



REFERENCE ONLY

UNIVERSITY OF LONDON THESIS

Degree *PhD* Year *2008* Name of Author *Cozzi, Marco*

**COPYRIGHT**

This is a thesis accepted for a Higher Degree of the University of London. It is an unpublished typescript and the copyright is held by the author. All persons consulting this thesis must read and abide by the Copyright Declaration below.

**COPYRIGHT DECLARATION**

I recognise that the copyright of the above-described thesis rests with the author and that no quotation from it or information derived from it may be published without the prior written consent of the author.

**LOANS**

Theses may not be lent to individuals, but the Senate House Library may lend a copy to approved libraries within the United Kingdom, for consultation solely on the premises of those libraries. Application should be made to: Inter-Library Loans, Senate House Library, Senate House, Malet Street, London WC1E 7HU.

**REPRODUCTION**

University of London theses may not be reproduced without explicit written permission from the Senate House Library. Enquiries should be addressed to the Theses Section of the Library. Regulations concerning reproduction vary according to the date of acceptance of the thesis and are listed below as guidelines.

- A. Before 1962. Permission granted only upon the prior written consent of the author. (The Senate House Library will provide addresses where possible).
- B. 1962-1974. In many cases the author has agreed to permit copying upon completion of a Copyright Declaration.
- C. 1975-1988. Most theses may be copied upon completion of a Copyright Declaration.
- D. 1989 onwards. Most theses may be copied.

***This thesis comes within category D.***

This copy has been deposited in the Library of \_\_\_\_\_

This copy has been deposited in the Senate House Library, Senate House, Malet Street, London WC1E 7HU.



Essays on Macroeconomic Models of Crime and the Labor  
Market

Marco Cozzi

A Dissertation submitted to the Department of Economics  
in partial fulfilment of the requirements for the degree of  
Doctor of Philosophy  
University College London

January 2008, London



UMI Number: U592540

All rights reserved

INFORMATION TO ALL USERS

The quality of this reproduction is dependent upon the quality of the copy submitted.

In the unlikely event that the author did not send a complete manuscript and there are missing pages, these will be noted. Also, if material had to be removed, a note will indicate the deletion.



UMI U592540

Published by ProQuest LLC 2013. Copyright in the Dissertation held by the Author.  
Microform Edition © ProQuest LLC.

All rights reserved. This work is protected against  
unauthorized copying under Title 17, United States Code.



ProQuest LLC  
789 East Eisenhower Parkway  
P.O. Box 1346  
Ann Arbor, MI 48106-1346

# Contents

<b>1</b>	<b>Introduction</b>	<b>13</b>
<b>2</b>	<b>Hard Drugs Addiction, Drug Violations and Property Crimes in the US</b>	<b>16</b>
2.1	Introduction . . . . .	16
2.1.1	Related Literature . . . . .	20
2.2	Hard Drugs and Crime in the US: the Empirical Evidence . . . . .	23
2.2.1	Data Sources . . . . .	23
2.2.2	Some Basic Facts . . . . .	26
2.3	The Model . . . . .	37
2.3.1	Demographics . . . . .	39
2.3.2	Preferences . . . . .	39
2.3.3	Endowments . . . . .	41
2.3.4	Criminal Opportunities . . . . .	42
2.3.5	Government . . . . .	45
2.3.6	Technology . . . . .	46
2.3.7	Timing . . . . .	46
2.4	Equilibrium . . . . .	46
2.4.1	Problem of the agents . . . . .	47
2.4.2	Recursive Stationary Equilibrium . . . . .	48
2.5	SMM Estimation and Numerical Solution . . . . .	51
2.5.1	Sources of Identification . . . . .	53
2.5.2	Model Fit . . . . .	58
2.6	Results . . . . .	63
2.6.1	Hard Drugs Vs. Property Crimes . . . . .	64
2.6.2	The Effects of an Ideal Treatment Technology . . . . .	65

2.6.3	A Legalization Experiment . . . . .	65
2.7	Discussion and Conclusions . . . . .	67
2.8	Appendix A - The Full Recursive Representation . . . . .	70
2.9	Appendix B - UCR . . . . .	72
2.10	Appendix C - Solution Algorithm . . . . .	73

**3 Accounting for the Racial Property Crime Gap in the US: A Quantitative Equilibrium Analysis** **75**

3.1	Introduction . . . . .	75
3.1.1	Related Literature . . . . .	77
3.2	Empirical Evidence . . . . .	79
3.3	The Baseline Model . . . . .	85
3.3.1	Demographics . . . . .	86
3.3.2	Preferences . . . . .	87
3.3.3	Endowments . . . . .	87
3.3.4	Property Crimes . . . . .	88
3.3.5	Government . . . . .	88
3.3.6	Technology . . . . .	89
3.3.7	Other market arrangements . . . . .	89
3.3.8	Timing . . . . .	90
3.4	Equilibrium . . . . .	90
3.4.1	Households' Problem . . . . .	90
3.4.2	Recursive Stationary Equilibrium . . . . .	92
3.5	Calibration and Computation . . . . .	94
3.6	Results . . . . .	96
3.6.1	Policy Functions . . . . .	96
3.6.2	Who Commits Crimes? . . . . .	101
3.6.3	Model Vs. Data . . . . .	103
3.6.4	Experiments . . . . .	104
3.7	Discussion and Conclusions . . . . .	107
3.8	Appendix A - Solution Algorithm . . . . .	108

