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WHAT ACCOUNTS FOR THE DECLINE IN CRIME?*

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In this article we analyze recent trends in aggregate property crime rates in the United States. We propose a dynamic equilibrium model that 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.

1. INTRODUCTION

An important phenomenon of the last 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. The most noticeable decline over this time has been observed for property crimes, which account for over 90 percent of all crimes. The property crime rate per 100 inhabitants in the United States peaked at 5.60 in 1980 and declined to 4.65 in 1996.[2]

What accounts for this decline? Both the popular press and the academic literature have been searching for answers to this important question. 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. The fraction of youths in the population has being declining

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[2] 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.

in the 1990s. For instance, the fraction of people between the ages of 15 and 25 was equal to 20.5 percent in 1980 and went down to 15.1 percent in 1996.

Another key factor is related to law enforcement. Expenditures on police protection have increased from 0.6 percent of GDP in 1980 to 0.7 percent 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—in 1980 the clearance rate for property crimes was equal to 16.8, increasing to 18.5 in 1996. At the same time, the "severity" of punishment has remained pretty much constant—the expected punishment for property crimes (measured by the average length of prison sentences multiplied by the fraction of offenders sentenced to prison) was equal to 12.5 and 12.3 months in 1980 and 1996, respectively.[3]

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. Average real earnings increased by approximately 10 percent 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. On the other hand, youth unemployment (for people between the ages of 15 and 19) has increased from 17.1 in 1980 to 17.8 in 1996 and, by virtually any measure, the distribution of real earnings has become substantially more unequal over the past 20 years.[4]

The goal of this article 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 these types of criminal activities.

To guide our quantitative investigation of the major determinants of observed patterns 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).[5] Our model shares many of the features of existing models and embeds

[3] See, e.g., 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 (Vol. 88) of the *Journal of Criminal Law and Criminology*. Donohue and Levitt (2001) argue that the legalization of abortion is responsible for a significant part of the decline in crime by eliminating unwanted children who supposedly are the population group most at risk to engage in criminal activities.

[4] A more detailed description of the data is contained in Section 3.

[5] See, e.g., Ehrlich (1996) for a survey.

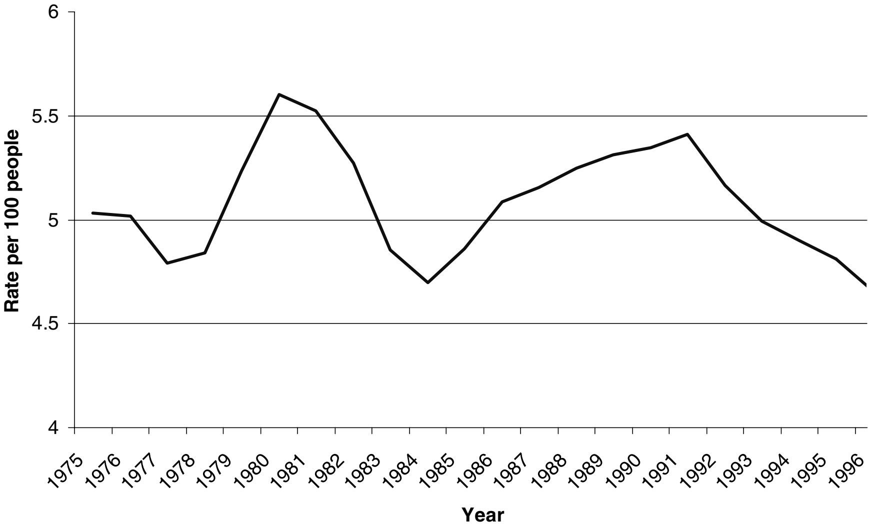

FIGURE 1

PROPERTY CRIME RATE

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. The equilibrium aspect of our model allows us to investigate the response of the aggregate crime rate to a variety of factors.[6]

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.

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

[6] Lochner (2004) also studies a dynamic model of criminal behavior that incorporates individual decisions to invest in human capital but abstracts from equilibrium considerations. Other general equilibrium models of crime include Burdett et al. (2003, 2004), Ehrlich (1981), Furlong (1987), Huang et al. (2004), and Imrohoroglu et al. (2000).

crime peaked in 1980, fell sharply during the first half of the 1980s, rose again during the second half of the 1980s, 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. This analysis also points out that income inequality and the probability and consequences of apprehension played a very important role in determining the time series behavior of the property crime rate in the United States between 1975 and 1996.

