4).

**Definition:** A Stationary Equilibrium for a given set of policy arrangements  $\{\tau, \theta\}$  and an apprehension probability  $\pi_a$  is a collection of value functions  $V_j^i(a, s)$ , individual policy rules  $c_j^i : A \times S \rightarrow R_+$ ,  $a_j^i : A \times S \rightarrow A$ ,  $\ell_j^i : A \times S \rightarrow \{0, 1\}$ , age and type dependent, time-invariant measures of agents  $\lambda_j^i(a, s)$  for each age  $j = 1, \dots, J$  and each type  $i = 1, \dots, I$ , an aggregate crime rate and victimization probability  $\{\chi, \pi_v\}$ , relative prices of labor and capital  $\{w, r\}$ , an average disposable income from legitimate activities  $\bar{y}$ , and a lump-sum transfer  $T$  such that:

i) Individual and aggregate behavior are consistent:

$$K = \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) a_{j-1}^i \quad (11)$$

and

$$N = \sum_{i,j,a} \gamma_i \mu_j \lambda_j^i(a, s=e) h \varepsilon_j^i; \quad (12)$$

ii) The aggregate crime rate and victimization probability are given by

$$\chi = \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) \ell_j^i(a,s), \quad (13)$$

and

$$\pi_v = \chi; \quad (14)$$

iii) Average disposable income from legitimate activities is given by

$$\bar{y} = \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) y_j^i(a,s), \quad (15)$$

where

$$y_j^i(a,s) = \begin{cases} \theta w h \varepsilon_j^i & \text{for } s = u \\ (1 - \tau) w h \varepsilon_j^i & \text{for } s = e; \end{cases}$$

iv) Relative prices  $\{w, r\}$  solve the firm's profit maximization problem by satisfying equations (8) and (9);

v) Given relative prices  $\{w, r\}$ , government policy  $\{\tau, \theta\}$ , probabilities  $\{\pi_a, \pi_v\}$ , average income  $\bar{y}$ , and transfer  $T$ , the individual policy rules  $c_j^i(a,s)$ ,  $a_j^i(a,s)$ , and  $\ell_j^i(a,s)$  solve the individuals' dynamic program (10);

vi) Commodity market clears,

$$\sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) [c_j^i(a,s) + a_j^i(a,s)] = f(K, N) + (1 - \delta) \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) a_{j-1}^i, \quad (16)$$

where the initial wealth distribution of agents,  $a_0^i$ ,  $i = 1, \dots, I$ , is taken as given;

vii) The collection of age and type dependent, time-invariant measures  $\lambda_j^i(a, s)$  for  $j = 1, \dots, J$  and  $i = 1, \dots, I$ , satisfies

$$\lambda_j^i(a', s') = \sum_{a \in \underset{a}{a}} \sum_s \pi_j(s, s') \lambda_{j-1}^i(a, s)$$

where  $\underset{a}{a} \equiv \{a : a' = a_j^i(a, s)\}$ , and the initial measures of agents at birth,  $\lambda_0^i$ ,  $i = 1, \dots, I$ , are taken as given;

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

$$\tau = \frac{\sum_{i,j,a} \gamma_i \mu_j \lambda_j^i(a, s = u) \theta w h \varepsilon_j^i}{\sum_{i,j,a} \gamma_i \mu_j \lambda_j^i(a, s = e) w h \varepsilon_j^i}; \quad (17)$$

The income of individuals who are convicted of a crime is confiscated and used to finance the consumption expenditures of convicted criminals  $\bar{c}$ . Any income in excess of these expenditures is distributed in a lump-sum fashion among all individuals who are not in jail:

$$T = \frac{\pi_a \left[ \sum_{i,j,a,s} \gamma_i \mu_j \ell_j^i(a, s) \lambda_j^i(a, s) (y_j^i(a, s) + \alpha \bar{y}) - \bar{c} \chi \right]}{1 - \pi_a \chi}. \quad (18)$$

### 3. Parameter Choice and Data

As mentioned above, the paper seeks to identify the extent to which each of several factors contributed to the change in the property crime rate evidenced between 1980 and 1996. In addition, since as illustrated in Figure 1 the property crime rate has not followed a steady trend over the past quarter century, several other years are examined. In particular, the additional years we focus on are 1975, 1985, and 1990, which represent key “turning points” in the time series of property crime rates. The strategy employed in this paper is to first benchmark the model to exactly match the crime rate in 1980.<sup>14</sup> To determine the crime rate for other years, data for the relevant year is then fed into the model, i.e. the age-specific unemployment rates ( $\Pi_j$ 's), age-efficiency profiles ( $\varepsilon_j^i$ 's), age distribution of the population

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<sup>14</sup>A detailed description of what is used to calibrate exactly to the 1980 crime rate is given below.

( $\mu_j$ 's), shares by human capital type ( $\gamma_j$ 's), the length of the prison term, and the ability of the police to capture criminals ( $\pi_a$ ), are set to the value for the year in question, with the rest of the model parameters left unchanged.