<b>4</b>	<b>Severance Payments: Equilibrium Welfare Effects in a Model with Heterogeneous Workers</b>	<b>110</b>
4.1	Introduction . . . . .	110
4.2	The Economy . . . . .	112
4.2.1	Demographics . . . . .	112
4.2.2	Preferences . . . . .	112
4.2.3	Endowments . . . . .	113
4.2.4	Technology . . . . .	113
4.2.5	Search frictions and labor markets . . . . .	114
4.2.6	Mutual Fund . . . . .	115
4.2.7	Other market arrangements . . . . .	115
4.2.8	Government . . . . .	115
4.2.9	Wage setting . . . . .	116
4.3	Stationary Equilibrium . . . . .	116
4.3.1	Problem of the agents . . . . .	116
4.3.2	Recursive Stationary Equilibrium . . . . .	120
4.4	Parameterization . . . . .	122
4.5	Results . . . . .	125
4.5.1	Wage profiles . . . . .	126
4.5.2	Equilibrium Effects . . . . .	128
4.5.3	Welfare Effects . . . . .	130
4.6	Discussion and Conclusions . . . . .	131
4.7	Appendix A - Computation . . . . .	132
4.8	Appendix B - Solution Algorithm . . . . .	134

# List of Tables

2.1	Prevalence of Hard Drugs Use - US Population, Males 16+ (Source: NHSDA 1996) . . . . .	27
2.2	Prevalence of Hard Drugs Use - US Inmates, Males 16+ (Source: Survey of Inmates 1996) . . . . .	27
2.3	Unemployment Rates by Drug Use - US Inmates (Source: Survey of Inmates 1997) . . . . .	33
2.4	Unemployment Rates by Drug Use - US Population (Source: NHSDA 1996)	33
2.5	Fired Because of Drug Use (Source: Survey of Local Jails Inmates 1996) . .	34
2.6	First Stage - Calibration . . . . .	55
2.7	Log Wage Regression, t statistics in parenthesis (Source: CPS 1996) . . . .	56
2.8	Actual Prison Time and Probability of Leaving Prison After One Period, By Offense Type (Source: NCRP 1996) . . . . .	56
2.9	Second Stage - SMM Estimation . . . . .	59
2.10	Model Fit - Simulations Vs. Data . . . . .	62
2.11	Hard Drugs Vs. Property Crimes . . . . .	64
2.12	The Effects of an Ideal Treatment . . . . .	65
2.13	A Hard Drugs Legalization Policy . . . . .	66
3.1	Race of Robbery Offenders - NCVS . . . . .	82
3.2	Property Crimes in the NLSY97 - 2001 . . . . .	83
3.3	Calibration . . . . .	97
3.4	Shares of Specific Groups Committing Crimes . . . . .	103
3.5	Model Vs. Data . . . . .	104
3.6	Counterfactual Experiments . . . . .	106
3.7	Policy Experiments . . . . .	107



4.1	Calibration . . . . .	123
4.2	Log Earnings Regression. t statistics in parenthesis (Source: CPS Feb 1996)	125
4.3	Equilibrium . . . . .	129
4.4	Equilibrium normalized by output in the benchmark economy . . . . .	129
4.5	Welfare Effects of the SP . . . . .	130

# List of Figures

2.1	Cocaine, Crack and Heroin Use - Age Distribution (Source: NHSDA 1996) .	29
2.2	Cocaine, Crack and Heroin Age at First Use - Age Distribution (Source: NHSDA 1996) . . . . .	30
2.3	Cocaine - Age at First Use (Source: NHSDA, several years) . . . . .	30
2.4	Number and shares of arrests, by type of Drug Law Violation (Source: UCR, several years) . . . . .	31
2.5	Inmates Hard Drugs Expenditure (Source: Survey of Local Jails Inmates 1996) . . . . .	32
2.6	Property crime (PC) and Drug abuse violations (DV) arrest rate by age (Source: UCR 1996) . . . . .	35
2.7	Cocaine and Heroin shares in the DEA seizures (Source: US Dept of Justice (2003)) . . . . .	54
2.8	Property Crimes - Policy Functions by Age (Employed - Drop Outs - Average Shock) . . . . .	60
2.9	Model Fit - Unemployment Rates by Age and Education . . . . .	63
3.1	Property crimes arrest rates per 100.000 males by race (Whites, blue line and right scale). Source: Uniform Crime Reports, FBI . . . . .	80
3.2	FBI Arrest Rates By Race Ratio . . . . .	81
3.3	Property Crime Rates and Share of Blacks in the US states, 2000. . . . .	82
3.4	Black (top) and White (bottom) Men (16+) Unemployment Rates . . . . .	84
3.5	Males Average and Median Unemployment Durations . . . . .	85
3.6	Saving Functions (Whites - Dropouts) . . . . .	98
3.7	Saving Functions (Blacks - Dropouts) . . . . .	99
3.8	Consumption Functions (Blacks - Dropouts and College) . . . . .	100
3.9	Crime Functions (Blacks - Unemployed) . . . . .	101

3.10 Crime Functions (Blacks - Dropouts) . . . . . 102  
3.11 Crime Functions (Whites - Dropouts) . . . . . 102  
  
4.1 The effects of SP on the Wage Profile (No Tenure) . . . . . 126  
4.2 The effects of SP on the Wage Profile (Tenure=1) . . . . . 127  
4.3 Workers Marginal Distributions over Productivity and Tenure . . . . . 128

## **Abstract**

This thesis develops three dynamic quantitative equilibrium models with heterogeneous agents, tackling issues related to the criminal participation of individuals and the labor market.

