
Volume 145 Issues 1–2 July 2008 ISSN 0304-4076
ELSEVIER
JOURNAL OF
Econometrics
THE USE OF ECONOMETRICS IN INFORMING
PUBLIC POLICY MAKERS
edited by
ROBIN C. SICKLES AND JENNIFER WILLIAMS
Editors:
Associate Editors:

Journal of Econometrics 145 (2008) 158–173

Contents lists available at ScienceDirect

Journal of Econometrics

journal homepage: www.elsevier.com/locate/jeconom

Turning from crime: A dynamic perspective[☆]

Robin C. Sickles[a,*], Jenny Williams[b]

[a] Rice University, United States

[b] University of Melbourne, Australia

ARTICLE INFO

Article history:
Available online 21 June 2008

JEL classification:
C1
C3
J2
K4

Keywords:
Social capital
Dynamic model
Panel data
Value function approximation
Simulated method of moments

ABSTRACT

This paper examines criminal choice using a variant of the human capital model. The innovation of our approach is that it attempts to disaggregate individual capital, not unlike production-based studies which disaggregate physical capital into equipment and structures. We disaggregate an individual's capital stock into the standard human capital component as well as a utility generating component that we call social capital. In our set-up, social capital is used to account for the influence of social norms on the decision to participate in crime. This is done by modeling the stigma of arrest as a reduction in the individual's social capital stock. We also allow individuals to account for the impact of their criminal actions on their probability of arrest. In order to estimate the structural parameters underlying the model, we make use of computationally intensive methods involving simulated generalized method of moments and value function approximation. The empirical results, based on panel data from the Delinquency in a Birth Cohort II Study, support the social capital model of crime and reveal significant state dependence in the decision to participate in crime.

Executive summary

The social cost of crime is substantial. In the US, for example, this cost was estimated to be in the order of $105–$450 billion a year almost a decade ago (Miller et al., 1996). This figure reflects not just the direct cost of the judicial and corrections systems, but also the value of lost or damaged property, the victims' medical bills and lost earnings as well as the valuation of their pain and suffering. The calculus of social costs of crime must also include the opportunity cost of the lives of those who become unproductive and taxing members on society, the criminals themselves.

The burden of its cost makes crime an important issue for policy makers. There are two main policy approaches to this social malaise: deterrence and prevention. Under the deterrence umbrella are policies such as mandatory sentencing and truth in sentencing that seek to deter criminals by raising the expected length of prison sentence for those caught engaging in crime. This approach essentially treats the disease of crime after it has presented. In contrast, prevention-based policies seek to change the social incentives and stigma associated with criminal activity, making crime less socially acceptable. This approach is akin to public policies of disease prevention advocated by public health practitioners.

Our research has focused on how these competing pubic policies impact potential criminal behavior. Our results suggest that individuals who are poorly endowed with social capital from their family tend to become criminally active when young and remain so later in life. Moreover, these 'at risk' individuals place a higher value on leisure than those better endowed with social capital, and are therefore less inclined to work and more likely to remain at the margin of productive society. Our results also indicate that while there is a deterrence perceived by criminal youth, this deterrence impacts criminal behavior much less than investments in the stock of social capital. Direct expenditures on prisons and police protection are relatively easy to document. Indirect expenditures on the social capital factors we have identified as impacting the criminal activities of youth are not. Our study suggests that the latter provide a key to reducing the criminal activity of those youth who are most vulnerable to succumbing to a life of crime.

1. Introduction

It is often said that crime is a young man's game and there is large empirical literature that finds this to be the case. The

☆ The authors would like to thank participants of the Labor Econometrics Workshop, Australian National University, the Economics Seminar Series, University of New South Wales, the University of Sydney, Centre for Microeconometrics at the University of Melbourne, and the Conference on "The Use of Econometrics in Informing Public Policy Makers" funded by the James A. Baker Institute for Public Policy at Rice University, April, 2006 for their insightful comments. We also thank Peter Hartley for his valuable and critical suggestions at earlier stages of the research, Levent Kutlu for providing his expertise and research assistance, and an anonymous referee for extensive comments and criticisms that substantially improved the paper. The usual caveat applies.

* Corresponding address: Rice University, Department of Economics, United States.

E-mail address: rsickles@rice.edu (R.C. Sickles).

0304-4076/$ – see front matter © 2008 Published by Elsevier B.V.
doi:10.1016/j.jeconom.2008.05.014

relationship between age and crime, referred to as the age–crime profile, was first documented by Quetelet (1984, 1831) using French cross-sectional data. Quetelet discovered that the arrest rate rose rapidly from the teen years to reach a maximum in the early twenties and then steadily declined. This pattern in the criminal activities of young men has been found in a number of studies based on different countries, cities and time periods, and criminal justice systems. The regularity of the relationship between age and crime raises the question of why crime becomes less attractive to men as they age. This question is of immediate policy relevance since an understanding of the mechanism that reduces criminal tendencies of men in their early twenties may be exploited to reduce or prevent their criminal behavior at earlier ages.

This research proposes an explanation of criminal desistence using a variant of the human capital model (Becker, 1968; Ehrlich, 1973; Flinn, 1986). The innovation of our model is that it attempts to disaggregate individual capital, not unlike the way that production-based studies disaggregate physical capital into equipment and structures. We disaggregate an individual's capital stock into the standard human capital component and a second component which may impact criminal and non-criminal choices differently. We call this latter capital stock social capital. Social capital was first introduced by Coleman (1988) as a means of integrating the framework of the rational agent with the social context in which decisions are made. In our application, social capital is used to account for the role of social norms on the decision to participate in crime (Akerlof, 1997). The model we use, which is an extension of Sickles and Williams (2006), is based on the assumption that social capital provides a flow of services associated with a good reputation that impacts on utility and labor market wages. We account for the stigma of arrest by modeling it as a reduction in the individual's stock of social capital.

Generally, the extent to which an individual may experience disutility from social sanctions imposed for criminal acts is likely to depend upon his attachment to the community which imposes these sanctions. At one end of the spectrum are young males living in urban ghettos as described by the ethnographic studies of Anderson (1999). For these individuals, the threat of legal and social sanctions is likely to impose a very low cost. At the other extreme are individuals living in the suburbs with careers and families and who are, in Anderson's terminology, heavily vested in 'decent' society and for whom social sanctions are very costly. For our purposes, we define the norms of the wider 'decent' community as the benchmark and measure the degree to which an individual is vested in this system of norms and behavior by his social capital stock. Our hypothesis is that as an individual accumulates social capital stock in the wider community, the expected cost of crime increases, making criminal acts less likely to occur (Akerlof, 1998; Sampson and Laub, 1993; Laub and Sampson, 1993).

The main difference between our approach and others found in the literature is that we attempt to account for the direct utility cost of the social stigma associated with arrest. Several previous studies in economics have sought to explain the temporal pattern of criminal behavior displayed by the age–crime profile. Flinn (1986) extended the economic model of crime to a dynamic setting by incorporating human capital, where human capital is accumulated at work. His numerical example suggests that human capital formation decreases crime directly because it increases wages. Lochner (2004) proposes a model along similar lines, but assumes that investment in human capital is costly. Leung (1994) shows that the hump-shape of the age–crime profile can result from the tension between an increase in the intensity of offending with age and a selection effect whereby older criminals leave crime. While the contributions of Flinn, Lochner, and Leung are theoretical, Imai and Krishna (2004) estimate a dynamic model of crime. In their model, the individual's choice to commit a crime potentially affects wages and employment probabilities through their arrest history. Their estimation results suggest that although arrest histories only have a small effect on current wage and employment outcomes, the anticipated future effect of arrest on employment probabilities is large, and these future costs act as a substantial deterrent to engaging in crime. Our model complements the work of Imai and Krishna by explicitly modeling choices about work as well as crime and by allowing crime, through its effect on social capital accumulation, to have a direct utility impact as well as effecting labor market outcomes.

This paper builds on our previous research by allowing a person to account for the effect of their actions on the probability that they are arrested. In Sickles and Williams (2006), we assume that the probability of arrest is exogenously determined. This allowed us to derive Euler equations, which were the basis of our empirical investigation. On average, the results from that investigation provided evidence consistent with a social capital theory of crime, although the model performed less well for those most at risk of a career in crime. We suspect that the model performed poorly for the more criminally involved because it failed to account for their ability to affect the probability of being arrested and hence mitigate the adverse consequences of their criminal behavior. The purpose of this paper is to relax the assumption of an exogenous probability of arrest and investigate this issue empirically.

Allowing the probability of arrest to depend on an individual's actions complicates estimation of the parameters of interest. This is because the first-order conditions for the optimal choice of time in crime and time in the labor market include terms involving the value function. We address this issue using a nested fixed-point algorithm within the estimation procedure to approximate the value function (Rust, 1994, 1995; Miller, 1997). An inner contraction fixed-point algorithm approximates the value function for each trial value of the parameters of interest and an outer algorithm estimates the structural parameters of interest. As with our earlier research, estimation of the structural parameters involves choices in future states that are unobserved and this is addressed using simulation techniques. Interestingly, our results are largely consistent with our earlier findings, when arrest probabilities were assumed to be exogenous. The major difference in our results is that by endogenizing the probability of arrest we are able to account for offenders' ability to mitigate the impact of their criminal behavior and this produces estimates that yield better global properties of the preference structures with respect to those heavily involved in crime.

The remainder of this paper is organized as follows. In the next section, we present a dynamic model of crime that extends our earlier research by endogenizing the probability of arrest. Section 3 provides a description of the data that is used to estimate our model, and explains the construction of key variables required for the analysis. In Section 4 we discuss the method for estimating the structural parameters of the model. Section 5 presents the results and Section 6 concludes the paper.

2. A dynamic model of crime with social capital accumulation

In the spirit of Ehrlich (1973), we cast our model of criminal choice in a time allocation framework, where time can be spent in three possible activities: legitimate work, L_t, leisure, ℓ_t, and income producing crime, C_t.[1] Our point of departure from this standard approach is that we allow individuals to accumulate social capital

[1] Alternatively, time in various activities could be modeled in a discrete choice framework. This approach is used by Imai and Krishna (2004) who focus on the

stock, S_t. An individual's social capital stock is assumed to produce a flow of utility generating services such as reputation and social acceptance. Social capital may also affect earnings if, for example, individuals use social networks as a source of information about opportunities for advancement, or employers use networks to seek out workers with good reputations.

As with other forms of capital, social capital (defined in terms of attachment to the wider culture) is assumed to be cumulative. In the Coleman tradition, social capital is built by engaging in legitimate activities that build bonds and networks to social institutions. Akerlof (1998) in the economics literature and Laub and Sampson (1993) in the sociology literature identify employment and marriage as key institutions for building social bonds. In the context of this theoretical model, we assume investment in social capital to be proportional to the time spent in the labor market, and generalize the investment process in the empirical application. While time spent in the labor market builds social capital, time in crime potentially erodes it. Specifically, we use social capital to account for the influence of social norms on the decision to participate in crime by assuming that the stigma of arrest depreciates an individual's social capital stock. This specification leads to a social capital accumulation process that is state contingent. If not arrested, (State 0), social capital accumulates according to:

$$S^0_{t+1} = (1-\delta)\,S_t + \gamma L_t \tag{2.1}$$

where δ is the depreciation rate of social capital and γ transforms resources spent in legitimate activity into social capital. If arrested for crimes committed in period t, (State 1), social capital at the beginning of $t+1$ is given by:

$$S^1_{t+1} = (1-\delta)S_t - \alpha C_t S_t \tag{2.2}$$

where α represents the technology that transforms resources spent in crime into stigma if arrested. This social capital accumulation process implies that the level of stigma imposed on an individual is increasing in the amount of time he spends in crime and is increasing in his stock of social capital. The former captures the idea that the greater the crime committed the greater the punishment imposed, while the latter ensures that, *ceteris paribis,* crime is more costly for those who have a greater attachment to the wider society. Each of these aspects of the social capital accumulation process works to deter crime because, as described below, both per period utility and labor market wages are assumed to be increasing in the individual's level of social capital.