The remainder of the article is organized as follows: Section 2 describes the model and Section 3 explains the calibration of the model economy for different years. Section 4 contains the results. Section 5 examines an extension of the model to incorporate stigma. Section 6 concludes.

2. THE MODEL

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

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

$$E\sum_{j=1}^{J}\beta^{j-1}U\left(c_j^i\right) \tag{1}$$

where β denotes the subjective discount factor, and c_j^i denotes consumption of a type-i individual of age j. The share of age-j individuals in the population is given by the fraction μ_j, $j = 1, \ldots, J$, $\sum_{j=1}^{J}\mu_j = 1$, where J is the maximum possible lifetime. The share of type-i individuals in the population is given by the fraction γ_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 ε_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 θ of the employed wage of a type-i worker of age j, $\theta wh\varepsilon_j^i$. The main role of government in this economy is to administer the unemployment insurance program.[7] Given unemployment insurance, the government chooses the tax rate τ so that its budget is balanced. Hence, the disposable income from legitimate activities of a type-i individual of age j is given by

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

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 $\pi_j(l,k) = \Pr(s_{j+1} = k \mid s_j = l)$, $j = 1, \ldots, J-1$. We allow for the unemployment rate to vary with age.

In this economy, criminal activities amount to theft. Each individual (including criminals) faces an equal probability π_v of being the victim of a crime, where π_v is equal to the (endogenous) fraction of criminals in the population. If victimized, an individual loses a fraction α of his disposable income from legitimate activities. For computational simplicity, we assume that criminals do not have the ability to target their victims based on their income and each criminal steals a fraction α of average disposable income from legitimate activities, $\bar{y}$. Criminals face a probability π_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).[8]

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

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

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

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

[7] The government also runs the jail system and administers punishment to apprehended criminals, as explained below. In addition, the government may use tax revenue to finance a technology that apprehends or deters criminals. In this article, we abstract from this using an exogenous probability of apprehension. For a model where expenditures on police are determined endogenously see Imrohoroglu et al. (2000).

[8] 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.

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. This specification does not restrict an individual to specialize, i.e., an individual may choose to work in the legitimate sector and also engage in crime. Additionally, individuals engaging in crime might also be victimized.

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

$$a_j^i \geq 0, \quad j = 1, \ldots, J, i = 1, \ldots, I \tag{5}$$

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:

$$a_J^i = 0, \quad i = 1, \ldots, I \tag{6}$$

2.3. *Technology.* The production technology of the economy is given by a constant returns to scale Cobb–Douglas function

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

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 capital stock is assumed to depreciate at a rate δ.

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

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

and the real wage

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

2.4. *Stationary Equilibrium.* The concept of equilibrium we use in this article 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, $\Omega^i_j(a, s) \in R^2_+ \times \{0, 1\}$, as the set of all three-tuples (c^i_j, a^i_j, ℓ^i_j) such that for $j = 1, \ldots, J$, and $i = 1, \ldots, I$, Equations (3) and (4) are satisfied, $c^i_j \geq 0$, $a^i_j \geq 0$, and a^i_o 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 $V^i_j(a, s)$ 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). $V^i_j(a, s)$ is defined as the solution to the dynamic program.

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

$$V^i(a, s) = \max\left\{V^i_{nc}(a, s), V^i_c(a, s)\right\} \tag{10}$$

subject to the budget constraints in Equations (3) and (4), where

$$\begin{aligned} V^i_{nc}(a, s) = (1 - \pi_v) \max_{a'} &\left\{U((1 + r)a^i - a^{i\prime} + y^i + T) + \beta \sum_{s'} \pi(s, s')V^i(a', s')\right\} \\ + \pi_v \max_{a'} &\left\{U((1 + r)a^i - a^{i\prime} + (1 - \alpha)y^i + T) + \beta \sum_{s'} \pi(s, s')V^i(a', s')\right\} \end{aligned}$$