The first chapter studies the effect of hard drugs addiction on property crimes and hard drugs selling in the US. A dynamic equilibrium model quantifying how much of the observed property crime rate is accounted for by hard drugs addiction is specified and estimated. The model is framed in both a rational addiction and a rational crime participation environment. The results show that a substantial part of property crimes, approximately 26%, is accounted for by predatory crime to finance addiction. The estimated model is in turn used to quantify the economic consequences of a compulsory drug treatment scheme for all arrested felons, and the effects of a legalization policy. The first policy experiment suggests a decrease in the property crime rate by 11%, while under the new legal regime the property crime rate is found to decrease by 18%.

The second chapter studies the effects of both labor market conditions and asset poverty on the property crimes involvement of American males. The property crimes arrest rate has consistently been four times higher for black males if compared to white ones. Another set of stylized facts show for the first demographic group lower educational levels and worse labor market performances. A dynamic equilibrium model is developed, exploiting these facts to quantitatively assess the race crime gap. The model is calibrated relying on US data and solved numerically. Simulation results show that the observed poverty and labor market outcomes account for as much as 90% of the arrest rates ratio. Finally, the model is used to compare two alternative policy experiments aimed at reducing the aggregate crime rate: increasing the expenditure on police seems to be cost effective, when compared to an equally expensive lump-sum subsidy targeted to the high school dropouts.

The last chapter studies the equilibrium welfare effects of introducing mandated severance payments in a labor market with costly mobility, where self-insurance through a riskless asset is the only way to smooth fluctuations in labor income due to unemployment shocks. The framework allows for wage flexibility at the level of the individual firm-worker match. Wages vary with both tenure and productivity of the workers. When severance payments are introduced, the firm can potentially undo their effect by modifying the wage profile. Workers entry wages fall by the expected present value of the future payment. However, because of incomplete markets, workers are unlikely to be indifferent

about the slope of the wage profile. The model is solved numerically and calibrated to the US economy. We compare a welfare measure for the baseline economy, i.e. without severance payments, to those of a series of counterfactual economies where the severance payments are introduced at increasing levels. Welfare gains and costs are heterogeneous in the population but seem to be quantitatively small for plausible values of the severance payments.

## **Acknowledgements**

During the time span needed to complete my PhD I have had the chance to interact with many interesting, exciting and inspiring people. Marco Airaud, Renata Bottazzi, Chiara Binelli, Carlos Henrique Corseuil, Marco Cosconati, Arianna Degan, Mario Fiorini, Miguel Foguel, Giovanni Gallipoli, Daniela Iorio, Elena Martinez-Sanchis, Andrea Mattozzi, Makoto Nakajima, Josep Pijoan-Mas, Elena Pastorino, Marina Pavan, Chiara Scotti, Katrien Stevens, and Melissa Tartari shared with me the good and the bad times.

I would also like to thank some former students of mine, with whom we managed to surpass the teacher-pupil relationship and build a friendship. Anjali and Julieta in particular.

I am extremely grateful to the Economics Department at the University of Pennsylvania for hosting me during two very long visits. Professor Victor Ríos-Rull was the first person taking care of me and making this fruitful experience possible. From the beginning of my second visit Professor Antonio Merlo 'adopted' me academically (and not only). They have been two challenging and inspiring figures, not only during my Philadelphia times, but also in the current days.

Prof. Gianluca Violante has represented an endless source of knowledge accumulation, provided sharp intellectual stimulus and helped me in countless occasions. It is now very clear to me that his influence has shaped me both as a researcher and as a person. His high quality research, professional but human attitude, and outstanding teaching have been an example and a constant reference point for me and the other students specializing in Macroeconomics at UCL.

I take this opportunity to extend my most sincere thanks and appreciation to Nicola Pavoni and Antonio Merlo, my supervisors at UCL and UPENN, respectively. They have been extremely patient and very encouraging with me. They were always available and I truly learned a lot from my discussions with them. They were demanding and challenging, but very optimistic at the same time. They made everything possible for my PhD to be an amazing learning and personal experience. Their high expectations and constant quest for the best possible answer to a question have sometimes been tough to cope with, but they taught me not to settle for less and to try to give everything I have got to achieve my goals.

On a less serious ground, I would like to acknowledge Ibanez, Charvel, Mesa, John, Mike, Jordan, John, James, Steve, Joe, Tori, Lene, Suzanne, Carmen, Daniele, Ludovico

and Giovanni for filling my non economics time and recharging my batteries.

To conclude with, I would like to thank my parents, Gisella and Enrico, and my sister, Laura. They have always been there for me during all these years, willing to help me in case I had to rely on them for literally anything, from trivial matters to extremely delicate issues I had to deal with.

I wish to dedicate this work to them.

## **Declaration**

1. No part of this thesis has been presented to any University for any degree.
2. Chapter Four was undertaken as joint work with Giulio Fella, Queen Mary College, and Gianluca Violante, New York University.

Marco Cozzi



# Chapter 1

## Introduction

The following three chapters, which constitute the original contributions of this thesis, specify, parametrize and numerically solve heterogeneous agents economies tackling issues related to hard drug abuse, criminal participation, the role of specific labor market institutions, and the equilibrium evaluation of public policies.

Although the questions asked in each chapter are intrinsically different, there are several common themes linking the various parts of the dissertation.