To be more concrete, we assume that in each period, in addition to allocating time to leisure, work and crime, the representative individual also chooses his level of consumption of the composite market good, X_t. His per period utility depends on his consumption of the composite market good, his leisure time, and the flow of services from his stock of social capital.[2] At time t, utility is given by:

$$U\left(X_t, \ell_t, S_t\right). \tag{2.3}$$

Denoting earnings within a period in terms of the composite good, X_t, the intertemporal budget constraint is given by:

$$A_{t+1} = (1+r)\left(A_t + W_L(L_t, S_t) + W_C(C_t) - X_t\right) \tag{2.4}$$

where income from crime $W_C\left(C_t\right)$ is assumed to depend on time spent in that activity, and labor market income $W_L\left(L_t, S_t\right)$ is assumed to depend upon hours worked and the individual's stock of social capital. Income from each activity is assumed to be increasing in its respective arguments.[3]

We allow the probability that an individual is arrested for engaging in crime to depend on the extent of his criminal actions as well as the level of resources devoted to law enforcement, R_t. The probability of being arrested at the beginning of time $t+1$ for crimes committed in time t is given by:

$$p_t = p\left(C_t, R_t\right). \tag{2.5}$$

While the probability of arrest is expected to be increasing in resources spent by the government on law enforcement, *a priori*, it is not clear whether the probability of arrest is increasing or decreasing in resources spent in crime by the individual.[4] On the one hand, we would expect that the greater the number of crimes an individual commits in a time period, the greater the chance that the offender will be arrested for any one offense. However, people who spend a lot of time in crime may also spend more time covering their illegal activity. By taking care, an offender can reduce the probability of detection. Since we do not know which effect dominates, the marginal effect of time in crime on the probability of arrest may be negative or positive.

Note that in this model, current period welfare is certain. This is because we assume that the state of the world (arrest, or escape arrest) is learned at the beginning of each period. Therefore, all current period state variables are known before the individual makes current period choices. However, the level of future period state variables depends upon which state of nature is realized (social capital stock is reduced in the event of arrest, and increased in the event of escaping arrest) and this introduces uncertainty about future welfare via the direct effect of social capital on utility, and through its effect on labor market earnings.

Agents are assumed to maximize their discounted expected utility. A representative individual's dynamic programming problem is characterized by his value function at period t, $V(A_t, S_t)$, which is the solution to the Bellman equation:

$$V(A_t, S_t) = \max_{X_t, L_t, C_t} U(X_t, \ell_t, S_t)$$
$$+ E_t\beta\left\{p(C_t, R_t)V(A_{t+1}, S^1_{t+1}) + (1-p(C_t, R_t))V(A_{t+1}, S^0_{t+1})\right\}.$$

Subject to:

(1) $T = \ell_t + L_t + C_t$

(2) $A_{t+1} = (1+r)\left(A_t + W_L(L_t, S_t) + W_C(C_t) - X_t\right)$

(3) $S^1_{t+1} = (1-\delta)S_t - \alpha C_t S_t$

(4) $S^0_{t+1} = (1-\delta)S_t + \gamma L_t$.

decision to participate in crime. However, in order to make their model tractable they ignore the decision to participate in the legitimate labor market. As time spent in the labor market is a crucial part of the social capital accumulation process, we do not follow the discrete choice approach here. A further shortcoming of adopting the neoclassical labor supply approach to crime is that we are unable to address general equilibrium effects. For example, by introducing crime into an equilibrium search model, Burdett et al. (2003) are able to explore the relationship between crime, wage inequality and unemployment.

[2] In earlier work both pure income and pure utility generating crimes were included in the model, where utility generating crime included rape and murder. However, the data did not contain sufficient information to identify the effect of utility generating crimes so we have simplified the model by only considering income generating crimes.

[3] Human capital stock is also expected to impact on labor market earnings. While we account for this in the empirical section by allowing wages to depend upon education and experience, allowing for human capital accumulation in the theoretical model added a substantial degree of complexity and for this reason we abstract from it here. Moreover, since we have no information on time spent in jail, we are, in practice, unable to account for the impact of being caught and convicted on the human capital accumulation process. We also explored the potential role of human and criminal capital in criminal earnings in our earlier paper but were unable to explain criminal earnings with variables that measured either forms of capital.

[4] See Imrohoroglu et al. (2000) for a general equilibrium model in which crime, income redistribution and police expenditures are determined through majority voting. In their model the affect of changes in police expenditures have an ambiguous impact on the crime rate.

By substituting (1) for ℓ_t, we eliminate it as a choice variable. Taking first-order conditions with respect to X_t, L_t, and C_t, and applying the envelope theorem to the derivative of the value function with respect to assets lead to the usual Euler equation for consumption. Applying the envelope theorem to the derivative of the value function with respect to social capital does not, however, allow the remaining conditions to be written in terms of this period's and next period's decision variables. This is because, in order to obtain a set of Euler equations, a model must contain at least one exogenous state variable. Since our state variables, assets and social capital, and implicitly, arrest status each depend on the actions chosen by the individual, our model does not meet this requirement.[5] Therefore, the expressions for the optimal choice of consumption, time in the labor market and time in crime are as follows:

$$X_t : U_1(t) - \beta(1+r)\left\{pU_1^1(t+1) + (1-p)U_1^0(t+1)\right\} = 0$$

$$\begin{aligned}
L_t &: U_1(t)\frac{\partial W_L(t)}{\partial L_t} - U_2(t) + \beta\gamma\left(1 - p\left(C_t, R_t\right)\right) \\
&\times \left\{\left(\frac{(1-\delta)}{\gamma} - \left(\frac{1-\delta-\alpha C_{t+1}^0}{\alpha S_{t+1}^0}\right)\right) U_2^0(t+1)\right. \\
&+ \left(\frac{\partial W_L\left(t+1^0\right)}{\partial S_{t+1}} + \left(\frac{1-\delta-\alpha C_{t+1}^0}{\alpha S_{t+1}^0}\right)\frac{\partial W_C(t+1^0)}{\partial C_{t+1}}\right. \\
&\left. - \frac{(1-\delta)}{\gamma}\frac{\partial W_L\left(t+1^0\right)}{\partial L_{t+1}}\right) U_1^0(t+1) \\
&+ U_3^0(t+1) + \beta\left(\frac{1-\delta-\alpha C_{t+1}^0}{\alpha S_{t+1}^0}\right)\frac{\partial p\left(C_{t+1}^0, R_{t+1}\right)}{\partial C_{t+1}} \\
&\left.\times \left[V\left(A_{t+2}, S_{t+2}^{0,1}\right) - V\left(A_{t+2}, S_{t+2}^{0,0}\right)\right]\right\} = 0
\end{aligned}$$

$$\begin{aligned}
C_t &: U_1(t)\frac{\partial W_C(t_t)}{\partial C_t} - U_2(t) - \beta\alpha p\left(C_t, R_t\right) S_t \\
&\times \left\{\left(\frac{(1-\delta)}{\gamma} - \left(\frac{1-\delta-\alpha C_{t+1}^1}{\alpha S_{t+1}^1}\right)\right) U_2^1(t+1)\right. \\
&+ \left(\frac{\partial W_L\left(t+1^1\right)}{\partial S_{t+1}} + \left(\frac{1-\delta-\alpha C_{t+1}^1}{\alpha S_{t+1}^1}\right)\frac{\partial W_C(t+1^1)}{\partial C_{t+1}}\right. \\
&\left. - \frac{(1-\delta)}{\gamma}\frac{\partial W_L\left(t+1^1\right)}{\partial L_{t+1}}\right) U_1^1(t+1) \\
&+ U_3^1(t+1) + \beta\left(\frac{1-\delta-\alpha C_{t+1}^1}{\alpha S_{t+1}^1}\right)\frac{\partial p\left(C_{t+1}^1, R_{t+1}\right)}{\partial C_{t+1}} \\
&\left.\times \left[V\left(A_{t+2}, S_{t+2}^{1,1}\right) - V\left(A_{t+2}, S_{t+2}^{1,0}\right)\right]\right\} \\
&+ \beta\frac{\partial p\left(C_t, R_t\right)}{\partial C_{t+1}}\left[V\left(A_{t+1}, S_{t+1}^1\right) - V\left(A_{t+1}, S_{t+1}^0\right)\right] = 0
\end{aligned}$$

where $S_{t+2}^{0,1}$ represents the level of social capital in $t+2$ when the individual is not arrested in $t+1$ (State 0) but is apprehended in $t+2$ (State 1).[6]

The usual condition for optimality in consumption is given by the Euler equation for the aggregate consumption good, with the ratio of the marginal utility of current period consumption to the expected marginal utility of next period's consumption equated to the gross real rate of interest. The equation for time spent in the labor market equates net current period costs associated with time at work to the expected value of the increase in social capital in terms of next period decision variables. These decision variables include time in crime. Therefore, the condition for the optimal choice of time in the labor market includes a term capturing the expected marginal difference in future welfare associated with next period's criminal choice. This term accounts for the effect of future criminal choice on the probability of arrest and on subsequent welfare as measured by the difference in the value function at time $t+2$ across the two states of nature. Similarly, the equation for time spent in crime equates the net marginal benefit in this period to the expected future cost. The condition for the optimal allocation of time to crime has two terms involving the value function. In addition to the expected marginal difference in the value function across the two states at time $t+2$, the expected marginal difference in the value function across states at $t+1$ also appears. The latter term captures the effect of the marginal unit of time in crime in the current period on the probability of arrest, and the subsequent impact on future welfare. These three equations form the basis of our empirical investigation.

3. Data

3.1. General

We use individual level data from the Delinquency in a Birth Cohort II Study (Figlio et al., 1990) to estimate our dynamic model of crime. The cohort is composed of subjects who were born in Philadelphia in 1958 and who resided in that city at least from their 10th until their 18th birthday. Once the 27,160 members of this universe were identified using the Philadelphia school census, the U.S. Bureau of Census, and public and parochial school records, data collection occurred in 2 phases. The first phase involved collecting the complete official criminal history of the cohort. These data cover the criminal careers, as recorded by the police, and juvenile and adult courts, for the entire 27,160 members of the cohort up to the age of 26.[7] The second stage of the Study entailed a retrospective follow-up survey for a sample from the cohort.[8] The follow-up survey took place during 1988 and provides detailed information on 576 men and 201 women.[9] Areas of inquiry covered by the survey include:

5 Sickles and Williams (2006) assume that the probability of arrest is exogenous, and were therefore able to obtain a full set of Euler equations.

6 In an infinite horizon model with a real-valued concave value function V, differentiability of the value function is usually based on a rather weak assumption of interiority which is itself met by two conditions. The first is the condition that the optimal solution is in the interior of the choice set (Benveniste and Scheinkman, 1979) and the second is the condition that the choice set is invariant with respect to the state vector (Lucas, 1978), although as Rincon-Zapatero and Santos (2007) point out the two conditions are mathematically equivalent if the policy function is continuous. We have a concave value function, no corner solutions are found for our optimal solution as indicated by the simulation results in Figs. 1–5, and the choice set is not indexed by the state vector.