Before we describe the data and the procedures we use to measure the various elements of our model that are allowed to vary over the different years we consider, we first describe the calibration of the components of the model that are set in our benchmark and that are held fixed throughout the analysis.

The utility function  $U(\cdot)$  is set to be logarithmic. A period in the model is one year which dictates setting the discount factor  $\beta$  equal to 0.989. An overlapping generations structure is imposed where individuals are assumed to be born at the real-time age of 15 and live  $J = 51$  years, to the real-time age of 65. The model economy's inhabitants are distinct not only with respect to their age, but also their human capital type. Specifically, we consider  $I = 4$  skill levels corresponding to the following categories: less than high school, high school degree but no higher degree, college degree, and more than a college degree.

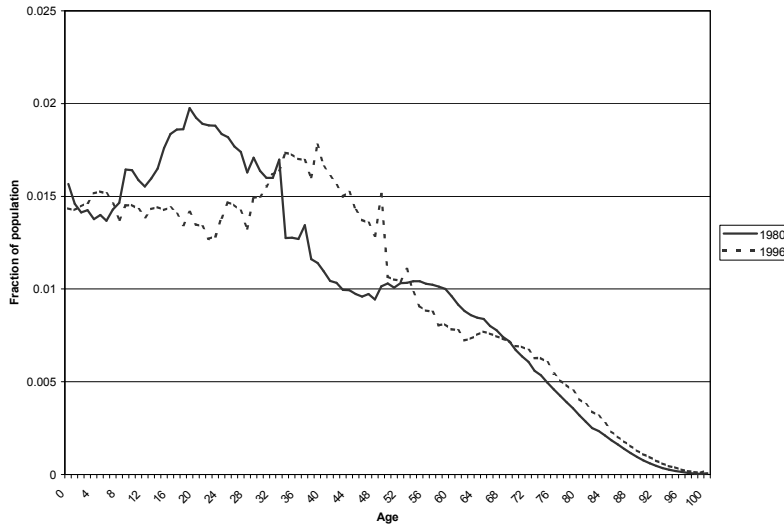
If an individual is employed, he spends a fraction  $h = 0.45$  of his time working. In the event that an individual becomes unemployed he receives unemployment insurance with a replacement rate  $\theta$  equal to 0.83. Unemployment duration in the model is one year (one period) while in the U.S. the replacement ratio is 0.25 and duration is about 12 weeks, which means individuals would receive 83% of their income if they were to be unemployed 12 weeks and employed the rest of the year.

The parameter  $\alpha$  that characterizes criminal earnings from property crimes as well as the costs of property crime to victims is set to be 0.15 (see Imrohoroglu, Merlo and Rupert (2000)). While in prison the apprehended criminal receives a per-period consumption level denoted by  $\bar{c}$ . Given that there is little data on consumption and utility while in prison,  $\bar{c}$  is treated as a free parameter and is used to calibrate the model to match the crime rate in the benchmark year 1980. The calibrated value of  $\bar{c}$  is equal to 0.052, which corresponds to about \$1,400 (in 1990 dollars).<sup>15</sup>

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<sup>15</sup>To provide a term of comparison, note that the per inmate annual expenditure on food (obtained by dividing total annual expenditures on food by the average daily population in federal correctional facilities for 1990) amounts to about \$1,600 (U.S. Bureau of Prisons, Office of Research and Evaluation, unpublished

Figure 2: Age Distribution



With respect to the production side of the economy, the following parameter values were chosen:  $B = 1.295$ ,  $\eta = 0.64$ , and  $\delta = 0.08$ . This parameterization is fairly standard and produces an economy where the capital output ratio is around 2.5. For a discussion of issues related to calibrating these parameters see, e.g., Cooley and Prescott (1995) or Imrohoroglu, Imrohoroglu and Joines (1999).

We now turn attention to the parameterization of the components of our model that take different values in the five different years we consider, i.e., 1975, 1980, 1985, 1990, and 1996. While presenting the data for all years, since the emphasis of the paper is on accounting for the change in the property crime rate evidenced between 1980 and 1996, much of what follows focuses on the changes that occurred between these two years.

For each year, the share of age- $j$  individuals in the population,  $\mu_j$ , is taken from the Bureau of the Census. Figure 2 documents the fact that between 1980 and 1996 the population in the U.S. has been aging. What is most striking is the large decline in the population share of the 20-28 year old cohorts in 1996 compared to 1980 and the large increase in the share of those in the 40-48 year old cohort over the same time period.

For each year, the share of type- $i$  individuals in the population,  $\gamma_i$ , is taken from the

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data, 1990).