The first shared feature is the framework in which each model is built. This thesis relies on economies with incomplete markets: this assumption is a crucial one if the goal of the researcher is to address questions related to distributional issues, welfare consequences of public policies and heterogeneous outcomes.

The heterogeneity of the agents interacting in the model economies is another common feature, closely related to the one just introduced. The heterogeneity has always two layers: the individuals differ both from an *ex-ante* perspective and from an *ex-post* one. The stochastic processes capturing the uncertainty in the various economies are such that the individuals are going to differ in an *ex-post* sense in several dimensions. More precisely, changes in the labor market status are going to be affected by a series of shocks that the agents face during their lifetimes. Moreover, the agents are going to differ in some endogenously accumulated state variable, the stock of habits in a model of rational addiction, and the asset holdings in both a model of property crimes and in a model of insurance against the labor market risk.

The equilibrium concept will be in all three models the recursive stationary competitive one. The equilibria we are going to look at are the ones characterized by a stationary

distribution over the state variables.

Given the richness of the models, their analytical characterization cannot be obtained. The models are then solved relying on sophisticated numerical techniques and simulation procedures.

The three chapters provide a combination of calibration, classical regression analysis and structural estimation to parametrize the models. When simple techniques are not deemed appropriate, or are not applicable because of lack of data, more challenging and rigorous estimation procedures are implemented, which try to take into account the selection and endogeneity problems arising in the set-up under consideration.

Finally, the overlap among the models is also represented by their attempt to evaluate several public policies on the basis of counterfactual analysis. The parametrized models are used both as a measurement device to quantify the relative importance of several factors in accounting for the observed outcome under analysis and to assess the equilibrium response arising from a change in public intervention, aimed at improving the welfare of the agents.

Interestingly, as far as the demographic structure is concerned, the models span all possibilities: overlapping generations, the dynastic framework and the perpetual youth model. The choice is dictated by the question addressed and by the superior tractability that one of the alternatives ensures if compared to the others.

More in detail, this thesis develops three dynamic stochastic equilibrium models to analyze issues related to the criminal participation of individuals and the labor market.

The second chapter studies the effect of hard drugs addiction on property crimes and hard drugs selling in the US. A dynamic equilibrium model quantifying how much of the observed property crime rate is accounted for by hard drugs addiction is specified and estimated. The model is framed in both a rational addiction and a rational crime participation environment. We exploit information on drug use in the American population, hard drugs expenditure, property crimes and drug abuse violations, obtained from the National Household Survey on Drug Abuse, the Surveys of Inmates, and the Uniform Crime Reports of the FBI, respectively. The equilibrium features of the model allow to pin down the response of hard drugs consumers to changes in prices, as well as to compute the revenues from drug selling, variables which are not available in the existing data. Moreover, the equilibrium framework allows to exploit data asked exclusively to inmates: by taking the selection problem explicitly into account, the model can predict moments which are representative of the whole population. The results show that a substantial part of property crimes, approximately 26%, is accounted for by predatory crime to finance addiction. The

estimated model is in turn used to quantify the economic consequences of a compulsory drug treatment scheme for all arrested felons, and the effects of a legalization policy. The first policy experiment suggests a decrease in the property crime rate by 11%, while under the new legal regime the property crime rate is found to decrease by 18%.

The third chapter studies the effects of both labor market conditions and asset poverty on the property crimes involvement of American males. The property crimes arrest rate has consistently been four times higher for black males if compared to white ones. Another set of stylized facts show for the first demographic group lower educational levels and worse labor market performances. A dynamic equilibrium model is developed, exploiting these facts to quantitatively assess the determinants of the racial crime gap. The model is calibrated relying on US data and solved numerically. Simulation results show that the observed poverty and labor market outcomes account for as much as 90% of the arrest rates ratio. Finally, the model is used to compare two alternative policy experiments aimed at reducing the aggregate crime rate: increasing the expenditure on police seems to be cost effective, when compared to an equally expensive lump-sum subsidy targeted to the high school dropouts.

The last chapter studies the equilibrium welfare effects of introducing mandated severance payments in a labor market with costly mobility, where self-insurance through a riskless asset is the only way to smooth fluctuations in labor income due to unemployment shocks. The framework allows for wage flexibility at the level of the individual firm-worker match. Wages vary with both tenure and productivity of the workers. When severance payments are introduced, the firm can potentially undo their effect by modifying the wage profile. Workers entry wages fall by the expected present value of the future payment. However, because of incomplete markets, workers are unlikely to be indifferent about the slope of the wage profile. The model is solved numerically and calibrated to the US economy. We compare a welfare measure for the baseline economy, i.e. without severance payments, to those of a series of counterfactual economies where the severance payments are introduced at increasing levels. Welfare gains and costs are heterogeneous in the population but seem to be quantitatively small for plausible values of the severance payments.

## Chapter 2

# Hard Drugs Addiction, Drug Violations and Property Crimes in the US

### 2.1 Introduction

Drug use, drug selling and property crimes are important phenomena in the US. Given the size of the US criminal justice system and the number of inmates convicted for these offenses, it is clear that they are very expensive and affect the lives of many Americans. For example, in 2003, the total justice expenditure attributable to those crimes was above 170 billions and more than one and a half million people were behind bars because of such crimes, US Dept of Justice (2003). Moreover, these numbers heavily underestimate the actual economic costs of drugs and crime: as suggested by Miron (2004), the income losses of the victims of crimes, the health costs induced by drug abuse, the foregone production of both convicted criminals and drug abusers should be added to the previous figure. Some economists and criminologists estimate the total burden for the US economy at more than 300 billions.