7 Information about adult arrests was obtained from the Philadelphia Police Department, the Common and Municipal Courts, and the FBI, ensuring offenses both within and outside the boundaries of Philadelphia are included in the data set.

8 The investigators employed a stratified sampling scheme to ensure that they captured the most relevant background and juvenile offense characteristics of the cohort and yield a sample size sufficient for analysis. The population was stratified by gender, race, socio-economic status, offense history (0, 1, 2–4, 5 or more offenses), and juvenile "status" offenses, which are offense categories only applicable to individuals less than 18 years of age.

9 Most respondents resided within the Philadelphia SMSA or within a 100-mile radius of the urban area. However, to insure that out-migration from Philadelphia of cohort members would not have any significant effect, sample members were traced and if possible contacted, throughout the United States (Figlio, 1994). Between thirty and forty percent of the members of each strata were interviewed, so that the relative response rate were roughly equal. Figlio (1994) reports that comparisons among strata indicate no apparent biases due to non-response.

Table 1

Variable	Definition	Mean	Standard deviation
Model variables			
L	Hours worked per year	1498.04	934.61
C	Hours in income generating crime per year	65.55	180.40
ℓ	Leisure hours per year	4260.42	916.79
X	Real consumption per year	119.23	84.65
S	Social capital index	102.81	20.84
W_L	Real annual labor income	100.69	91.83
W_C	Real annual crime income	3.08	17.04
R	Real police resources per offense	31.9	4.5
Determinants of social capital			
Socio-economic status	Binary equal to 1 if socio-economic status of family during childhood up is high	0.57	0.50
White	Binary equal to 1 if race is white	0.56	0.50
Dad at home	Binary equal to 1 if father present in childhood home	0.86	0.35
Dad not arrested	Binary equal to 1 if father not arrested during childhood	0.92	0.28
Not in gang	Binary equal to 1 if not a gang member during childhood	0.82	0.39
Number of Siblings/10	Number of siblings (divided by ten)	0.32	0.23
Proportion of friends not picked up by the police	Proportion of best 3 friends not picked up by the police during high school	0.63	0.44
Number of police contacts	Number of police contacts as a juvenile	0.72	0.45
Proportion of official police contacts	Proportion of police contacts as a juvenile that were official contacts	0.24	0.41
Proportion of arrests	Proportion of contacts as a juvenile that result in an arrest	0.16	0.32
M	Binary equal to 1 if begin a marriage that year	0.05	0.21
N	Binary equal to 1 if end and then begin a job that year	0.10	0.30
ARREST	Binary equal to 1 if arrested for a property offense that year	0.03	0.17
Other personal characteristics			
Married	Binary equal to 1 if married	0.13	0.33
Common law	Binary equal to 1 if in a common law marriage	0.08	0.28
Number of children	Number of children	1.00	1.13
No mum at home	Binary equal to 1 if mother not present in childhood home	0.02	0.13
Moved out of parental home	Binary equal to 1 if moved out of childhood home	0.08	0.26
High school graduate	Binary equal to 1 if gradated from high school	0.81	0.39
School	Binary equal to 1 if still in education	0.21	0.40

personal history of delinquency and criminal acts; gang membership; work and education histories; composition of current and childhood households; marital history; parental employment and educational histories; parental contact with the law; and personal, socio-economic and demographic characteristics. The individual level data from the Birth Cohort Study is augmented with state level information on total expenditure on police protection and corrections for Pennsylvania, and the number of offenses known to police in that state. This aggregate data, along with the CPI, is used to construct real police expenditure per offense which is our measure of resources spent on law enforcement.

Our final data set used for estimation consists of a panel of 423 men covering the six year period of 1977 to 1982 when the cohort was 19 to 24 years old. This paper focuses on males since very few female arrests are observed in the data. The sample size reflects the need to limit attention to those (males) interviewed as part of the follow-up survey for whom we have information on all variables, such as employment, required to estimate the model. A definition of variables and summary statistics is presented in Table 1.[10]

3.2. Measuring time in income generating crime and income from crime

For our purposes, income generating crime consists of robbery, burglary, theft, forgery and counterfeiting, fraud and buying, receiving or possessing stolen property. Selling drugs has not been included because, although the Philadelphia crime code classifications allow police to distinguish between selling, manufacturing, and possession, the data we have does not. Our approach to measuring time spent in crime is based on the assumptions that (1) more serious crimes require greater time for planning and commission than less serious crimes, and (2) the degree of seriousness of a crime can be measured using the Sellin–Wolfgang seriousness scoring index (Sellin and Wolfgang, 1964).

The self-reported information on crime available in the Delinquency in a Birth Cohort II Study is reported for the age category 19–24 years of age. However, we require the total number of crimes for each year. We construct this by distributing the self-reported crimes to each of the 6 years covered by the age category 19–24 using weights reflecting the proportion of arrests for the cohort for each of the relevant years.[11] Converting the quantity of crimes into *time* in crime requires a basis for comparison and aggregation across the different crime types. Sellin and Wolfgang (1964) propose a seriousness scoring scale that uses the effects of the crimes rather than specific legal labels to index the gravity of criminal behavior. We use the index of severity as a metric for comparison and aggregation of different crimes.[12] Annual observations on crime are obtained by aggregating seriousness scores for each individual within a year. Next, we use information from the 1989 Boston Youth Survey, reported in Freeman (1991) to benchmark our severity index to hours spent in crime. Freeman reports that individuals who engage in crime at least once a week earn, on average, $5400 per year, and that, on the basis of reported hours spent on the most recent crime, their hourly wage was $9.75.

[10] Since our data are from a stratified random sample, the statistics in Table 1 are calculated using weights to reflect the population from which the sample is drawn.

[11] This requires assumptions about both participation and frequency of offending during this time period. Figlio's (1994) analysis of the self-reported crimes for males in the follow-up survey found that the percentage of individuals committing offenses was constant between the 19–24 and 25+ age groups when all offense types were considered. On this basis, we make the assumption that there is a constant participation in crime during the years 1977–1982. If the participation rate is constant, then the total number of arrests per period for this cohort should reflect the intensity (or frequency) with which participants commit crimes.

[12] To score a crime, detailed information is required. This data was collected from the rap sheets on arrests and seriousness scores calculated. However, the information is unknown for crimes for which no arrests take place. In this case, seriousness scores are generated by taking random draws from the distribution of seriousness scores for arrests in the corresponding crime category.

This implies these individuals spent about 554 h per year in crime. However, Freeman also reports that the average annual income from crime for those who report positive criminal earnings is $3000, with an average hourly wage of $19. This implies an average of 158 h per year spent in crime for those who report positive criminal earnings. We take a weighted average of these estimates of annual hours spent in crime, benchmarking our average time in crime at 290 h per year for individuals who have a seriousness score value greater than zero.

Annual income from crime is defined as the sum of income from crimes for which the individual was arrested and the income from those self-reported crimes for which no arrest occurs. For actual arrests, we use the value of stolen property recorded on the rap sheet (and collected by the Study) as our measure of income from crime. In order to generate observations on income from self-reported crime that did not result in an arrest, we take random draws from the value of stolen property for arrests in the same category as the self-reported crime. For the criminally active, the annual average income from crime (in nominal terms) is about $1212. This is somewhat less than the annual income from crime reported by the respondents to the inner City Youth Survey of $1607 (in 1980 dollars) or by respondents to the Boston Youth Survey of $3000 reported in Freeman (1991), although it is very similar to Grogger's (1995; 1998) estimate of $1187 (1979 dollars) based on information in the National Longitudinal Survey of Youth. We note that we do not include income from selling drugs, which is likely to be the reason our estimate of income tends to be at the low end of the range of others' estimates.

3.3. Measuring time in the labor market and labor market income

The follow-up survey contains detailed information on employment histories for individuals in the study. In particular, for each job (whose tenure was at least six months), the month and year the individual began and ended employment was recorded, along with the wage received when employment began and ended, whether the job was part-time or full-time, the pay period (hourly, weekly, monthly, or yearly), and the average hours worked per week. This information was used to construct annual observations on the number of hours worked per year in the labor market and the annual income received. Unfortunately, there is no information on savings or expenditure in the follow-up survey. Therefore, we assume that consumption and income are equal and that expected assets are zero, with the difference between actual and expected assets treated as measurement error. As we are dealing with a cohort of young men, many of whom are criminally active, it is unlikely that they are undertaking much savings and so we expect that this should not have a large impact on our results.

3.4. Measuring social capital

Since cohort members are eighteen years of age at the beginning of our analysis, we assume that the level of social capital stock they possess on entering the sample period is inherited from their family. During the sample period, social capital accumulates according to a generalized version of the process described in Section 2.

3.4.1. Inherited social capital stock

Becker (1991) notes that the fortunes of children are linked to their parents through endowments such as family reputation and connections, knowledge, skills, and goals provided by the family environment. Similar sentiments are expressed by Coleman (1988). The variables that we have in our data to measure these concepts are: the socio-economic status of the individual's family during his childhood, race, whether the father was present in the childhood home, the number of siblings, whether the father was arrested during the individual's childhood, whether high school friends were in trouble with the police, gang involvement during childhood, and the number of juvenile arrests relative to police contacts. Obtaining a set of weights for aggregating these variables raises the classic index number problem. Maasoumi (1986, 1989, 1993) shows that the (normalized) first principal component from the data on attributes can be used as weights to summarize these attributes into a composite index. We follow this approach and conduct a principal component analysis of the variables related to inherited social capital stock. The resulting weights are reported in Table 2. The signs of the weights indicate that coming from a white two-parent household with a high socio-economic status, having a father with no arrests (during the individual's childhood), not being involved in a gang, and having friends who were not in trouble with the police contribute to the social capital stock an individual accumulates during childhood. The negative weight on the number of siblings indicates that the social capital stock a child inherits from his family is decreased by the presence of siblings.[13] Involvement in criminal activity in youth, as measured by juvenile arrests also has a negative weight, indicating that juvenile arrests reduce the social capital stock accumulated during childhood. An index of inherited social capital is constructed using the weights given in Table 2.

Table 2
Construction of the initial stock of social capital

Variable	Weight
Father present in childhood home	0.15
Father not arrested during childhood	0.07
Number of siblings	−0.04
Race is white	0.25
Socio-economic status is high	0.29
Not a gang member	0.28
Proportion of best 3 high school friends not picked up by police	0.18
Proportion of police contacts as a juvenile that result in arrest	−0.18

Table 3
Time in crime

Age	Most at risk time in crime	Least at risk time in crime
19	192	36
20	170	30
21	138	30
22	138	24
23	134	27

We can assess the ability of the index of inherited social capital to measure social attachment, and hence risk of criminal participation, by comparing the criminal involvement of those at the bottom quartile of the distribution of inherited social capital with those from the top quartile. These groups represent the most and least 'at risk' individuals respectively. Table 3 reports the average time in crime for both the high and low risk groups, and shows that the high risk group does spend a much larger amount of time in crime relative to the low risk group. This confirms that the initial level of social capital stock is a good predictor of propensity for crime.