Current Population Survey (CPS), where  $\gamma_1$  denotes the fraction of individuals with less than a high school degree,  $\gamma_2$  the fraction of individuals with a high school degree but no higher degree,  $\gamma_3$  the fraction of individuals with a college degree, and  $\gamma_4$  the fraction of individuals with more than a college degree. Table 1 reports the values we use in our analysis.<sup>16</sup>

**Table 1: Skill Distribution**

Year	1975	1980	1985	1990	1996
Less than high school	0.16	0.11	0.10	0.10	0.09
High school	0.61	0.64	0.64	0.64	0.61
College	0.16	0.17	0.19	0.18	0.23
Post graduate	0.07	0.08	0.07	0.07	0.07

Table 1 indicates that the fraction of the population with less than a high school education and with a high school education has declined between 1980 and 1996; while those with a college education have increased.

The age-earnings profiles,  $\varepsilon_j^i$ , are constructed from the CPS for each year by regressing the log of real weekly earnings on age, age-squared, and dummy variables for different human capital types (the omitted category being those with less than a high school degree). Table 2 presents the regression results.

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<sup>16</sup>These fractions were obtained for each year by separating individuals in the CPS who were between the ages of 25 and 35 into the relevant schooling groups. We believe this age group is most representative to capture changes in schooling at the five year frequency.

**Table 2: Earnings Regressions**

(Dep. Var.: log of real weekly earnings; standard errors in parentheses)					
Year	1975	1980	1985	1990	1996
constant	2.61 (0.027)	2.84 (0.026)	2.50 (0.029)	2.63 (0.026)	2.60 (0.030)
age	0.138 (0.002)	0.125 (0.002)	0.138 (0.002)	0.132 (0.002)	0.134 (0.002)
age <sup>2</sup>	-0.0015 (0.00002)	-0.0014 (0.00001)	-0.0015 (0.00002)	-0.0014 (0.00002)	-0.0015 (0.00002)
High school	0.382 (0.008)	0.371 (0.008)	0.395 (0.009)	0.389 (0.009)	0.386 (0.010)
College	0.693 (0.013)	0.671 (0.017)	0.786 (0.012)	0.810 (0.011)	0.781 (0.012)
Post graduate	0.819 (0.017)	0.808 (0.015)	0.950 (0.016)	0.953 (0.014)	1.08 (0.015)

The data show that earnings of individuals with less than a high school education have shown a relative decline in 1996 compared to 1980 while earnings of those with more than a college degree in 1996 have increased relative to their 1980 counterparts. This is evidence of a marked increase in earnings inequality between 1980 and 1996.

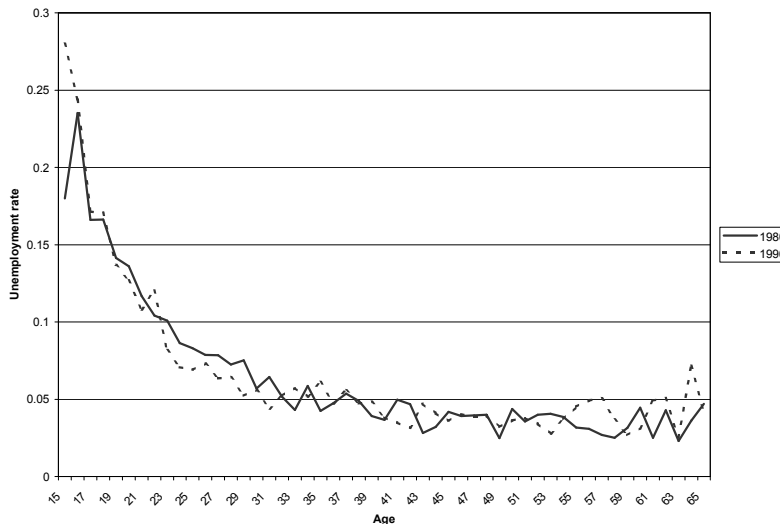
Using the estimated earnings profiles together with the skill and age distribution of the population, for each year we can summarize the properties of the distribution of real earnings that we use in our analysis. Table 3 reports the mean and standard deviation of real earnings after normalizing the data so that the average for 1980 equals 1.

**Table 3: Earnings Distribution**

Year	1975	1980	1985	1990	1996
Mean	0.995	1.000	0.997	1.040	1.095
Standard deviation	0.426	0.397	0.433	0.441	0.476

As we can see from this table, both the mean and the standard deviation of real earnings are higher in 1996 relative to 1980.

Figure 3: Unemployment by Age



Age-specific unemployment rates are obtained from the appropriate year of the CPS. Table 4 summarizes aggregate and youth unemployment rates for the five years we focus on.

**Table 4: Unemployment Rates**

Year	1975	1980	1985	1990	1996
Unemployment rate (15-65 yrs.)	9.4	6.9	7.7	5.5	6.0
Unemployment rate (15-19 yrs.)	20.1	17.1	18.9	15.2	17.8

Table 4 documents the fact that while aggregate unemployment is lower in 1996 than in 1980, the reverse is true for youth unemployment. Figure 3 shows the decomposition of unemployment by age in 1980 and 1996.