Despite widespread interest in the topic, little is known on the relationship among hard drugs addiction, drug selling and property crimes. This chapter provides an attempt to shed more light on these complex phenomena. More in detail, we want to address the following questions: How much of the property crime rate is accounted for by hard drugs addicts stealing in order to pay for their consumption of drugs? What would be

the effect on both the property crime rate and the drug violations of effective treatment schemes targeted at arrested felons? How do hard drugs prices and consumption respond to policies that modify the severity of the criminal justice system? What would be the consequences of legalizing such substances?

The following analysis tries to answer these questions in the context of both the rational addiction theory of Becker and Murphy (1988) and the rational crime participation framework of Becker (1968). A dynamic equilibrium model of hard drugs addiction, hard drugs selling at the street level and involvement in property crimes is specified and estimated. This represents a novelty in the economics of crime literature, surveyed for example in DiIulio (1996), Ehrlich (1996), and Freeman (1996), since the previous contributions have focused mainly on the role of unemployment, poor legitimate economic opportunities, effectiveness of police and severity of the punishment in shaping the criminal decisions.<sup>1</sup>

This paper considers a channel complementary to the ones outlined above, namely hard drugs. Hard drugs are extremely expensive goods, a fact which has been mainly attributed, by Miron (2003) among others, to their illegal nature. Not only are hard drugs expensive, but also they are addictive, Leshner (1997), implying that regular hard drugs users spend an increasing share of their income to finance their habit. Studies conducted on convicted criminals, as reported by Chaiken and Chaiken (1990), show that hard drugs abusers spend up to 90% of their total income to finance their addiction, considering both legal and illegal sources. On the other hand, hard drugs represent also a source of income, since addicts tend to be involved in drug dealing at the street level, Reuter, MacCoun and Murphy (1990) and Wilson and Abrahamse (1992). In light of these considerations, it seems reasonable to think that hard drugs play an important role in affecting the number of property crimes in the US.

The nexus between hard drugs and property crimes has been studied extensively in the sociology and criminology literatures, as surveyed by Wish and Johnson (1986). Quite surprisingly, unlike in other disciplines, the economics research has devoted far less attention to the relationship between drugs and crime, even though there seems to be a growing interest in this phenomenon, Becker, Murphy and Grossman (2006), Caulkins, Reuter and Taylor (2006), Corman and Mocan (2000) and Grogger and Willis (2000). A plausible explanation is the lack of rich and large datasets, representative of the US population at a

---

<sup>1</sup>Notable exceptions considering the effect of drugs on crime are Corman and Mocan (2000) and Grogger and Willis (2000). The strengths and limitations of these contributions, and the differences from this paper will be discussed in the related literature section.

more detailed level than the national one, including information on both current and past drug abuse, variables necessary to conduct classical econometric analysis. At the available level of aggregation, it is impossible to rely on any measure of punishment of the criminal justice system, making room for omitted variable bias in econometric models of crime.

Although there is no a definitive answer on whether drug abuse causes crime or the other way round, there seems to be a strong link between the two variables. From an empirical perspective, due to the lack of high quality longitudinal data on hard drugs use, it is very challenging to identify the direction of causation.<sup>2</sup> From a theoretical point of view, there are mainly three possible hypotheses that can describe the relationship between crime and drug abuse. Possibly, the most common point of view is that drug abuse causes property crimes. According to this interpretation, drug users develop an addiction over time, which is both detrimental for the likelihood of employment and very costly to finance, hence the involvement in property crimes. The second hypothesis is embraced mostly by behaviorist scholars, as discussed in Gruber (2001). In their view there are several environmental factors, such as growing up in a dysfunctional family, that drive youths to get involved in risky behaviors. Youths start from minor misdemeanors and, by climbing the risk ladder, step by step they get into abusing drugs. Notice that, in their view, drug use is also made possible thanks to the (small) amount of money made during this "criminal career". The third hypothesis considers drug abuse and crimes as interrelated phenomena, which are determined through the evaluation of similar trade-offs.

This paper relies on a framework which is somewhat in between of the first and third interpretations. Agents choose in each period of their finite lives whether to be involved in income generating crimes and in using drugs. The consumption of hard drugs involves the accumulation of a stock of habits, which affects the likelihood of employment. The higher the stock of habits, the more likely an agent is to be unemployed. Moreover, individuals are hit by shocks during their life-cycle, which affect the utility they get from using hard drugs. In this sense, the model extends the rational additional framework, allowing for both a stochastic marginal rate of substitution between drugs and (legal)

---

<sup>2</sup>The majority of studies discussed in Wish and Johnson (1986) are based on samples of small size and that rarely satisfy basic criteria of representativeness. Usually the unit of analysis are people taking part in various treatment programs, that is they are part of a choice based sample. The NLSY is one of the few longitudinal studies providing information on both drug use and crime. However, it seems likely that sample attrition does not happen randomly, being the hard drug abusers more probable to drop out from the study as time goes by. For a study based on UK data see Pudney (2003).

consumption and for stochastic legitimate opportunities that depend on the accumulated stock of habits. People who consume drugs heavily accumulate a large stock of habits: this increases the probability of an unemployment spell and, at the same time, the likelihood of being convicted through a reinforcement effect. The latter implies that drug consumption, drug selling and property crimes are all increasing functions in the stock of habits. Due to the presence of uninsurable unemployment risk, addicts in this framework are not necessarily "happy". Ex-ante they make rational choices taking into consideration all the negative effects of both drug consumption and involvement in criminal activities. Ex-post, according to the realization of the shocks, they can be "unhappy".