3.4.2. Current social capital stock

During the sample period, gross investment in social capital is assumed to be generated through engagement in legitimate activities. In our empirical specification we follow the informal

[13] This is consistent with Coleman (1988) who finds that siblings dilute parental attention, which negatively affects the transmission of social capital from parents to child.

social control approach of Sampson and Laub, allowing the life-course turning points of getting married (M_t) and leaving and beginning a new job in the same period (N_t) to build stock in society.[14] We account for the stability of labor market attachment in our measure of social capital through annual hours worked. Social capital also depends on the state of the world, which is learned at the beginning of each period. In the event of not being arrested (State 0) for crimes committed in time t, social capital at $t+1$ is given by:

$$S^0_{t+1} = (1-\delta)\,S_t + \gamma_1 L_t + \gamma_2 M_t + \gamma_3 N_t. \tag{3.1}$$

As described in Section 2, in the event of apprehension, (State 1) social capital at the beginning of $t+1$ is given by:

$$S^1_{t+1} = (1-\delta)\,S_t - \alpha C_t S_t. \tag{3.2}$$

To obtain the unknown weights $(\delta, \alpha, \gamma_1, \gamma_2, \gamma_3)$ in the capital accumulation process, we use an iterative process.[15] Starting with period 1 for which social capital is measured by inherited social capital, we partition the data into arrest observations and non-arrest observations. Principal component analysis is performed separately on the appropriate variables (S, L, M, N if not arrested; S and $S \times C$ if arrested) for each of these data sets. The resulting weights are used to construct the next period's social capital stock, S_2. These weights are then updated by partitioning the data of period 1 and 2 into arrest and non-arrest observations and performing principal components on each of the two data sets (using the relevant variables for each). This process is repeated until a full set of observations on social capital is obtained. For the sub-sample consisting of observations for which an arrest occurs, there are 2 factors determining social capital accumulation and hence 2 principal components. In the final iteration, the first principal component of these data accounts for 67% of the variation in the data (and the second accounts for 33%). For the sub-sample consisting of observations for which no arrest occurs, social capital is determined by 4 factors and hence there are 4 principal components. In this case, the first principal component accounts for 42% of the variation in the data, the second accounts for 30% of the variation, the third for 18% and the fourth for 9% of the variation in the data in the final iteration.

To filter out the variation in weights arising from this iterative procedure, we use OLS in order to obtain a final set of weights. The resulting weights are shown in Table 4. These results imply a rate of depreciation on social capital of 3% a year. If apprehended, and assuming the average value for resources devoted to crime of 290 h per year by those participating in crime, the penalty is a further loss of 6% of social capital. Time spent in employment, getting married, and changing jobs all have a positive impact on creating stock in society, as indicated by the positive sign of their respective weights. These weights are used to construct our index of social capital stock.

Table 4
Construction of the stock of social capital

Variable	Coefficient	Standard error
Constant	−0.61	0.2223
S_t	0.97	0.0023
Not arrested		
L_t	0.0008	0.00005
M_t	4.17	0.2213
N_t	14.91	0.1597
Arrested		
C_tS_t	−0.00021	0.00008

4. Econometric model

Standard GMM estimation of the equations governing the optimal choice for consumption, time at work, and time in crime derived in Section 2 is complicated by two issues. First, the conditions for the optimal choice of time spent in crime, C_t, and the labor market, L_t, include terms involving the value function. This means that once functional forms are specified for the utility, probability of arrest, and earnings functions, the system of first-order conditions and earnings equations does not give a closed-form solution for the optimal allocation of resources. The second complication can be viewed as an omitted regressor problem. This problem arises because agents make current choices before they know which state of nature they will face next period. Therefore, the conditions for the optimal choice of time spent in crime and work contain the probability weighted choices in both possible future states: *arrest* (State 1), and *escaping arrest* (State 0). In practice, only one state is realized and therefore observed. The unobserved choice variables in future states are, in this sense, omitted variables.

Each of these issues arises in estimating the conditions for the optimal allocation of time across the two income earning activities, crime and work, and not in estimating the earnings equations for these activities. To focus on the estimation issues, we calibrate the parameters in the earnings equations at values obtained in Sickles and Williams (2006), and develop a strategy for obtaining estimates of the parameters in the utility function and probability of arrest function from the conditions for optimality.[16] Our estimation strategy draws on simulation techniques to overcome the omitted variable problem in the first-order conditions. The simulated conditions are then used to form a method of moments estimator of the parameters of interest. We nest within this optimization routine an algorithm that numerically approximates the value function for each trial value of the utility and probability of arrest parameters.[17] The Bellman equation is iterated to obtain a fixed point for the value function approximation. The approximation to the value function is passed to the outer algorithm that updates the estimates of the structural parameters in the utility and probability of arrest function, treating the value function approximation parameters as given. These estimates are then used to update the value function approximation, which in turn, is used to update the parameter estimates. Iteration between the value function approximation and parameter estimation continues until convergence is reached. The following sections present a more specific description of the value function approximation and simulated method of moments procedures used in our estimation strategy.

[14] While much of the criminology literature has emphasized stability and continuity, Sampson and Laub argue that transitions are also important in understanding an individual's criminality, as these events may modify long term patterns of behavior. We assume that leaving a job and starting a new one *in the same period* is attributable to upward employment mobility, and that this increases attachment to the legitimate sector because the employer's act of investing in the individual will be reciprocated. Additionally, a better job increases an individual's system of networks. Each of these effects tends to increase an individual's ties to the legitimate community and thus increase his social capital stock.

[15] In Sickles and Williams (2006), the equations for social capital accumulation are substituted into the Euler equations and the coefficients are estimated using a procedure that iterates between optimizing with respect to the structural parameters of the utility function given the parameters for the social capital accumulation process, and optimizing with respect to the social capital accumulation parameters given the parameters of the utility function, until both have converged. This more complex estimation procedure yields estimates for the social capital accumulation process that are quantitatively similar to those arrived at using the computationally simpler procedure used here.

[16] These results are reported in Appendix (Table A.1).

[17] Since we approximate the value function, we could use the Bellman equation to solve for the unobserved choices in future states. However, in order to facilitate a comparison of the results from this paper with our earlier work, we address the issue of unobserved choices using simulation techniques.

4.1. Simulated method of moments

The Simulated Method of Moments (SMM) framework was introduced by McFadden (1989) and Pakes and Pollard (1989) and is based on methods developed by contributors to R. Moffit's *Symposium on Simulation Methods in Econometrics* (Moffit, 1994), among them Huh and Sickles (1994), Gallant and Tauchen (1996), and Carrasco and Florens (2002), among others. These procedures provide generic approaches to construction of simulation estimators wherein closed-form expressions for the likelihood and scores are not available or when moment conditions such as those used in our analysis are constructed from the first-order conditions of the solutions to the Bellman equation.

We motivate our SMM estimator within the context of the Generalized Method of Moments (GMM) approach. The conditions for the optimal choice of consumption, time in the labor market and time in income producing crime derived in Section 2 form the basis of our moment conditions. We begin by assuming a panel of T periods of observations on a random sample of N individuals and that all arguments of the optimality conditions for labor, crime and consumption are observed without error. Assume that the earnings functions for the legal sector and crime are known. Also note that although the conditions for optimality contain terms involving the value function at period $t+1$ and $t+2$, these have been evaluated in the iterative loop that approximates the value function and are treated as known in the estimation process. Utility is assumed to have the following transcendental logarithmic form

$$\begin{aligned} U\left(X_t, \ell_t, S_t\right) &= \alpha_1 \ln X_t + \alpha_2 \ln \ell_t + \alpha_3 \ln S_t \\ &\quad + \frac{1}{2}\left\{\beta_{11}\left(\ln X_t\right)^2 + \beta_{22}\left(\ln \ell_t\right)^2 + \beta_{33}\left(\ln S_t\right)^2\right\} \\ &\quad + \beta_{12} \ln X_t \ln \ell_t + \beta_{13} \ln X_t \ln S_t + \beta_{23} \ln \ell_t \ln S_t \end{aligned}$$

and the probability of arrest is given by:

$$p\left(C_t, R_t\right) = \frac{\exp\left(M_0 + M_1 C_t + M_2 R_t\right)}{1 + \exp\left(M_0 + M_1 C_t + M_2 R_t\right)}.$$

Let the parameters be collected into

$$\theta_0 = \left(\alpha_1, \alpha_2, \alpha_3, \beta_{11}, \beta_{22}, \beta_{33}, \beta_{12}, \beta_{13}, \beta_{23}, M_0, M_1, M_2\right).$$

Let S_{it} denote the value of the state variable, social capital stock, for the ith individual in period t, x_{it} denote the vector of choice variables entering the ith individual's optimal choice equations in period t, and let x_{it+1} be those variables dated $t+1$.[18] Examining the Euler equations from Section 2, we can see that each of these equations can be written in the form of $f_j\left(x_{it}, S_{it}, \theta_0\right) - g_j\left(x_{it+1}, S_{it+1}, \theta_0\right), j = 1, 2, 3$, where $f(.)$ is the observed response function which depends on current period variables, and $g(.)$ is the expected response function, which depends on next periods' variables, and θ_0 is the px1 vector of parameters to be estimated. A stochastic framework is introduced by adding idiosyncratic error terms to each equation and by representing the ith individual's system of equations as:

$$f\left(x_{it}, S_{it}, \theta_0\right) - g\left(x_{it+1}, S_{it+1}, \theta_0\right) = u_{it}.$$

Suppose there exist conditional moment restrictions of the form, $E\left[u_{it} \mid z_{it}\right] = 0$, where z_{it} are observed data. These moment restrictions can be used to form a generalized method of moments estimator of θ_0. Given panel data covering T years for each of the N individuals, the population orthogonality conditions can be written as:

$$E_N\left[\frac{1}{T}\sum_{t=1}^{T}\left(f\left(x_{it}, S_{it}, \theta_0\right) - g\left(x_{it+1}, S_{it+1}, \theta_0\right)\right) \otimes z_{it}\right] = E_N\left[M\left(x_i, S_i, z_i, \theta_0\right)\right] = 0.$$

Suppose then a law of large numbers can be applied to $M(x_i, S_i, z_i, \theta_0)$ for all admissible θ, so that the sample average of $M(x_i, S_i, z_i, \theta_0)$ converges to its population mean:

$$\lim_{N\to\infty} \frac{1}{N}\sum_{i=1}^{N}\left[M\left(x_i, S_i, z_i, \theta_0\right)\right] = E_N\left[M\left(x_i, S_i, z_i, \theta_0\right)\right].$$

Under the regularity conditions outlined in Hansen (1982), the unknown parameter vector θ_0 can be estimated by minimizing the generalized quadratic distance of the sample moments from zero (the value of the population moments):

$$\left[\frac{1}{N}\sum_{i=1}^{N}\left[M\left(x_i, S_i, z_i, \theta_0\right)\right]\right]' W_N \left[\frac{1}{N}\sum_{i=1}^{N}\left[M\left(x_i, S_i, z_i, \theta_0\right)\right]\right]$$

where W_N is a symmetric positive definite weighting matrix that satisfies:

$$\lim_{N\to\infty} W_N \overset{\text{as}}{\to} W_0.$$ [19]

In practice, forming this Generalized Method of Moments estimator, θ_{mm}, for the parameters in the utility and probability of arrest functions is hampered by the fact that observed future welfare is state contingent: there are two possible future states of the world — arrest and escaping arrest. While agents' decisions are based on ex ante expectations of the future, ex post, only one state is realized for each individual and subsequently observed by the econometrician. Our problem is that x_{it+1} is not observed for individual i in the state not realized in period $t+1$. Consequently, we cannot form sample averages of $M(.)$ since x_{it+1} enters $M(.)$ through $g\left(x_{it+1}, S_{it+1}, \theta_0\right)$. We resolve this problem by replacing $M(.)$ with a simulator, $\mu(.)$. McFadden (1989) proposes this simple modification of the conventional Method of Moments estimator as the basis for the Method of Simulated Moments.[20]

The intuition behind our approach is that it is possible to infer the behavior of an individual who was arrested had he not been arrested by observing the behavior of those not arrested.[21] In particular, the unobserved choices can be inferred by non-parametrically estimating the joint distribution of choice variables and the state variable, and taking Monte Carlo draws from the empirical distribution, conditional on the individual's value for the state variable.[22] Having replaced the unobserved data with

[18] We take the estimated earnings equation parameters in Appendix to be the true values, and the parameters governing the law of motion for social capital accumulation to be those obtained using principal components. We assume a real rate of interest of 3%, and a time rate of preference of 0.95. Substituting these parameters, the derivatives of the income functions and the translog utility functions and the value function parameters into the equations for optimal choice from Section 2 results in the representative individual's per period optimal choice of time allocations (L_t, C_t) and consumption (X_t) parameterized by $\theta_0 = (\alpha_1, \alpha_2, \alpha_3, \beta_{11}, \beta_{22}, \beta_{33}, \beta_{12}, \beta_{13}, \beta_{23}, M_0, M_1, M_2)$.