Given the age-specific unemployment rates, the transition probabilities of the employment opportunities state,  $\Pi_j$ , are computed so that the fraction of the time the employment opportunity is offered equals the employment rate of that age group. For example, if the unemployment rate of 16-year old individuals in the data is 20.2%, the transition probabilities for this age group are chosen so that the probability of unemployment will equal 0.202, independent of the availability of the opportunity the previous period. Thus, the transition



probabilities matrix for age-16 individuals would be given as

$$\mathbf{\Pi}_{16}(s, s') = \begin{bmatrix} 0.748 & 0.252 \\ 0.994 & 0.006 \end{bmatrix}$$

The average duration of unemployment is therefore  $1/(1 - 0.006) = 1.006$ .<sup>17</sup>

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. These are crimes typically motivated by the prospect of monetary gain.<sup>18</sup> When considering whether to engage in criminal activity, individuals in our model are assumed to know the probability of apprehension they face as well as the extent of punishment that would result after apprehension. The apprehension technology of the police is summarized by the clearance rate, which is the fraction of crimes cleared (solved) by arrest. The first row of Table 5 gives the clearance rate for property crime for various years, which represents our measure of the probability of apprehension,  $\pi_a$ .

**Table 5: Clearance Rates and Prison Terms**

Year	1975	1980	1985	1990	1996
Clearance rate	18.9	16.8	18.1	18.4	18.5
Expected prison time (months)	12.5	12.6	13.9	9.48	12.3

When apprehended, criminals face a prison term. In our analysis, the length of the prison term for each year is calibrated using data on expected prison time, measured by the average length of prison sentences multiplied by the fraction of offenders sentenced to prison, as

<sup>17</sup>The elements of the  $\prod_j^d$  matrix are obtained by solving the following equations for all ages:

$$\bar{e}_j \pi_j(e, u) + \bar{u}_j \pi_j(u, u) = \bar{u}_j \text{ and } (1 - \pi_j(u, u))^{-1} = \bar{d}_j$$

where  $\bar{e}_j$  and  $\bar{u}_j$  are the age-specific employment and unemployment rates and  $\bar{d}_j$  is the average duration of unemployment. In addition,  $\pi_j(e, e) = 1 - \pi_j(e, u)$  and  $\pi_j(u, e) = 1 - \pi_j(u, u)$ .

<sup>18</sup>The definition of property crime in this paper differs slightly from the one used by the FBI, which places robbery under the heading of violent crime rather than property crime and includes arson.

reported in Table 5.<sup>19</sup> As we can see from this table, while the probability of arrest increased substantially from 1980 to 1996, the length of the prison term for property offenses did not change much.

Before we present our findings, a few computational remarks are in order. In most of the simulations, the discrete set  $A$  for asset values is chosen so that maximum asset holdings are about fifteen times the annual income of an employed individual, and the lower bound on asset holdings is zero. When necessary, the size of the maximum assets and the size of the grid (typically 1001) was changed to make sure that they were never binding in the simulations.

In the model described in section 2 above, all age-15 individuals within each skill group are identical. This implies that either all of them engage in criminal activities or none of them does. This lumpiness is rather unpleasant (since small changes in the model parameters may induce big changes in the aggregate crime rate), and obviously counterfactual. To eliminate this problem, when we solve our model we endow agents in their first period of life with small levels of assets that are randomly drawn from a uniform distribution over the first ten asset levels (out of the 1001 possible asset levels). This small amount of additional heterogeneity at model-age 1 is sufficient to induce smoothness.

## 4. Findings

In this section we present our findings. We begin by describing the properties of our benchmark economy calibrated to 1980. We then compare the time series of property crime rates generated by our model to the data. Finally, we investigate the change in property crime

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<sup>19</sup>The figures reported in Table 5 are from the Sourcebook of Criminal Justice Statistics by the Bureau of Justice Statistics. Recall that a model period is one year. When the expected prison term is shorter than a year, we assume that an apprehended criminal goes to jail and consumes  $\bar{c}$  for a fraction of the year. After being released from jail, the apprehended criminal is unemployed for the remaining portion of the year and receives unemployment insurance benefits equal to 25% of his wage if he had been employed for that fraction of the year. When the expected prison term is longer than a year, we assume that an apprehended criminal goes to jail and consumes  $\bar{c}$  for the entire year when he is apprehended and also for a fraction of the following year. After being released from jail, he receives a stochastic employment opportunity and his income is scaled down to reflect the fact that there is only a portion of the year left.

rate evidenced between 1980 and 1996.

#### 4.1. Benchmark

We begin this section by presenting some of the properties of the benchmark economy calibrated to 1980.<sup>20</sup> In Table 6, we investigate the implications of our model with respect to the composition of the criminal population. First, note that our model predicts that about 79% of the people engaging in criminal activities are employed and only the remaining 21% are unemployed. This implies that approximately 5% (16%) of the employed (unemployed) population engages in criminal activities. This (perhaps surprising) implication of the model is consistent with the data. According to the Bureau of Justice Statistics, in 1979, 71% of all state prisoners were employed prior to their conviction.<sup>21</sup> Studies by Grogger (1998) and Witte and Tauchen (1994) that use other data sets provide further evidence in support of this finding.