In order to assess the effect of hard drugs abuse on property crimes a quantitative equilibrium framework is developed. The model considers the endogenous response of the market for hard drugs, which is affected by several elements. The likelihood of the punishment for each illegal activity and the related severity of the criminal justice system, the competition between street level drug sellers together with the conditions of demand affect the hard drugs equilibrium price and quantity. Notice that the equilibrium features of the model allow to pin down both the response of hard drug consumers to changes in prices and to compute the revenues from drug selling, variables which are not available in the existing data. Moreover, the equilibrium framework allows to exploit information asked exclusively to inmates: by taking explicitly into account the selection problem, the model can predict moments which are representative of the whole population.

The model is estimated in two steps. First, a subset of the parameters are obtained directly from several data sources. Second, a Simulated Method of Moments (SMM) procedure, Hansen (1992) and Gouriéroux and Monfort (1996), is implemented to search for the set of parameters that minimizes the weighted distance between a set of empirical moments and the same moments obtained by simulating the model. Once estimated, the model is then used as a measurement tool and as a device to perform counterfactual analysis.

The results show that a substantial part of property crimes, about 26%, is accounted for by predatory crime to finance hard drugs addiction. This value is obtained by comparing the property crime rate of the baseline economy (4.3%) to that of a counterfactual economy where hard drugs do not exist (3.18%). This finding provides a measure of the magnitude of a specific kind of negative externalities, the ones driven by predatory crime, which make room for public intervention.

We consider policy experiments aimed at reducing the property crime rate, by affecting

the conditions in the market for hard drugs. Namely, the economic consequences of an ideal drug treatment scheme for all arrested felons are computed: such a policy would decrease the property crime rate by 11%. Finally, with another counterfactual experiment, we assess the effects of a legalization policy: under this new regime, the property crime rate would decrease by 18%. Such counterfactual analysis gives a sense of the potential benefits and the detrimental effects of policies alternative to the current ones and called by many commentators and scholars, e.g. Friedman (1991), MacCoun and Reuter (2001) and Miron (2004).

### **2.1.1 Related Literature**

Several contributions are related to this paper. We briefly discuss them in what follows.

One of the most influential papers on addiction in the economics literature is Becker and Murphy (1988). Becker and Murphy develop a theory of rational addiction: agents are assumed to be fully rational when deciding on the consumption of addictive goods, taking into account the future (negative) effects of their choices. One of the most important implications of this framework is the lack of usefulness of public policy interventions. Individuals make optimal choices, hence any attempt to forcefully reduce their drug consumption would lead to a welfare loss. The rational addiction framework has been tested empirically by Becker, Grossman and Murphy (1994), among others, with an application to cigarettes smoking. Their findings are in favor of the rational addiction model. Another contribution, Adda and Lechene (2001), structurally estimates a version of the rational addiction model: also their results support the empirical validity of the rational theory of addiction.

The empirical successes of the rational addiction hypothesis notwithstanding, the paradigm has been challenged by several authors.

In a series of papers, Orphanides and Zervos (1994), (1995) and (1998), the two authors assess one of the main critiques to the rational framework: in Becker and Murphy's theory addicts are happy, i.e. there is no possibility of regret for their addiction. They do so by introducing either a learning framework or a myopic one. Notice that our model allows for addicts to be "unhappy", given the presence of uninsurable unemployment risk, which is affected by the hard drugs consumption decisions. Ex-post some addicts, in particular the heavily addicted ones, experience long unemployment spells, with associated low levels of consumption. These agents, when comparing their level of utility to that of employed



ones, regret the fact of having accumulated a large stock of habits, which at the same time makes them to participate more often into criminal activities and, in turn, spend more time in prison.

Another paper, Gruber and Koszegi (2001), depart from the rational addiction approach, by assuming that individuals have time inconsistent preferences. In their framework young individuals show a higher degree of impatience, since they discount the future consequences of their actions more heavily. The main message of this contribution is that people seem to be forward-looking with respect to addictive behaviors, but the policy implications of their model are very different from the standard rational addiction approach. Public intervention should take into account not only the externalities of consumption of addictive goods, but also what Gruber and Koszegi call "internalities", or the effects of addiction on the future selves.

Bernheim and Rangel (2004) propose a model of addiction based on some lessons learned from psychology, neuroscience and clinical practice. The model takes into account the fact that use among addicts can be a mistake, that drugs consumption leads to the development of environmental cues that trigger these mistakes, and that addicts understand and are capable of managing these cues. However, notice that in order to be implemented in an empirical study, this framework needs data on both the decision of consuming the drugs and the presence of the cues. To the best of our knowledge, this kind of data are not currently available, making the empirical test of the model and the study of its quantitative predictions very hard to implement.

More recently, Gul and Pesendorfer (2006) have developed a theoretical framework where agents can develop harmful addictions. They define a good as addictive if its consumption leads to more compulsive consumption of the same good, where consumption is compulsive if the individual would have made a different choice had commitment been available. The authors find that taxing drugs decreases welfare, while prohibition policies might increase it.