is the value of not committing a crime in the current period, and

$$\begin{aligned} V^i_c(a, s) = {} & (1 - \pi_v)(1 - \pi_a) \max_{a'} \left\{U((1 + r)a^i - a^{i\prime} + y^i + \alpha\bar{y} + T) \right. \\ & \left. + \beta \sum_{s'} \pi(s, s')V^i(a', s')\right\} \\ & + \pi_v(1 - \pi_a) \max_{a'} \left\{U((1 + r)a^i - a^{i\prime} + (1 - \alpha)y^i + \alpha\bar{y} + T) \right. \\ & \left. + \beta \sum_{s'} \pi(s, s')V^i(a', s')\right\} \\ & + \pi_a\left\{U(\bar{c}) + \beta \sum_{s'} \pi(s, s')V^i(a', s')\right\} \end{aligned}$$

is the value of committing a crime in the current period, where $i = 1, \ldots, I$, and y^i is equal to $(1 - \tau)wh\varepsilon^i$ for $s = e$ and $\theta wh\varepsilon^i$ for $s = u$.

DEFINITION. A stationary equilibrium for a given set of policy arrangements $\{\tau, \theta\}$ and an apprehension probability π_a is a collection of value functions $V^i_j(a, s)$, individual policy rules $c^i_j : A \times S \to R_+$, $a^i_j : A \times S \to A$, $\ell^i_j : A \times S \to \{0, 1\}$, age and type dependent, time-invariant measures of agents $\lambda^i_j(a, s)$ for each age $j = 1, \ldots, J$ and each type $i = 1, \ldots, I$, 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.

(ii) The aggregate crime rate is $\chi = \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s)\ell_j^i(a,s)$, and the victimization probability is $\pi_v = \chi$.

(iii) Average disposable income from legitimate activities is given by $\bar{y} = \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) y_j^i(a,s)$.

(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) The commodity market clears

$$\sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s)\big[c_j^i(a,s) + a_j^i(a,s)\big] = f(K,N) + (1-\delta) \sum_{i,j,a,s} \gamma_i \mu_j \lambda_j^i(a,s) a_{j-1}^i \tag{11}$$

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

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

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

where $\Omega_a \equiv \{a : a' = a_j^i(a,s)\}$, and the initial measures of agents at birth, λ_0^i, $i = 1, \ldots, I$, are taken as given.

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

$$\tau = \frac{\sum_{i,j,a} \gamma_i \mu_j \lambda_j^i(a, s = u)\theta w h \varepsilon_j^i}{\sum_{i,j,a} \gamma_i \mu_j \lambda_j^i(a, s = e) w h \varepsilon_j^i} \tag{12}$$

(ix) 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:

$$T = \frac{\pi_a\big[\sum_{i,j,a,s} \gamma_i \mu_j \ell_j^i(a,s)\lambda_j^i(a,s)\big(y_j^i(a,s) + \alpha\bar{y}\big) - \bar{c}\chi\big]}{1 - \pi_a\chi} \tag{13}$$

3. PARAMETER CHOICE AND DATA

As mentioned above, the article 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 article is to first benchmark the model to exactly match the crime rate in 1980. 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 (Π_js), age-efficiency profiles (ε_j^is), age distribution of the population (μ_js), shares by human capital type (γ_j's), the length of the prison term, and the ability of the police to capture criminals (π_a), are set to the values 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 1 year, which dictates setting the discount factor β equal to 0.989. Individuals are assumed to be born at age 15 and live $J = 51$ years, to the age of 65. Individuals also differ with respect to 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.

On average, time series evidence admits working hours to be about one-third of discretionary time. Given that the model has age-specific efficiency profiles, as well as age-specific shares of the population, if an individual is employed, he spends a fraction $h = 0.45$ of his time working, leading to an average labor input of one-third. In the event that an individual becomes unemployed he receives unemployment insurance with a replacement rate θ equal to 0.83. Unemployment duration in the model is 1 year (one period), whereas in the United States the replacement ratio is 0.25 and duration is about 12 weeks, which means individuals would receive 83 percent of their income if they were to be unemployed for 12 weeks and employed for the rest of the year.