[19] The choice of a weighting matrix that produces the efficient or optimal GMM estimator is $W_0 = \Omega^{-1}$, where Ω is consistently estimated by

$$\Omega_N = \frac{1}{N}\sum_{i=1}^{N}\left[(u_i \otimes z_i)(u_i \otimes z_i)'\right].$$

[20] Sufficient conditions for the MSM estimator to be consistent and asymptotically normal involve the same regularity assumptions and conditions on instruments as classical GMM, in addition to the two following assumptions that concern the simulator, $\mu(.)$: (i) the simulation bias, conditional on W_0 and x_{it}, is zero, and (ii) the simulation residual process is uniformly stochastically bounded and equicontinuous in θ.

[21] A similar approach is found in Altug and Miller (1993).

[22] Recall that S_{t+1} depends on last periods' choices, and whether or not the individual is apprehended in period $t+1$. So we are able to construct social capital stock in period $t+1$ in the unobserved state.

the Monte Carlo draws, we then form a simulator of our moment conditions as follows:

$$\frac{1}{T}\sum_{t=1}^{T}\left[\frac{1}{S}\sum_{s=1}^{S}\left(f\left(x_{it},S_{it},\theta_0\right)-g\left(x_{it+1}^{s},S_{it+1},\theta_0\right)\right)\otimes z_{it}\right] = \mu(x_i,S_i,z_i,\theta_0)$$

where

$$\lim_{N\to\infty} E_N\left[\frac{1}{N}\sum_{i=1}^{N}\left[\mu(x_i,S_i,z_i,\theta_0)\right]\right] = E_N\left[M(x_i,S_i,z_i,\theta_0)\right].$$

We use this framework to form a simulator of the moment conditions and obtain an estimator for the preference parameters and probability of arrest parameters by minimizing the weighted quadratic distance of the simulated moments from zero.[23]

4.2. Value function approximation

Smooth approximation methods treat the value function as a smooth function of the state variable and a finite-dimensional parameter vector θ. The objective of this method is to choose a parameter $\widehat{\theta}$ such that the approximation $V_{\widehat{\theta}}$ 'best fits' the true solution V according to some metric. In order to ensure convergence of a smooth approximation method, we need a parameterization that is sufficiently flexible to allow us to approximate arbitrary value functions V. A natural choice of smooth approximations to V is

$$V_\theta\left(s\right)=\sum_{i=1}^{k}\theta_i p_i\left(s\right)$$

where $p_i\left(s\right)=s^i$ is the ith standard polynomial in the state variable s_i. In our case, we approximate the value function at time t with a third-order polynomial in S_t. Under the least squares criterion of goodness of fit, the problem is to choose $\theta\in\Theta\in R^k$ to minimize the function $\sigma_N\left(\theta\right)$ defined by

$$\sigma_N(\theta)\equiv\sqrt{\sum_{i=1}^{N}\left|V_\theta(s_i)-\widehat{\Gamma}(V_\theta(s_i))\right|^2}$$

where $\widehat{\Gamma}$ is a computable approximation to the Bellman operator Γ defined as

$$\Gamma\left(V\left(s_t\right)\right)=\max_{a\in A(s)}\left[U\left(s_t,a_t\right)+\beta E_t V\left(s_{t+1}\right)\right]$$

and where a_t is the action taken at time t and V is a fixed point of the mapping.[24] To compute $\widehat{\Gamma}$ we require an initial set of values for the parameters of the utility function, probability of arrest function, and polynomial approximation to the value function. Given these parameters, the utility maximizing choices for the action, a_t (in our case, consumption, time in labor and crime) is found by solving the first-order conditions. This enables us to evaluate the Bellman equation and provides us with a value for $\widehat{\Gamma}$. Treating $\widehat{\Gamma}$ as the dependent variable to be explained by a polynomial in current period social capital, we then choose the parameters in the polynomial approximation to minimize the squared distance between the fitted polynomial approximation to the value function V_t and the approximation to the Bellman equation $\widehat{\Gamma}$. Having obtained a set of parameter estimates for the approximation V_t, we can update our approximation to the Bellman operator, and re-estimate the parameters in the polynomial approximation. Iteration between the Bellman operator and the polynomial approximation is continued until the parameters in the approximation meet the conditions for convergence. They are then passed to the SMM procedure, which treats the value function approximation as data in estimating the parameters in the utility and probability of arrest functions. The updated SMM parameter estimates are then passed back to the value function approximation algorithm and iteration between the two procedures continues until convergence is reached.

Table 5
Parameter estimates

Variable	Coefficient	Standard error
Translog utility function		
$\ln X_t$	0.2162	0.0073
$\ln \ell_t$	0.4699	0.0378
$(\ln X_t)^2$	0.00033	0.00003
$(\ln \ell_t)^2$	0.00425	0.0047
$(\ln S_t)^2$	−0.05857	0.0079
$\ln X_t \ln \ell_t$	−0.02340	0.0008
$\ln X_t \ln S_t$	−0.00296	0.0002
$\ln S_t \ln \ell_t$	−0.07446	0.0039
Probability of arrest function		
C_t	−0.08110	0.0078
R_t	0.00504	0.0002
Value Function Approximation		
$\ln S_t$	0.51344	
$(\ln S_t)^2$	−0.01109	
$(\ln S_t)^3$	0.00006	

5. Results

5.1. Parameter estimates and value function approximation results

The probability of arrest and utility function parameters are estimated from the conditions for optimal choice derived in Section 2 using panel data on 423 men over the period 1977–1981. For identification, the coefficient on the logarithm of social capital in the translog utility function (α_3) is normalized at unity. The constant term in the probability of arrest function is not identified, and is also normalized. This leaves a total of 10 coefficients to be estimated: Eight parameters from the utility function and two from the probability of arrest function. With three equations and eleven instruments, the number of overidentifying restrictions is twenty three. The Hansen test statistic for overidentifying restrictions is 3.06, compared to a $\chi^2_{0.05,23} = 35.17$. On the basis of this evidence we cannot reject the null hypothesis that the system is overidentified. The parameter estimates for the probability of arrest function, utility function, and polynomial approximation to the value function are presented in Table 5.

Beginning with the approximation to the value function, we note that the estimated coefficients imply that the approximated value function is concave in the state variable, social capital. Turning to the probability of arrest function, we find that real expenditure on police protection and corrections per offense (R_t) has the expected positive (and significant) effect on the probability of arrest. We find that individuals who spend a larger amount of time in crime (C_t) are less likely to be arrested than those who spend less time in crime. This suggests that more serious crimes are undertaken with greater care and planning in order to reduce the probability of detection. An examination of the estimates of the translog preference parameters reveals that the coefficients on the interaction term between consumption and leisure ($\ln X_t \ln \ell_t$), consumption and social capital ($\ln X_t \ln S_t$), and leisure and social capital ($\ln \ell_t \ln S_t$) all are significant. This indicates that utility is

[23] We note that the Kuhn–Tucker conditions imply that constraints embodied in the Euler equations for time allocations are not binding for certain observations.

[24] Note that Γ is a contraction mapping. This property ensures the existence and uniqueness of the solution V to Bellman's equation.

Table 6

Age	Probability of arrest	Time in crime	Real police resources per offense
19	0.020	97	37.2
20	0.021	78	37.3
21	0.021	68	29.6
22	0.021	68	28.1
23	0.021	65	27.3

Table 7
Marginal utility of consumption, leisure and social capital

Age	Consumption	Leisure	Social capital
19	9.35×10^{-5}	1.49×10^{-5}	0.00103
20	8.56×10^{-5}	1.42×10^{-5}	0.00110
21	9.43×10^{-5}	1.44×10^{-5}	0.00114
22	9.91×10^{-5}	1.44×10^{-5}	0.00117
23	10.10×10^{-5}	1.46×10^{-5}	0.00121

Evaluated at each observation and averaged over individuals.

not contemporaneously separable in any of its arguments. Our estimates imply that consumption and leisure are complements in utility. The relationships between consumption and social capital, and leisure and social capital, are also found to be complementary.

Table 6 reports the average probability of arrest over the period covered by the sample. The likelihood of detection and apprehension for property crime is small, at approximately 2%. The average time in crime has fallen over the five years covered in this study. However, the associated increase in the probability of apprehension has been offset by a decrease in real resources spent on the criminal justice system per offense.

Table 7 shows that the estimated marginal utility of consumption, leisure, and social capital are positive for all time periods.[25] While not reported, the second-order conditions confirm that the estimated utility function is concave in each of its arguments. This can be taken as evidence that the model is not rejected by the data. As shown in Table 7, marginal utility of consumption for our sample declines between the age of nineteen and twenty, but rises thereafter. A similar pattern is displayed in the marginal utility of leisure. The marginal utility of social capital is shown to be positive and increasing over the sample period. Since social capital represents past investment, increasing marginal utility of social capital can be interpreted as evidence that preferences exhibit state dependence. To gauge the relative importance of consumption, leisure, and social capital, we consider the marginal rate of substitution between the three arguments of the utility function. Table 8 reports the average rates for the sample. The marginal rate of substitution of leisure for consumption (MU_X/MU_ℓ) and social capital for consumption (MU_X/MU_S) are reported in 1977 dollars, and the marginal rate of substitution of social capital for leisure (MU_ℓ/MU_S) is measured in hours. These results indicate that the marginal value of leisure decreases over the sample period in terms of consumption and social capital. This is reflected by a falling marginal rate of substitution of leisure for consumption and an increasing marginal rate of substitution of social capital for leisure.

Finding that our model performs well at the mean of the data is consistent with our earlier paper. In that paper, however, the model performed less well for those who were most criminally prone, and therefore, the most relevant. In order to assess the contribution of generalizing the model to allow for the endogeneity of the probability of arrest, we investigate the properties of the model for those most and least at risk of criminal involvement as determined by their inherited social capital stock.

[25] These are obtained by evaluating at each observation and averaging across individuals.

Table 8
Marginal rate of substitution

Age	Leisure for consumption	Social capital for consumption	Social capital for leisure
19	9.66	667.57	69.1
20	10.08	777.71	77.2
21	9.26	734.17	79.3
22	8.83	717.09	81.2
23	8.77	725.56	82.8

Evaluated at each observation and averaged over individuals.

Table 9
Marginal utility of consumption, leisure and social capital — high risk

Age	Consumption	Leisure	Social capital
19	0.000136	2.02×10^{-5}	0.00153
20	0.000114	1.98×10^{-5}	0.00164
21	0.000122	2.02×10^{-5}	0.00171
22	0.000138	2.07×10^{-5}	0.00173
23	0.000141	2.13×10^{-5}	0.00181

Evaluated at each observation and averaged over individuals.