**Table 6: 1980 Benchmark**

Fraction of criminals who are employed	78.6
Fraction of criminals who are unemployed	21.4
Fraction of criminals who are recidivists	40.0
Fraction of criminals 18 years of age or younger	76.1
Fraction of criminals with less than a high school degree	46.1

Next, we turn our attention to the composition of the criminal population by age and educational attainment. Our model predicts that about 76% of the people who commit property crimes are 18 years of age or younger. According to the Federal Bureau of Investigation, in 1980, 47.7% of all people arrested for property offenses were 18 years of age or younger. While the figure in the data is much lower than the one generated by the model, juvenile property offenders are often released without being formally arrested and charged of a crime.

<sup>20</sup>Notice that in addition to the (calibrated) crime rate that is equal to 5.6, average consumption and the capital output ratio generated by our model are equal to 0.83 and 2.76, respectively.

<sup>21</sup>This statistic is taken from the Profile of State Prison Inmates (NCJ-58257), August 1979. Unfortunately, this information is not available for criminals convicted for property offenses only.

Nevertheless, we believe the model may overstate the amount of juvenile delinquency and we explore this issue further in Section 5 below. Furthermore, the model predicted fraction of criminals without a high school diploma is equal to 46.1%. In 1979, 52.7% of the correctional population in state prisons did not have a high school diploma.<sup>22</sup> Hence, the model seems to be capable of reproducing certain dimensions of the socio-demographic composition of the criminal population fairly well.

Our model also has implications on the amount of recidivism present in the economy.<sup>23</sup> In our benchmark economy, 40% of all criminals had a prior conviction. This percentage is lower than the one in the data. According to the Bureau of Justice Statistics, in 1979, 61% of those admitted to state prisons were recidivists.<sup>24</sup> We address the issue of recidivism further in Section 5 below.

## 4.2. Time Series

We now turn our attention to the time series performance of our model. The experiments we perform, the results of which are reported in Table 7, can be described as follows. Take the calibrated model (which generates a crime rate equal to the one observed in 1980), and input data relative to unemployment rates, age-efficiency profiles, age distribution of the population, shares by human capital type, the ability of the police to capture criminals, and the length of the prison term for a different year. For 1975, 1985, 1990 and 1996, compute the steady-state equilibrium of the model and compare the crime rate generated by the model to the one in the data.<sup>25</sup>

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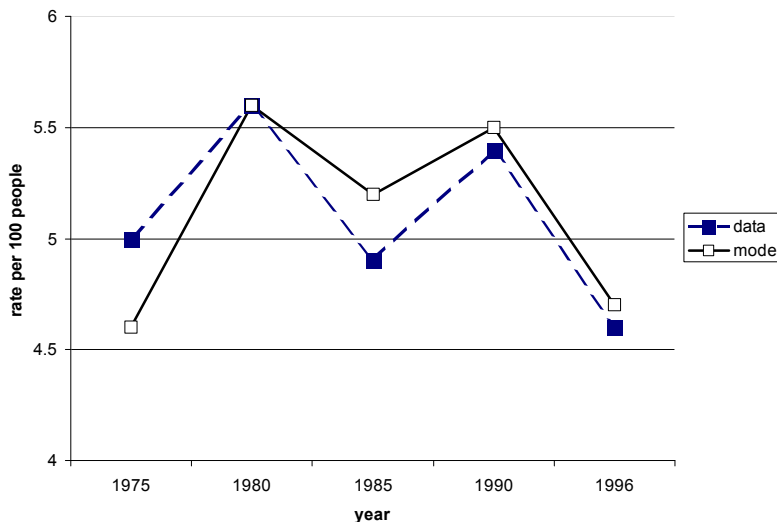
<sup>22</sup>This statistic is also taken from the Profile of State Prison Inmates (NCJ-58257), August 1979.

<sup>23</sup>When we solve our model we introduce an additional state variable that keeps track of individuals who are incarcerated. This allows us to quantify recidivism. This state variable was not introduced in the description of the model contained in Section 2 above to simplify notation.

<sup>24</sup>This statistic is taken from the Bureau of Justice Statistics Special Report “Examining Recidivism” (NCJ-96501), February 1985.

<sup>25</sup>Notice that the capital output ratio generated by the model is equal to 2.79 for 1975, 2.76 for 1980, 2.72 for 1985, 2.74 for 1990, and 2.77 for 1996.