The parameter α 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 et al., 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).

With respect to the production side of the economy, the following parameter values were chosen: $\eta = 0.64$ and $\delta = 0.08$. This parameterization is fairly standard and $B = 1.295$ was chosen to produce an economy where the capital output ratio

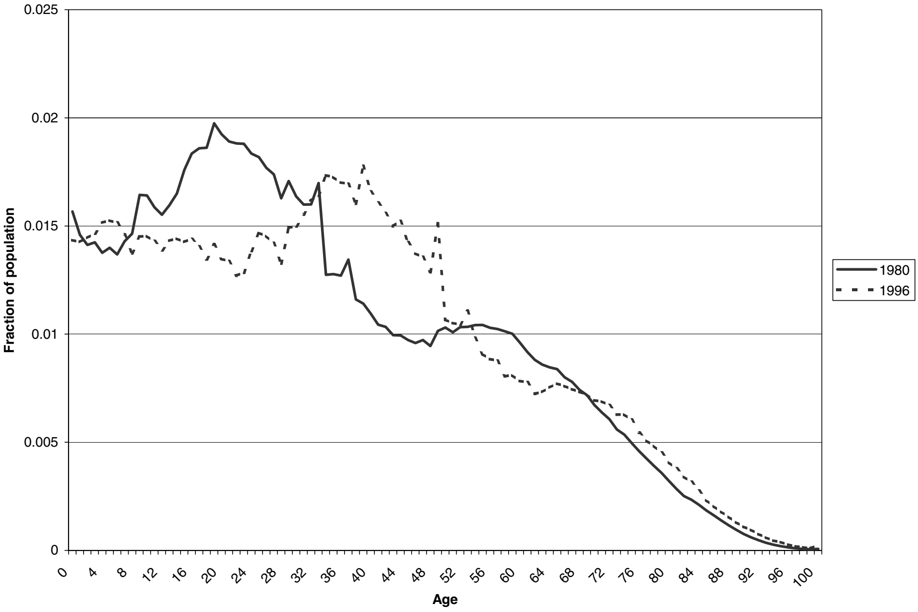

FIGURE 2

AGE DISTRIBUTION

is around 2.5. For a discussion of issues related to calibrating these parameters see, e.g., Cooley and Prescott (1995) or Imrohoroglu et al. (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 article 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.

In our analysis, we treat the age distribution and the distribution of human capital types in the population as exogenous. For each year, the share of age-j individuals in the population, μ_j, is taken from the Bureau of the Census (P25 917). Figure 2 documents the fact that between 1980 and 1996 the population in the United States has been aging. What is most striking is the large decline in the population share of the 20 to 28-year-old cohorts in 1996 compared to 1980 and the large increase in the share of those in the 40 to 48-year-old cohort over the same time period.[9]

For each year, the share of type-i individuals in the population, γ_i, is taken from the Current Population Survey (CPS), where γ_1 denotes the fraction of individuals with less than a high school degree, γ_2 the fraction of individuals with a high

[9] Note that we do not model demographic transitions as an endogenous outcome resulting from changes in survival probabilities. Instead we take the observed age distribution in each of the 5 years we consider as parametric.

TABLE 1
SKILL DISTRIBUTION

Year	1975	1980	1985	1990	1996
Less than high school	0.16	0.11	0.10	0.11	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 2
EARNINGS REGRESSIONS

Year	1975	1980	1985	1990	1996
constant	2.61	2.84	2.50	2.63	2.60
	(0.027)	(0.026)	(0.029)	(0.026)	(0.030)
age	0.138	0.125	0.138	0.132	0.134
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
age^2	−0.0015	−0.0014	−0.0015	−0.0014	−0.0015
	(0.00002)	(0.00001)	(0.00002)	(0.00002)	(0.00002)
High school	0.382	0.371	0.395	0.389	0.386
	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)
College	0.693	0.671	0.786	0.810	0.781
	(0.013)	(0.017)	(0.012)	(0.011)	(0.012)
Post graduate	0.819	0.808	0.950	0.953	1.08
	(0.017)	(0.015)	(0.016)	(0.014)	(0.015)

NOTE: Dependent variables: log of real weekly earnings; standard errors in parentheses.

school degree but no higher degree, γ_3 the fraction of individuals with a college degree, and γ_4 the fraction of individuals with more than a college degree. Table 1 reports the values we use in our analysis.[10] 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; whereas those with a college education have increased.