Table 10
Marginal utility of consumption, leisure and social capital — low risk

Age	Consumption	Leisure	Social capital
19	6.29×10^{-5}	1.12×10^{-5}	0.00068
20	6.28×10^{-5}	1.00×10^{-5}	0.00074
21	7.35×10^{-5}	0.98×10^{-5}	0.00077
22	7.89×10^{-5}	0.96×10^{-5}	0.00081
23	7.81×10^{-5}	0.94×10^{-5}	0.00083

Evaluated at each observation and averaged over individuals.

Table 11
Marginal rate of substitution of leisure for consumption

Age	Most at risk MRS	Least at risk MRS
19	9.03	10.74
20	10.56	9.66
21	10.03	8.07
22	9.10	7.40
23	9.16	7.32

Evaluated at each observation and averaged over individuals.

Table 12
Marginal rate of substitution

Age	Most at risk: Social capital for consumption	Least at risk: Social capital for consumption	Most at risk: Social capital for leisure	Least at risk: Social capital for leisure
19	682.45	658.85	75.6	61.3
20	872.76	713.00	82.7	73.8
21	847.76	637.78	84.5	79.0
22	760.84	624.28	83.6	84.3
23	781.06	643.33	85.2	87.9

Evaluated at each observation and averaged over individuals.

Tables 9 and 10 report the marginal utilities of consumption, leisure, and social capital for those most at risk of crime (those in the first quartile of inherited social capital) and those least at risk of crime (those in the fourth quartile of inherited social capital) respectively. The marginal utility of each argument is positive over all time periods for both the high risk and low risk groups. This is evidence that the social capital model of crime is not rejected by either the high or low risk individuals in our sample. This is a significant improvement over our previous paper in which the marginal utility of social capital is negative for the high risk group for all time periods. Table 11 compares the marginal rate of substitution of leisure for consumption for the low and high risk groups. These results show that the high risk, more criminally involved group, places a higher value on an hour of leisure at

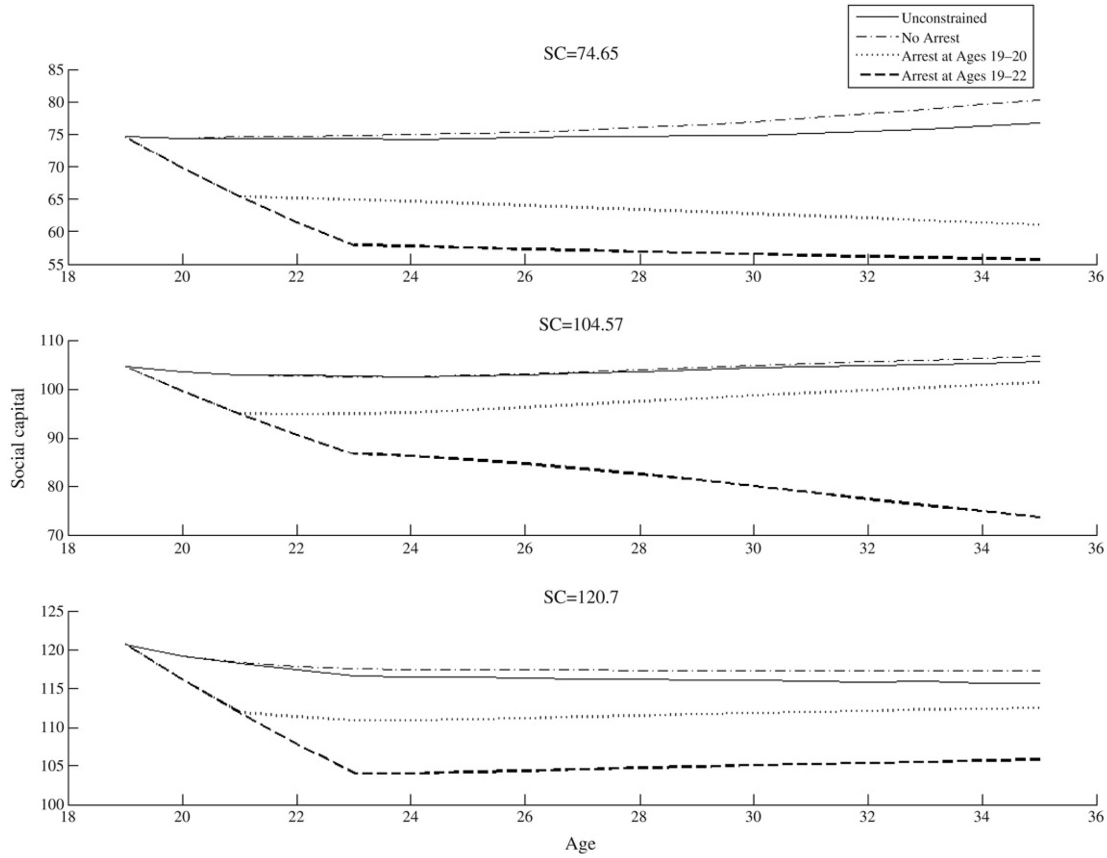

Fig. 1. Simulation of social capital accumulation.

the margin than the low risk group does. Table 12 contains the marginal rates of substitution of social capital for consumption and social capital for leisure for these two groups. The marginal rate of substitution of social capital for leisure increases monotonically for the least at risk group, while it remains comparatively flat after the age of 20 for the high risk group. This, along with the results in Table 11, indicates that as the cohort ages, the high risk group places a relatively greater value on leisure in terms of consumption and social capital compared to the low risk group. In terms of our model, the relative increasing preference for leisure of the high risk group implies they are less likely to work, and thereby build social capital, compared to the low risk group. This translates into a lower penalty in terms of the utility cost of apprehension. Thus, we would expect the high risk group to continue to be more likely to engage in crime in the future compared to the low risk group. Our findings suggest that low levels of social capital inherited from the family may explain why some individuals become career criminals, while individuals who are more richly endowed experience relatively short careers in crime.

5.2. Simulations

In structural models, it is difficult to gain clear insights into the practical implications of the parameter estimates. In order to aid interpretation of the model and parameter estimates, we perform a series of simulations. The simulations are designed to show the effect on the life-cycle trajectories of social capital accumulation, consumption, hours worked, time in crime and utility, of inheriting different levels of social capital from one's family and experiencing different arrest profiles.

In order to perform these simulations, we use the parameter estimates and the value function approximation to solve for current period control variables (hours of work, hours in crime and consumption) that maximize the value function

$$V(S_t) = \max_{X_t, L_t, C_t} U(X_t, \ell_t, S_t) + E_t \beta \left\{ p(C_t, R_t) V(A_{t+1}, S^1_{t+1}) + (1 - p(C_t, R_t)) V(S^0_{t+1}) \right\}$$

where $S^j_{t+1}, j = 0, 1$ is evaluated at the optimal level of the control variables using the equations for the social capital accumulation process.

In our first experiment, we set the probability of arrest at the average for the sample period. We create arrest histories by taking a draw from a uniform random variable defined over the [0, 1] interval and assigning the simulated observation to the state arrest if the value of the draw is less than the probability of arrest. Otherwise, the observation is assigned to the state no arrest. This is carried out for each age from 19 to 35, generating a state vector containing a 17 year arrest history. For each state vector, we obtained the optimal control variables given the initial value of the state variable (social capital). This process was replicated 1000 times. The average values of these control variables over the ages 19–35 are reported as the unconstrained simulation in Figs. 1–5. We also examined three extreme arrest history scenarios: no arrest, arrest at ages 19 and 20, and arrest at ages 19, 20, 21 and 22. For these cases, instead of randomly determining the arrest state vectors, they are set at [0 0 0 0 ...], [1 1 0 0 ...] and [1 1 1 1 0 0 ...] respectively. For each of these vectors optimal control variables are obtained and plotted. We have previously identified inherited social capital as significant in determining who becomes a criminal, and who does not. We further explore the importance of inherited social capital by simulating the evolution of dynamic decisions about work, crime and consumption for three types of individuals who differ in their inherited social capital stock. The three levels of

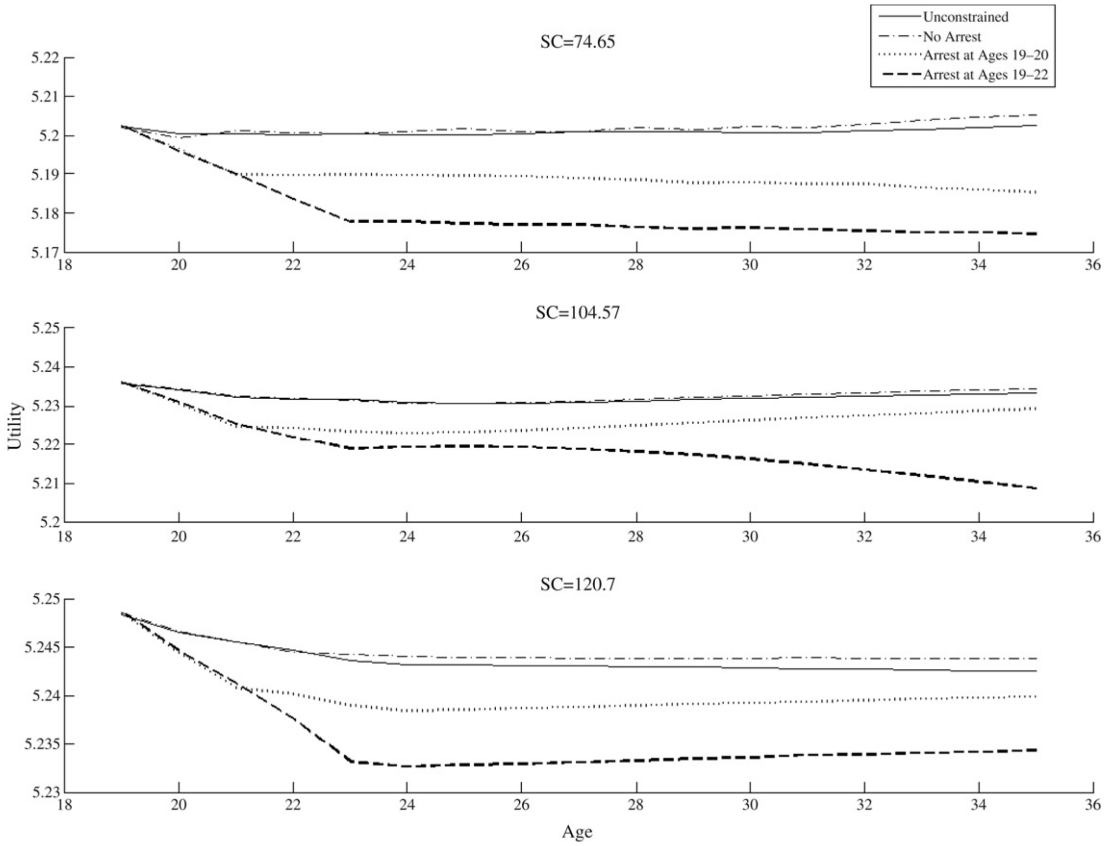

Fig. 2. Simulation of life-time utility.