This paper relies on the rational addiction framework for at least two reasons: a) it is relatively simple, making the empirical implementation of the model more neat, b) there is evidence that hard drugs abusers (even the ones who recognize to have developed a tolerance to the drug) do not check-in into rehab programs, doing so only when forced by the criminal justice system, National Research Council (2001). This behavior can be considered consistent with rational drug users.

In an applied study, Corman and Mocan (2000) consider the relationship between

crime, deterrence and drug abuse in New York City. They rely on a high frequency time series framework over the period 1970-1990. Their results show that two out of three property crime categories are positively affected by a proxy of drug abuse, i.e. the growth rate of drug related deaths. However, their findings show a stronger effect on the crime rate of a deterrence variable, namely the growth rate of police officers. Unfortunately, the measure of drug use the authors rely on is far from being an ideal one. The change in the number of drug related deaths could have been due to the documented increase in the purity of hard drugs, which makes unexperienced users more at risk of physical damages, rather than to an increase in the population of hardcore users, possibly the relevant one for studies related to property crimes. To deal with such issues, our framework models explicitly the addiction process, making the stock of habits, i.e. the degree of addiction, endogenous.

Another empirical study of the effect of drugs on crime is Grogger and Willis (2000). The authors study whether the arrival of crack cocaine in inner cities is responsible for the rise in urban crime rates in the late 80's and early 90's. They rely on two different sources of information to date the emergence of crack in 27 metropolitan areas in the US and implement a difference-in-differences estimation strategy. Grogger and Willis consider the difference in the urban crime rate before and after the arrival of crack as the effect of the treatment. The second stage of differencing is taken with respect to the growth rate in crime in the suburbs of the same metropolitan area, which represents the outcome of the non treated group. The results show that the emergence of crack lead to a substantial increase in property crimes. Notice, however, that a likely effect that would imply biased estimates is the "migration" of criminals from inner cities to suburban areas. If the criminals substituted the targets of their crimes because of the response of police to an increased inner city crime, a general equilibrium effect would have taken place, contaminating the outcome of the control group: this would make the "Diff-in-Diff" estimator inconsistent.

Becker, Murphy and Grossman (2006) propose an analysis of illicit markets, with a focus on drug markets. They find that when the demand for a good is highly inelastic, the optimal policy to fight drug use consists of legalizing the good and taxing it, rather than prohibiting its legal use. Our analysis provides a quantitative comparison of these two different regimes.

Another stream of literature related to ours is the one trying to assess the price elasticity of addictive goods. Becker, Grossman and Murphy (1991) and van Ours (1995) are two

of the most widely cited references. The former contribution puts more emphasis on the theoretical considerations, while the latter provides empirical estimates for a particular drug (opium), in a particular period of time (1923-1938), in a particular place (Dutch East Indies).

Becker, Grossman and Murphy (1991) point out that the price elasticity of addictive goods is higher in the long run rather than in the short run, since the stock of addictive capital is fixed in the short run.

The beauty of van Ours (1995) consists of considering a period and a place where opium was legal, so that, in the empirical strategy, he can exploit quite reliable time series for both the price and the quantity consumed. His findings suggest an estimate of the short run elasticity of -0.7 and of the long run one of -1.0, corroborating the predictions of the rational addiction model.

To the best of our knowledge, this paper is the first contribution developing a dynamic general equilibrium model of drug addiction, drug selling and property crimes.

The rest of the chapter is organized as follows. Section 2 discusses some general facts related to crime participation and hard drugs use in the US. The theoretical model is presented in Section 3, while Section 4 is devoted to the definition of the equilibrium concept used in the model: the recursive competitive equilibrium. Section 5 presents the estimation procedure. Section 6 provides the main results and predictions of the model, while Section 7 concludes.

## **2.2 Hard Drugs and Crime in the US: the Empirical Evidence**

This Section is devoted to discuss the main facts about hard drugs and crime in the US. It consists of two parts. The first one provides a short description of the datasets that are going to be used in the empirical implementation of the model. The second one presents some descriptive statistics obtained from these datasets.

### **2.2.1 Data Sources**

In the US there are several data sources providing information about hard drugs and crime. This paper exploits data taken from the National Household Survey on Drug Abuse, the Surveys of Prison and Local Jail Inmates, the System To Retrieve Information on Drug

Evidence, the Uniform Crime Reports, the National Crime Victimization Survey and the National Corrections Reporting Program. Details on each dataset follow.

- National Household Survey on Drug Abuse (NHSDA)

The NHSDA, US Dept of Health and Human Services (1998), is designed to produce drug use incidence and prevalence estimates and to report the consequences and patterns of use and abuse in the general US civilian population aged 12 and older. Questions include age at first use, as well as lifetime, annual, and past-month usage for several drugs. Respondents are also asked about several demographic variables, including gender, race, age, ethnicity, level of education, job status, income level and household composition.

Public files are available for the period 1979-2004. However, the survey has been conducted on a yearly basis only since 1990. The NHSDA oversamples youth and minorities and implements several procedures to decrease the likelihood of under-reporting.

- Surveys of Prison and Local Jail Inmates (SI)

The SI, US Dept of Justice (2001) and US Dept of Justice (1999), provide nationally representative data on persons held in local jails, in state prisons or in federal correctional facilities. Data cover individual characteristics of inmates, current offenses, sentences and time served, criminal histories, jail/prison activities, conditions and programs, prior drug and alcohol use and treatment, and health care services provided while in jail/prison.

The surveys are available for the period 1977-2002, but they have been conducted irregularly, roughly every 5/6 years.