The age-earnings profiles, ε_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. The data show that earnings of individuals with less than a high school education have shown a relative decline in 1996 compared to 1980, whereas 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.

[10] 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 5-year frequency.

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

TABLE 4

UNEMPLOYMENT RATES

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

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

Age-specific unemployment rates are obtained from the appropriate year of the CPS. Table 4 summarizes aggregate and youth unemployment rates for the 5 years we focus on. Table 4 documents the fact that whereas 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, Π_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 percent, 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

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

The average duration of unemployment is, therefore, $1/(1 - 0.006) = 1.006$.[11]

[11] The elements of the $\prod_j^d$ matrix are obtained by solving the following equations for all ages:

$$\overline{e_j}\pi_j(e, u) + \overline{u_j}\pi_j(u, u) = \overline{u_j} \text{ and } (1 - \pi_j(u, u))^{-1} = \overline{d_j}$$

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

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

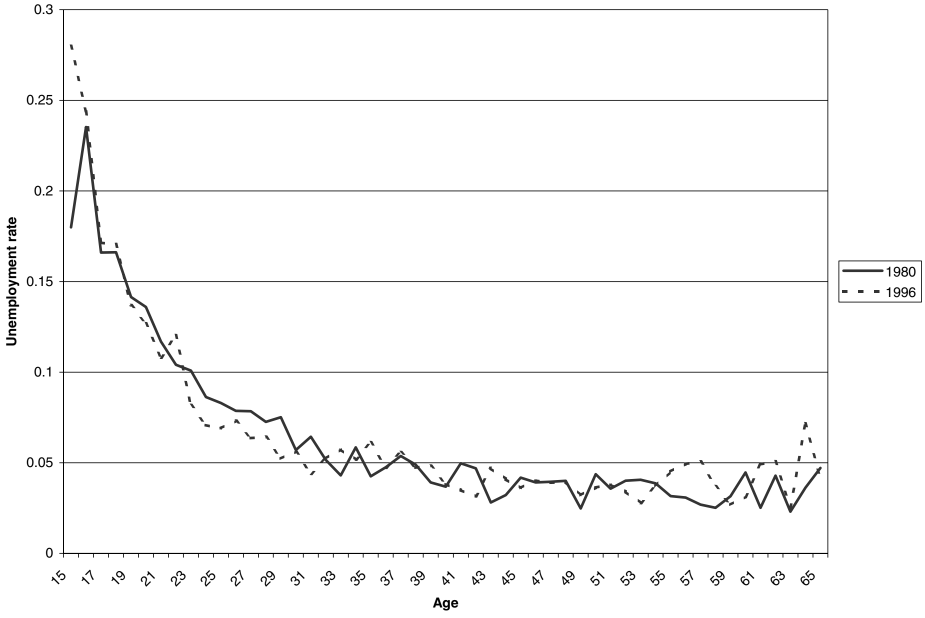

FIGURE 3

UNEMPLOYMENT BY AGE

The types of crimes considered in this article 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. 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 by arrest. Clearance is the term used by the FBI and the reporting agencies and simply means that the police have obtained enough evidence to arrest a person for the particular offense. Note this does not imply that the arrested individual is necessarily guilty of the crime. 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, π_a.

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 reported in Table 5.[12] As we can see from this table, the probability of arrest increased substantially from 1980 to 1985 and then remained flat. The length of the prison term for property offenses increased in 1985, declined in 1990, and returned back to approximately 12 months in 1996.

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 15 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 do. 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 10 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

We begin this section by describing the properties of our benchmark economy calibrated to 1980 and by investigating the change in the property crime rate between 1980 and 1996. We then compare the time series of property crime rates generated by our model to the data and examine the main determinants of the changes in the crime rate over the past quarter century.

4.1. *Benchmark.* In Table 6, we present some of the properties of the benchmark economy calibrated to deliver a crime rate of 5.6 percent for 1980. In particular, 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 percent of the people engaging in criminal activities are employed and only the remaining

[12] 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 1 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 percent 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.