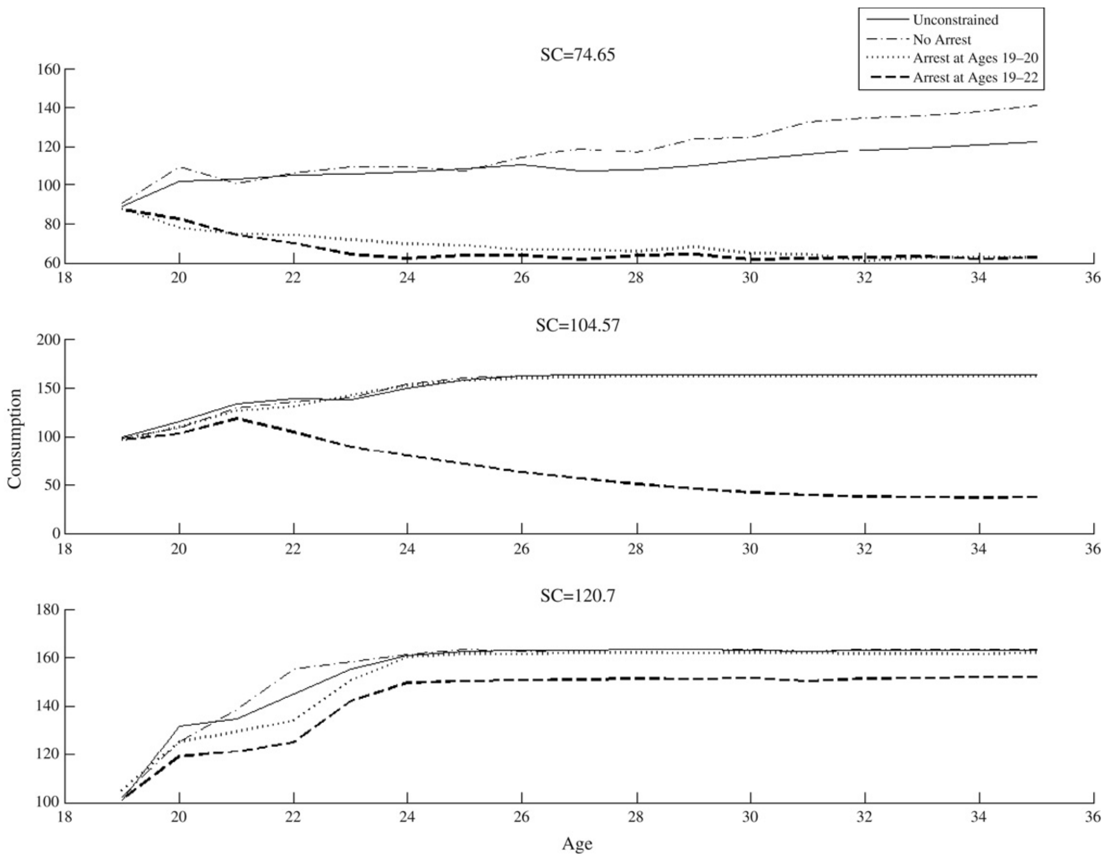

Fig. 3. Simulation of life-time consumption.

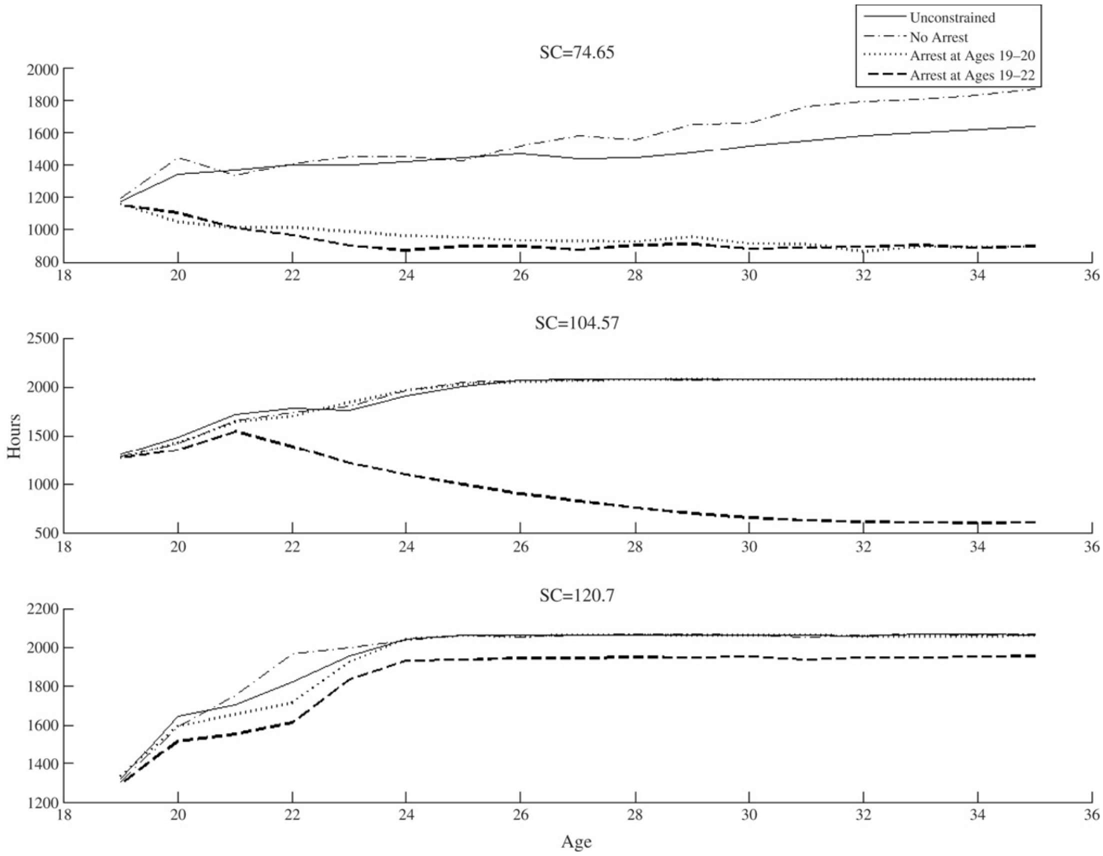

Fig. 4. Simulation of life-time labor hours worked.

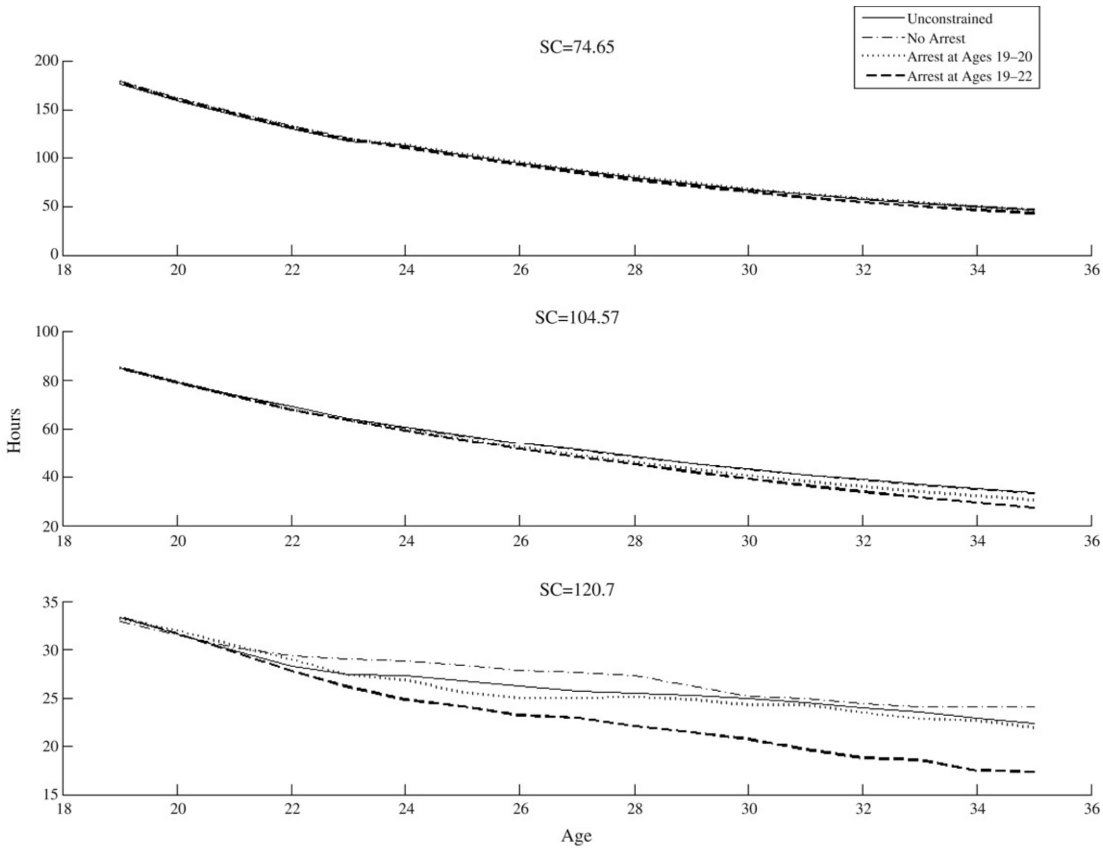

Fig. 5. Simulation of life-time hours in crime.

inherited social capital stock we select are (1) the average value for individuals in the initial sample period which is 105.5, (2) a lower value equal to the average initial social capital stock for those from the first quartile of the inherited social capital distribution, and (3) an upper value of 120.70 equal to the average value for those from the fourth quartile of the inherited social capital stock distribution. By examining the different arrest scenarios for high, low and average social capital types, we are able to see how different arrest histories and different levels of inherited social capital interact in the evolution of social capital and utility and on decisions regarding consumption, work, and crime.

It should be noted that the ability of our model to simulate behavior over the course of the life cycle is compromised by the fact that we only have data for the very early stages of a youth's adult life. Even so, the patterns that are revealed in the simulations (Figs. 1–5) illustrate the deleterious impacts of crime on the accumulation of social capital and life-time utility. As we can see from Fig. 1, social capital accumulation from ages 19 to 35 is substantially reduced by an arrest record. The figures fit the sample data quite well and social capital increases over time as expected. In earlier periods, social capital stock decreases, even for those with a high level of inherited social capital stock. This decrease stems from the pursuit of higher levels of education, which essentially entails consuming the initial stock of social capital in order to invest in human capital. Our simulations indicate that it takes some time for the individual to reach the initial level of social capital inherited from the family. The figures for total utility show a similar pattern to those of social capital. Total utility is reduced by the erosion of social capital due to the stigma of arrest, although its impact diminishes for medium and relatively high initial levels of social capital as the legacy of youth crime is seen in an ever-receding rear-vision mirror.

Since we have no formal wealth information in our sample and assume that consumption and income are equal, the simulated path for hours worked is very similar to that for consumption. As expected, consumption is substantially reduced by both low initial levels of social capital as well as a record of arrest when young. There appears to be a low level social capital equilibrium trap, much like that in the development growth literature, such that as social capital falls below a certain level, those whose are also arrested and fall below this level cannot recover. Similarly, those with the average level of social capital are not able to recover from a substantial arrest history (arrested at ages 19–22). However, those with a high level of inherited social capital stock (or medium levels but a less serious arrest history), consumption increases rapidly in the early part of adulthood before leveling off. This seems consistent with standard life-cycle consumption behavior. At low levels of initial social capital stock those who are arrested are less likely to work as the marginal benefit of working (wage) is correspondingly low. Time in crime falls as young men age irrespective of inherited levels of social capital stock or arrest history. However, while the arrest history has very little impact on time spent in crime by those who have inherited low levels of social capital stock, it has a considerably larger effect on those who have inherited high levels of social capital stock. This suggests that specific deterrence is least effective for those who are most at risk of a life in crime.