Figure 4: Crime Rates: Data and Model



**Table 7: Time Series**

Year	Crime Rate	
	Model	Data
1975	4.6	5.0
<b>1980</b>	<b>5.6</b>	<b>5.6</b>
1985	5.2	4.9
1990	5.5	5.4
1996	4.7	4.6

Table 7 clearly indicates that the factors identified in our analysis as the main determinants of aggregate property crime rates can account for the behavior of the time series of property crime rates between 1975 and 1996. In particular, not only can our analysis qualitatively account for the increase in property crime rates in the 1970s, the drop observed in the first half of the 1980s, the subsequent rise in the later part of the decade and the sharp decline in the 1990s, but it can also reproduce the quantitative changes in the time series. The performance of the model is illustrated in Figure 4 where we plot the model generated time series of property crime rates against the data.

Next, we turn our attention to the decomposition of the changes and the assessment

of the relative contribution of each specific factor to the overall decline in property crime between 1980 and 1996.

### 4.3. 1980 versus 1996

An important result reported in Table 7 is that the model is capable of reproducing the drop in crime observed between 1980 and 1996. In particular, the table shows that the combined effect of the changes in unemployment rates, age-efficiency profiles, age distribution of the population, shares by human capital type, and the ability of the police to capture criminals that have occurred between 1980 and 1996 can account for about 90% of the observed decline in property crime. Our next goal is to decompose this effect and evaluate the relative contribution of each factor to the overall decline in crime.

In Table 8, we examine the contribution of each component by adding them to the 1980 benchmark one at a time. The first column presents the crime rate while the second column normalizes the crime rate for 1980 to equal 100 and presents all the other crime rates in terms of the 1980 benchmark. The first row repeats the information for 1980 and the remaining rows are ordered to start with the components that result in the largest decrease in the crime rate.

**Table 8: Decomposition 1980-1996**

<b>Component</b>	<b>Crime Rate</b>	<b>Percent</b>
1980 Benchmark	5.6	100
1996 Police	3.2	57
1996 Average income	4.5	80
1996 Age distribution	5.0	89
1996 Human capital shares	5.5	98
1996 Unemployment rate	5.6	100
1996 Income inequality	8.9	159
1996 All	4.7	84

The three most important components of the decrease in the crime rate are the higher apprehension probability, the richer economy, and the aging of the population. For example, the second row shows the crime rate in the case where the only change that was made to

the 1980 benchmark was to use the apprehension probability for 1996. This change causes a 43% decrease in the crime rate, by far the largest drop in the crime rate.<sup>26</sup> The third row shows that the impact of the change in average income alone would have amounted to a 20% decrease in the crime rate. Notice that a richer economy not only induces an increase in the returns from market activities but also an increase in the returns from illegitimate activities. However, an increase in market income also induces an increase in the opportunity cost of being apprehended, since the conditions for a criminal who is incarcerated are unchanged. The overall effect results in a decrease in the crime rate. The fourth row shows the impact of demographics on the crime rate. That is, if the only change that took place in 1996 were to be the change in demographics, the crime rate would have decreased by 11%. This effect is due to the large decline in the fraction of youth in the population in 1996 relative to 1980.<sup>27</sup>

In addition to a higher mean, the income profiles of 1996 exhibit more income inequality as opposed to the profiles in 1980. According to our results, if we were to only change the income profiles the crime rate would have increased by 59% from 1980 to 1996, as shown in the row before last. This result is due to the fact that when income inequality increases relatively more people find it profitable to engage in criminal activities.<sup>28</sup> The decrease in the unemployment rate on the other hand does not seem to have any impact on the crime rate. This finding is mostly due to the following two factors. First, even though the overall unemployment rate is lower in 1996 as opposed to 1980, youth unemployment rates were actually higher in 1996. Second, as illustrated in Table 6 above, the overwhelming majority of criminals in our economy are employed.

These results indicate that the two most important determinants of the crime rate are the apprehension probability and income inequality. The higher apprehension probability lowers the crime rate by 43% and the higher income inequality increases the crime rate by

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<sup>26</sup>Several econometric studies also find evidence of a strong deterrent effect of police activities on crime (see, e.g., Tauchen, Witte and Griesinger (1994) and Witte (1980)).

<sup>27</sup>Note that this finding is somehow consistent with the results obtained by Donohue and Levitt (2000), who claim that demographic effects account for about 50% of the overall drop in crime in the 1990s.

<sup>28</sup>For a more detailed discussion of the relation between inequality and crime see, e.g., Imrohorglu, Merlo and Rupert (2000) and the references therein.

59%. The relative magnitude of these opposing effects plays a very important role in the resulting crime rate.

To explore this issue further and to evaluate the extent to which different factors interact with each other, in Table 9 we report the results of experiments where we combine some of the changes. In particular, in the second row we combine the growth in average income with the change in unemployment (we refer to this experiment as 1996 Economy). In the next row we report the effect of simultaneously changing the age and skill distribution of the population using 1996 data (1996 Demographics). In the fourth row we combine the two largest opposing effects by simultaneously changing the apprehension probability and the earnings profiles (holding the average constant). As before, the experiments are ordered according to their effect on crime.