TABLE 6
1980 BENCHMARK

Crime rate	5.6
Percent of criminals who are employed	78.8
Percent of criminals who are unemployed	21.2
Percent of criminals who are recidivists	40.0
Percent of criminals 18 years of age or younger	76.1
Percent of criminals with less than a high school degree	46.1

21 percent are unemployed. This implies that approximately 5 percent (16 percent) 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 percent of all state prisoners were employed prior to their conviction.[13] Studies by Grogger (1998) and Witte and Tauchen (1994) that use other data sets provide further evidence in support of this finding.

Next, we turn our attention to the composition of the criminal population by age and educational attainment. Our model predicts that about 76 percent 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 percent of all people arrested for property offenses were 18 years of age or younger. Although 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. 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 percent. In 1979, 52.7 percent of the correctional population in state prisons did not have a high school diploma.[14] 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 (however, for notational simplicity the state variable used to identify previous arrests was not included in the description of the model). In our benchmark economy, 40 percent 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 percent of those admitted to state prisons were recidivists.[15] We address the issue of recidivism further in Section 5.

4.2. *1980 versus 1996.* We now turn our attention to investigating whether the model is capable of reproducing the drop in crime observed between 1980 and 1996. We take the calibrated model (which generates a crime rate equal to the one observed in 1980), replace the 1980 data with data relative to unemployment rates,

[13] 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.

[14] This statistic is also taken from the Profile of State Prison Inmates (NCJ-58257), August 1979.

[15] Bureau of Justice Statistics Special Report "Examining Recidivism" (NCJ-96501), February 1985.

TABLE 7
DECOMPOSITION 1980–1996

Component	Crime Rate	Percentage
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

age-efficiency profiles, age distribution of the population, shares by human capital type, and the ability of the police to capture criminals for 1996, and compute the new steady-state equilibrium. Indeed, the crime rate generated by the model for the 1996 calibration is equal to 4.7 percent. The crime rate in the data for 1996 was 4.6 percent. Our next goal is to decompose this effect and evaluate the relative contribution of each factor to the overall decline in crime.

In Table 7, we examine the contribution of each component separately, i.e., each row shows the crime rate that would occur if it were the only change from the benchmark. The first column presents the crime rate, whereas 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.

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 percent decrease in the crime rate, by far the largest drop in the crime rate. The third row shows that the impact of the change in average income alone would have amounted to a 20 percent 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 the age distribution, the crime rate would have decreased by 11 percent. This effect is due to the large decline in the fraction of youth in the population in 1996 relative to 1980.

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 dispersion of the income profiles the crime rate would have increased by 59 percent from 1980 to 1996, as shown in the row before last. This

TABLE 8
DECOMPOSITION 1980–1996

Component	Crime Rate	Percentage
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

result is due to the fact that when income inequality increases, relatively more people find it profitable to engage in criminal activities. 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 percent and the higher income inequality increases the crime rate by 59 percent. 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 8 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.

Several observations are noteworthy. First, there is a substantial amount of interaction between individual components and the effects are highly nonlinear. In other words, due to the nonlinear 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.

To better assess the extent of the nonlinearity of the individual effects, in Table 9 we perform a different set of experiments. Instead of 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 Table 9, the rank order of the effects is the same as the one in Table 7. Their magnitude is, however, different. One can imagine this table

TABLE 9
REVERSE DECOMPOSITION 1980–1996

Component	Crime Rate	Percentage
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

TABLE 10
TIME SERIES

Year	Crime Rate Model	Crime Rate Data
1975	4.6	5.0
1980	**5.6**	**5.6**
1985	5.3	4.9
1990	5.5	5.4
1996	4.7	4.6

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 percent drop in property crime as opposed to a 17 percent drop. Of course, these are counterfactual exercises that completely ignore how such changes could have been implemented.

4.3. *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 10, are similar to the experiments in Section 4.2. We take the benchmark model (which generates a crime rate equal to the one observed in 1980), and input the data on 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 1975, 1985, and 1990. We then compute the steady-state equilibrium of the model for each of these years and compare the crime rate generated by the model to the one in the data. We repeat the information for 1996 for comparison reasons.[16]

Table 10 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

[16] 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.