6. Conclusion

This study investigates a dynamic model of crime in which current period decisions affect future outcomes through the probability of arrest and the social capital stock accumulation process. We introduce social capital stock into the preference structure to account for the influence of social norms on the crime decision by allowing stigma of arrest to depreciate an individual's social capital stock.

Our results suggest that criminals account for future consequences of current period decisions. In particular, they account for the effect of their level of criminal activity on the probability of arrest by taking greater care. This self-protection has the effect of reducing the probability of apprehension, which increases future welfare. Further, criminals take account of the potential welfare cost of apprehension and the ensuing social sanctions by requiring higher monetary rewards in crime than are available in the legitimate sector. We also find support for the social capital hypothesis of criminal desistence. The estimated marginal value of social capital is positive and increases over the life cycle for the sample as a whole, as well as for the high and low risk groups. This implies that the potential social capital costs associated with crime increase over the life cycle, making criminal acts less likely.

By focusing on desistence from crime, we hope to enhance our ability to address the question 'how can we prevent crime?'. This research focuses on one mechanism by which preventative policies may impact potential criminal behavior: social capital accumulation. Our results suggest that individuals who are poorly endowed with social capital from their family tend to remain criminally active later in life. Moreover, these 'at risk' individuals place a higher value on leisure in adulthood than individuals who are relatively well endowed. This later outcome may be due to a lack of information regarding the non-monetary benefits associated with employment due to low levels of inherited social capital. These findings suggest that programs targeting 'at risk' youth which focus on mentoring, may be able to provide the social bonds and information that their families failed to provide, and prevent at least some individuals from pursuing crime.

Our finding that the probability that an individual is arrested for committing crime is increasing in resources spent on law enforcement is reassuring from a policy perspective. However, the general equilibrium effect on crime of greater police resources is less than clear. For example, Imrohoroglu et al. (2000) develop a general equilibrium model in which crime, income redistribution and police expenditures are determined through majority voting.[26] In their model, while an increase in police expenditure increases the probability of apprehension, the overall effect on the crime rate may be positive or negative, depending on whether an increase in wages or an increase in wage inequality generated the increase in police expenditures. Empirically examining the general equilibrium effects on crime of increasing the levels of resources devoted to law enforcement remains a task for future research.

Appendix. Earnings in the legitimate and criminal sectors

The following functional forms are assumed for earnings in the legitimate and illegitimate sectors

$$\begin{aligned} W_L(L_t, S_t) &= \eta_0 + \eta_1 L_t + \eta_2 L_t^2 + \eta_3 L_t S_t + \eta_4 \text{HIGHSCHOOLGRAD}_t \\ &\quad + \eta_5 L_t x\text{HIGHSCHOOLGRAD}_t + \eta_6 \text{SCHOOL}_t + \varepsilon_{Lt} \end{aligned}$$

$$W_C(C_t) = \mu_0 + \mu_1 C_t + \mu_2 C_t^2 + \varepsilon_{Ct}.$$

HIGHSCHOOLGRAD_t is a categorical variable equal to one if the highest level of education the individual attains is at least a high school diploma and equal to zero otherwise, SCHOOL_t is a categorical variable equal to one if the individual has not yet completed his education and zero otherwise, and e_{Lt} and e_{Ct} are random error terms. If the decision to work (in either activity) depends on unobservable characteristics which also influence earnings, then the problem of sample selection exists. We make use of standard econometric techniques to account for the possibility of sample selection bias. As actual hours worked (in either activity) are observed, we adopt the methodology suggested in Vella (1998).

[26] We thank an anonymous referee for this suggestion.

Table A.1

Work			Crime	
Variable	Hours	Wage	Hours	Wage
CONSTANT	1054.5	0.5936	−277.21	0.1849
	(17.31)	(0.035)	(−6.59)	(0.228)
HOURS (L, C)		0.0702		0.0189
		(4.22)		(0.786)
HOURS SQUARED		-1.985×10^{-6}		5.4316×10^{-5}
		(−4.99)		(2.822)
L*S		0.00010		
		(1.954)		
HIGHSCHOOL GRAD	297.53	−19.58	−101.83	
	(6.12)	(−1.586)	(−3.21)	
L*HIGH SCHOOL GRAD		0.011		
		(1.758)		
SCHOOL	−802.31	−1.1604	47.44	
	(−12.26)	(−0.207)	(1.10)	
WHITE	314.51		31.56	
	(6.82)		(1.04)	
SES	131.33		−53.58	
	(2.98)		(−1.84)	
MARRIED	542.30		−90.54	
	(8.72)		(−2.08)	
DEFACTO	198.02		195.40	
	(2.70)		(4.41)	
NUMBER OF KIDS	6.37		195.40	
	(0.37)		(4.41)	
MOVEOUT OF HOME	−110.81		18.34	
	(−1.31)		(0.33)	
NO MUM AT HOME	−430.18		383.63	
	(−2.93)		(4.65)	
RESID		-2.7630×10^{-3}		1.2314×10^{-2}
		(−0.350)		(0.272)
RESID2		5.0240×10^{-6}		1.2172×10^{-5}
		(0.896)		(0.121)
RESID3		-1.2586×10^{-9}		-5.0680×10^{-8}
		(−0.389)		(−0.124)
RESID4		-1.4990×10^{-12}		1.5611×10^{-11}
		(−0.936)		(0.738)

[a] Figures in parentheses are t-ratios.

References

Akerlof, G.A., 1997. Social distance and social decisions. Econometrica 65, 1005–1027.

Akerlof, G.A., 1998. Men without children. The Economic Journal 108, 287–309.

Altug, S., Miller, R., 1993. The effects of aggregate shocks and job experience on female labor supply and anticipation. Mimeo. Department of Economics, University of Minnesota.

Anderson, E., 1999. Code of the Street: Decency, Violence, and the Moral Life of the Inner City. W.W. Norton, New York.

Becker, G., 1991. A Treatise on the Family. Harvard University Press, Cambridge, MA.

Becker, G., 1968. Crime and punishment: An economic approach. Journal of Political Economy 76, 169–217.

Benveniste, L.M., Scheinkman, J.A., 1979. On the differentiability of the value function in dynamic models of economies. Econometrica 47, 727–732.

Burdett, K., Lagos, R., Wright, R., 2003. Crime, inequality, and unemployment. The American Economic Review 93, 1764–1777.

Carrasco, M., Florens, J.P., 2002. Simulation-based method of moments and efficiency. Journal of Business and Economic Statistics 20, 482–492.

Coleman, J.S., 1988. Social capital in the creation of human capital. American Journal of Sociology 94, S95–S120.

Ehrlich, I., 1973. Participation in illegitimate activities: A theoretical and empirical investigation. Journal of Political Economy 81, 521–565.

Figlio, R., 1994. Self-reported and officially defined offenses in the 1958 Philadelphia birth cohort. In: NATO ASI, Series D. Behavioral and Social Sciences 76, 267–280.

Figlio, M., Tracy, P.E., Wolfgang, M.E., 1990. Delinquency in a birth cohort II: Philadelphia 1958–1986: Computer file, second release, Philadelphia, PA. Sellin Center for Studies in Criminology and Criminal Law and National Analysts, Division of Booz-Allen and Hamilton, Inc. Producers, Ann Arbor, MI. ICPSR 1991.

Flinn, C., 1986. Dynamic models of criminal careers. In: Blumstein, A., et al. (Eds.), Criminal Careers and 'Career Criminals', vol. II. National Academy Press, Washington, DC, pp. 356–379.

Freeman, R.B., 1991. Employment and earnings of disadvantaged young men in a labor short economy. In: Jencks, C., Peterson, P.E (Eds.), The Urban Underclass. Brookings Institute, Washington, DC.

Gallant, R., Tauchen, G., 1996. Which moments to match. Econometric Theory 12, 657–681.

Grogger, J., 1995. The effect of arrests on employment and earnings of young men. Quarterly Journal of Economics 110, 51–72.

Grogger, J., 1998. Market wages and youth crime. Journal of Labor Economics 16, 765–791.

Hansen, L.P., 1982. Large sample properties of generalized method of moments estimators. Econometrica 50, 1029–1054.

Huh, K., Sickles, R.C., 1994. Estimation of the duration model by nonparametric maximum likelihood, maximum penalized likelihood and probability simulators. Review of Economics and Statistics 75, 683–694.

Imai, S., Krishna, K., 2004. Employment, dynamic deterrence and crime. International Economic Review 45, 845–872.

Imrohoroglu, A., Merlo, A., Rupert, P., 2000. On the political economy of income redistribution and crime. International Economic Review 41, 1–25.

Laub, J.H., Sampson, R.J., 1993. Turning points in the life course: Why change matters to the study of crime. Criminology 31, 301–325.

Leung, S.F., 1994. An economic analysis of the age–crime profile. Journal of Economic Dynamics and Control 18, 481–497.

Lochner, L., 2004. Education, work, and crime: A human capital approach. International Economic Review 45, 811–843.

Lucas, R.E., 1978. Asset prices in an exchange economy. Econometrica 46, 1426–1445.

Maasoumi, E., 1986. The measurement and decomposition of multi-dimensional inequality. Econometrica 54, 991–997.

Maasoumi, E., 1989. Continuously distributed attributes and measures of multivariate inequality. Journal of Economics 42, 131–144.

Maasoumi, E., 1993. A compendium to information theory in economics and econometrics. Econometric Reviews 12, 137–181.

McFadden, D., 1989. A method of simulated moments for estimation of discrete response models without numerical integration. Econometrica 57, 995–1026.

Miller, E., Cohen, M., Wiersema, B., 1996. Victim Costs and Consequences: A new Look. National Institute of Justice Research Report.

Miller, R., 1997. Estimating models of dynamic optimization with microeconomic data. In: Pesaran, M., Schmidt, P. (Eds.), Handbook of Applied Econometrics, vol. 2. Basil Blackwell, Oxford, pp. 246–299.

Moffit, R. (Ed.), 1994. Symposium on simulation methods in econometrics. Journal of Business and Economic Statistics 76, 591–702.

Pakes, A., Pollard, D., 1989. Simulation and the asymptotics of optimization estimates. Econometrica 57, 1027–1058.

Quetelet, A., 1984. Research on the propensity for crime at different ages, (Trans. Sawyer Sylvester) Anderson, Cincinnati, OH.

Rincon-Zapatero, J.P., Santos, M.S., 2007. Differentiability of the value function without interiority assumptions. Universidad Carlos III De Madrid. Working Paper 07-14.
Rust, J., 1994. Estimation of dynamic structural models, problems and prospects: Discrete decision processes. In: Sims, C. (Ed.), Advances in Economics, Sixth World Congress, vol. II. Cambridge University Press, Cambridge, pp. 119–170.
Rust, J., 1995. Numerical and dynamic programming in economics. In: Amman, H., Kendrick, D., Rust, J. (Eds.), Handbook of Computational Economics. Elsevier, Amsterdam.
Sampson, R.J., Laub, J.H., 1993. Crime and deviance in the life course. Annual Review of Sociology 18, 63–84.
Sellin, T., Wolfgang, M.E., 1964. The Measurement of Delinquency. John Wiley and Sons, New York.
Sickles, R.C., Williams, J., 2006. An intertemporal model of rational criminal choice. In: Baltagi, B.H. (Ed.), Panel Data Econometrics: Theoretical Contributions and Empirical Applications. Elsevier Science, Amsterdam, pp. 135–166.
Vella, F., 1998. Estimating models with sample selection bias: A survey. Journal of Human Resources 33, 127–172.