**Table 9: Decomposition 1980-1996**

<b>Component</b>	<b>Crime Rate</b>	<b>Percent</b>
1980 Benchmark	5.6	100
1996 Economy	4.5	80
1996 Demographics	4.6	82
1996 Largest opposing effects	6.6	118
1996 All	4.7	84

Several observations are noteworthy. First, there is a substantial amount of interaction between individual components and the effects are highly non-linear. In other words, due to the non-linear nature of the model economy the contribution of each factor depends on the other existing factors in the economy. Second, the negative effect of increased inequality dominates the positive effect of the increased apprehension probability.



**Table 10: Reverse Decomposition 1980-1996**

<b>Component</b>	<b>Crime Rate</b>	<b>Percent</b>
1996 Benchmark	4.7	100
1980 Police	6.9	147
1980 Average income	6.0	128
1980 Age distribution	5.7	121
1980 Human capital shares	5.1	109
1980 Unemployment rate	4.7	100
1980 Income inequality	2.5	53
1980 All	5.6	119

To better assess the extent of the non-linearity of the individual effects, in Table 10 we perform a different set of experiments. Rather than starting from the 1980 benchmark economy and evaluating the effects of introducing 1996 data, we do the reverse. We start from the 1996 model economy and we evaluate the effect of replacing each feature of this economy with its 1980 counterpart one at the time.

As we can see from this table, the rank order of the effects is the same as the one in Table 8. Their magnitude is however different. One can imagine this table attempting to answer the following question: If there was one factor that can be chosen to be eliminated from the economy in 1996 what would it be? The answer is obvious. By holding inequality constant at its 1980 level we could have observed a 55% drop in property crime as opposed to a 17% drop. Of course these are counterfactual exercises which completely ignore how such changes could have been implemented.

## **5. Extensions: A Model with Stigma**

As we pointed out in the previous section, a possible limitation of our model is that it may overstate the amount of juvenile delinquency and understate the amount of recidivism present in the economy. In this section, we ask whether a simple extension of our framework that incorporates the “stigma” effect of incarceration can improve the model performance along these dimensions.

In our model described above, if agents choose to commit a crime they may be apprehended and punished. The extent of punishment amounts to a prison term. However, in reality, convicted criminals may also be “stigmatized”. That is, after a conviction individuals may face lower wages than if they had not been convicted. This additional component of punishment is not legislated but occurs as a societal outcome that stigmatizes the ex-prisoner. This stigma may force the individual onto an earnings path that is lower than their pre-conviction path.

Several empirical studies have analyzed the effect of this type of stigma. Waldfogel (1994) shows the decline in earnings to be roughly 10% and quite persistent, taking eight years to get halfway back to pre-conviction levels. Allgood, Mustard and Warren (1999) find a decline of 12% and that effect did not disappear for the six years following release. Grogger (1995) and Kling (1999), on the other hand, find only a small decline that is quite temporary. Grogger (1995) finds a drop of only 4% lasting just six quarters. Kling (1999) finds an even smaller effect when looking at street criminals, but a larger effect when considering white-collar crime.

We introduce stigma in our model by assuming that the labor income of an agent who is given an opportunity to work is equal to  $(1 - dx)wh\varepsilon_j^i$ , where  $x$  denotes the loss in earnings induced by stigma and  $d \in D = \{0, 1\}$  denotes the “stigma” state, where  $d = 1$  indicates an agent who at some point in his life was convicted of a crime, and  $d = 0$  indicates an agent who either never committed a crime or who was never apprehended. Notice that, to simplify the analysis, we assume that the effect of stigma is permanent (i.e., apprehended criminals are “stigmatized” for the rest of their lives). If an individual is unemployed, he receives unemployment insurance benefits equal to a fraction  $\theta$  of the employed wage,  $(1 - dx)\theta wh\varepsilon_j^i$ . Hence, the disposable income from legitimate activities of a type- $i$  individual of age  $j$  is given by

$$y_j^i = \begin{cases} (1 - \tau)(1 - dx)wh\varepsilon_j^i, & \text{if } s = e \\ (1 - dx)\theta wh\varepsilon_j^i, & \text{if } s = u. \end{cases}$$

Thus, stigma is introduced as a loss in income from legitimate activities if an agent has ever been incarcerated. Income from illegitimate activities remains unchanged. The dynamic programming problem is also modified to reflect the difference between an individual who is

stigmatized and an individual who has never been incarcerated. In particular, the dynamic programming problem faced by an individual of a given skill-type  $i$  who has never been incarcerated and who may or may not have received an employment opportunity can be written as:

$$V^i(a, s, d = 0) = \max \left\{ \begin{array}{l} (1 - \pi_v) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + y^i + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 0) \right\} \\ + \pi_v \max_{a'} \left\{ U((1+r)a^i - a^{i'} + (1-\alpha)y^i + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 0) \right\}, \\ (1 - \pi_v)(1 - \pi_a) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + y^i + \alpha\bar{y} + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 0) \right\} \\ + \pi_v(1 - \pi_a) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + (1-\alpha)y^i + \alpha\bar{y} + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 0) \right\} \\ + \pi_a(U(\bar{c}) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 1)) \end{array} \right\}$$

where  $i = 1, \dots, I$ ,  $y^i$  is equal to  $(1 - \tau)wh\varepsilon^i$  for  $s = e$  and  $\theta wh\varepsilon^i$  for  $s = u$ , and the maximization problem is subject to (3) and (4).