TABLE 11

CRIME RATE DECOMPOSITIONS

Component	75–80	80–85	85–90	90–96
Base year	100	100	100	100
Police	159	73	98	96
Unemployment rate	91	105	98	104
Human capital shares	89	98	102	107
Age distribution	100	96	92	111
Income inequality	72	154	92	105
Prison term	–	79	136	87
All	122	95	104	85

FIGURE 4

CRIME RATES: DATA AND MODEL

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 some of 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 change in property crime over time. In particular, we consider the following comparisons: 1975–1980, 1980–1985, 1985–1990, and 1990–1996.

Table 11 summarizes the decomposition of the changes in the crime rate for each pair of years. In particular, we examine the contribution of each component of the data by adding them to the base year one at a time.[17] For example, the column labelled 75–80 starts with 1975 as the base year and adds components of the 1980 data one at a time. Crime rates for each base year are normalized to be 100. This procedure allows us to examine the main factors that have contributed to the change in the crime rate in these pairs of years.

75–80 period. Some of the important characteristics of the data for this period include a decrease in the unemployment rate, an improvement in the skill distribution of the population, and a decrease in income inequality. These factors all contribute toward a lower crime rate as can be seen from Table 11. For example, if the only factor that changed between 1975 and 1980 were the decreased unemployment rate, the crime rate in 1980 would have been 9 percent less than the crime rate in 1975. Similarly, the decrease in income inequality alone would have caused a 28 percent decrease in the crime rate. However, in the same time period there has been a decrease in the clearance rate from 18.9 to 16.8. This factor alone causes a significant increase in the crime rate. Overall, according to these results, the main reason for the 22 percent increase in the crime rate between 1975 and 1980 was due to the decrease in apprehension probability.

80–85 period. Crime rate in the model goes down from 5.6 to 5.3. The three important characteristics of this period are the significant increase in income inequality, which alone would have caused the crime rate to go up by 54 percent; the increase in the apprehension probability, which would have caused the crime rate to decrease by 27 percent; and the increase in expected prison term, which also would have caused the crime rate to decrease by 21 percent. Overall, if it wasn't for the increases in the probability and the severity of punishment the crime rate would have increased due to worsening income inequality.

85–90 period. Crime rate in the model goes up from 5.3 in 1985 to 5.5 in 1990. In this time period there is a small increase in police apprehension rate and a decrease in unemployment. There is also a decrease in the fraction of youth in the population. All of these factors contribute to a lower crime rate. However, there is also a significant decrease in the prison term in 1990. This factor is responsible for the overall increase in the crime rate.

90–96 period. Crime rate in the model in this period goes down from 5.5 to 4.7. This is a period characterized by increasing income inequality, rising fraction of young individuals in the population, and higher unemployment, all of which contribute to a higher crime rate. The resulting lower crime rate is a product of a slightly higher apprehension probability and a longer prison term.

5. EXTENSION: 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

[17] Since relative changes in average income for each pair of years are small, we omitted the row about average income.

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 preconviction path.

Several empirical studies have analyzed the effect of this type of stigma. Waldfogel (1994) shows the decline in earnings to be roughly 10 percent and quite persistent, taking 8 years to get halfway back to preconviction levels. Allgood et al. (1999) find a decline of 12 percent and that effect did not disappear for the 6 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 percent lasting just 6 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 θ 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.

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 percent decrease in postconviction 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 12 contains our main results.

TABLE 12
1980 BENCHMARK WITH STIGMA

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

Note that compared to our benchmark economy without stigma (see Table 6), the presence of stigma induces a lower amount of juvenile delinquency (59.9 vs. 76.1) and a higher amount of recidivism (75.0 vs. 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 as follows: By 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, the presence of stigma discourages juvenile delinquency relatively more. In addition, stigma has a direct effect on recidivism. By reducing postconviction 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 percent 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 percent. Thus, introducing stigma into the analysis improves the ability of the model to match salient features of the data.[18] When confronted with the time series evidence, however, the performance of the model with stigma is less satisfactory. In particular, although 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

[18] 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.

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 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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