Similarly, the problem faced by an individual of a given skill-type  $i$  who has a prior conviction and who may or may not have received an employment opportunity can be written as:

$$V^i(a, s, d = 1) = \max \left\{ \begin{array}{l} (1 - \pi_v) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + y^i + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 1) \right\} \\ + \pi_v \max_{a'} \left\{ U((1+r)a^i - a^{i'} + (1-\alpha)y^i + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 1) \right\}, \\ (1 - \pi_v)(1 - \pi_a) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + y^i + \alpha\bar{y} + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 1) \right\} \\ + \pi_v(1 - \pi_a) \max_{a'} \left\{ U((1+r)a^i - a^{i'} + (1-\alpha)y^i + \alpha\bar{y} + T) + \beta \sum_{s'} \pi(s, s') V^i(a', s', 1) \right\} \\ + \pi_a(U(\bar{c}) + \beta \sum_{s'} \pi_j(s, s') V^i(a', s', 1)) \end{array} \right\}$$

We calibrate this version of our model to 1980 using the data described above and setting the stigma parameter  $x$  equal to 0.02. A permanent 2% decrease in post-conviction wages due to stigma is consistent with the estimates reported in the empirical studies we mentioned

above. Notice that to match the aggregate crime rate in 1980 we now have to increase the value of  $\bar{c}$  from 0.052 to 0.082. This adjustment is necessary to counterbalance the presence of stigma which increases the extent of punishment and hence decreases the amount of crime in the economy. Table 11 contains our main results.

**Table 11: 1980 Benchmark with Stigma**

Fraction of criminals who are employed	83.6
Fraction of criminals who are unemployed	16.4
Fraction of criminals who are recidivists	75.0
Fraction of criminals 18 years of age or younger	59.9
Fraction of criminals with less than a high school degree	53.8

Notice that compared to our benchmark economy without stigma (see Table 6), the presence of stigma induces a lower amount of juvenile delinquency (59.9 versus 76.1) and a higher amount of recidivism (75.0 versus 40.0) in the economy. These two effects are obviously related. Holding the aggregate crime rate constant, in an economy with relatively more recidivism relatively more crimes are committed by older people (the recidivists). The intuition for why stigma is associated with higher recidivism and lower juvenile delinquency is rather subtle and interesting. By essentially increasing the “severity” of punishment, stigma discourages the involvement in criminal activities. The more persistent the effect of stigma, the more severe is the relative increase in punishment for a young individual relative to an older individual. Hence, *ceteris paribus*, the presence of stigma discourages juvenile delinquency relatively more. In addition, stigma has a direct effect on recidivism. By reducing post-conviction wages, stigma reduces the opportunity cost of engaging in criminal activities for individuals with a criminal record. This effect generates recidivism.

Recall that in 1980, 47.7% of all people arrested for property offenses were 18 years of age or younger. Moreover, the recidivism rate among state prisoners in 1979 was equal to 61%. Thus, introducing stigma into the analysis improves the ability of the model to match salient features of the data.<sup>29</sup> When confronted with the time series evidence, however, the

<sup>29</sup>Notice that the model predictions with respect to the fraction of criminals who are employed or unemployed and the fraction of criminals without a high school degree are fairly similar with or without stigma.

performance of the model with stigma is less satisfactory. In particular, while the model can still account for the qualitative behavior of the time series of property crime rates evidenced between 1975 and 1990, it fails to reproduce the drop in crime in 1996. Clearly, it is possible that the amount of stigma in the U. S. economy has changed over time and our analysis is not well equipped to capture these subtleties.

## 6. Conclusion

The results suggest that our analysis has identified some key factors to help further our understanding of the complex phenomenon of crime. At the same time, however, they clearly display the limitations of our current analysis and help us identify future avenues of research. In particular, a richer model is needed to confront the micro evidence on participation rates in criminal activities by different age and population groups identified by a variety of demographic characteristics. Preliminary attempts to incorporate learning and group-specific, history-dependent apprehension probabilities in our model produced encouraging results. For example, incorporating into the model learning-by-doing in criminal activities (i.e., the more an individual engages in criminal activities the higher his returns from these activities), not only produces results that are similar to the ones induced by stigma (i.e., lower juvenile delinquency and higher recidivism than in the baseline model), but can also account for heterogeneity in participation rates by population groups. The increased flexibility, however, comes with the difficult challenge of collecting the necessary data to calibrate the additional components of the model.

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