- System To Retrieve Information on Drug Evidence (STRIDE)

Since the 70's, the Drug Enforcement Agency (DEA) has been recording in STRIDE evidence obtained from seizures, purchases, and other drug acquisition activities conducted by undercover agents and informants. The database collects information on the type of drug obtained, the price paid, the quantity, the location and the date of purchase, together with the purity of the drug sample, an analysis performed in DEA laboratories.

The drug acquisitions data are available for the 1974-2003 period.<sup>3</sup>

---

<sup>3</sup>Horowitz (2001) and National Research Council (2001) discuss the limitations of the STRIDE data. Notice that, for the purpose of this study, the focus will be on the cross sectional distribution of prices in 1996, eliminating the problem of non comparability of prices over time. Still, relying on just one year,

- Uniform Crime Reports (UCR)

Since 1930, the Federal Bureau of Investigation (FBI) has compiled the UCR to serve as periodic nationwide assessments of reported crimes not available elsewhere in the criminal justice system. Each year participating law enforcement agencies contribute reports to the FBI either directly or through their state reporting programs. The UCR provides information on (reported) property crimes and the number of arrests by type of crime.

The period covered is 1930-2004.

- National Crime Victimization Survey (NCVS)

The NCVS is the primary source of information on criminal victimization in the US. Each year, data are obtained from a nationally representative sample of about 42,000 households comprising nearly 76,000 persons on the frequency, characteristics and consequences of criminal victimization in the United States.

The period covered is 1973-2004.

- National Corrections Reporting Program (NCRP)

The NCRP, US Dept of Justice (1998), provides a comprehensive description of prisoners entering and leaving the custody or supervision of state and federal authorities. The information included in the NCRP consists of the list of offenses the prisoners were convicted for, the actual time spent in prison (for the individuals leaving custody) and the maximum and minimum sentence length.

This reporting program began in 1983.

Finally, all labor market related statistics are computed from the Current Population Survey.

---

does not guarantee that the STRIDE represents a random sample of the drug market sales. In order to avoid the major problem of this dataset (the limited number of small size purchases and the debated representativeness of street level transactions) the model is going to specify explicitly the supply of drugs at the street level, making the price of hard drugs endogenous for these sales. Notice that the model is going to keep the drugs prices for high level dealers exogenous: however, these are likely to be the kind of dealers the STRIDE has been developed to keep track of. Moreover, the usual argument put forward by researchers relying on the STRIDE applies also in this case: the DEA undercover agents have to make their purchases at credible prices, otherwise they would endanger both themselves and the likelihood of success of the undercover operation. Finally, notice that these data currently represent the best source of information about prices of illegal drugs in the US. Other studies relying on the same dataset are, for example, Caulkins and Padman (1993), Dave (2004) and Kuziemko and Levitt (2004).

- Current Population Survey (CPS)

The CPS is a monthly survey of about 50.000 households conducted by the Bureau of the Census for the Bureau of Labor Statistics. The survey has been conducted for more than 50 years. It is the primary source of information on the labor force characteristics of the US population. The sample is scientifically selected to represent the civilian non-institutional population.

As a final remark, notice that all datasets, but STRIDE, are a representative sample of the population of interest, with a sufficiently large number of observations. Possibly, the major limitation of these data is related to the expenditure on drugs. This variable has been asked in the SI only once, in 1996, and refers to the 30 days before the arrest. As a consequence, in order to exploit such information, the empirical implementation of the model will focus on that year.

The following Section presents some descriptive statistics obtained from the datasets outlined above. The reported facts represent the characteristics of drug consumption and crime participation that motivate some modelling assumptions.

### 2.2.2 Some Basic Facts

For the sake of the analysis, it is necessary to take a stand on what a hard drug is. We consider as hard drugs the three following illegal substances: cocaine, crack and heroin.<sup>4</sup> As a matter of fact, studies on the potency of drugs, as discussed in Kaplan (1985) and Edwards and Lader (1991), provide evidence that these three are the most addictive ones, in increasing order. Moreover, they are by far the most commonly used and their prices are available in the STRIDE, unlike other less common drugs. A comprehensive description of both the production steps and the addictive properties of cocaine, crack and heroin can be found in Miron (2003) and UNODC (2003).

Notice that, when available, sample weights were used to compute the statistics reported below.

---

<sup>4</sup>Methamphetamine, or Meth, has become in more recent years quite a diffused hard drug. Unfortunately, in the NHSDA they started collecting information on this drug only after 1996.

### Prevalence of Hard Drugs Use (US Population Vs. Inmates, 1996)

Tables 1 and 2 provide estimates for the year 1996 of the prevalence of hard drugs use for both the general US population and the inmates one, respectively. As for the non-institutional population, such information is computed from the NHSDA.

<i>Hard Drugs Use - Population</i>	<i>Lifetime</i>	<i>Last Year</i>	<i>Last Month</i>
<i>Heroin</i>	2.13%	0.29%	0.14%
<i>Crack</i>	3.82%	1.13%	0.57%
<i>Cocaine</i>	17.5%	3.22%	1.53%

Table 2.1: Prevalence of Hard Drugs Use - US Population, Males 16+ (Source: NHSDA 1996)

The information on inmates is taken from the SI, and refers to periods of time before the arrest took place. To be consistent with the focus of the paper, only the inmates charged with Property Crimes (PC) or Drug Violations (DV) were selected. Notice that in both surveys only males at least 16 year old were kept in the sample.

<i>Hard Drugs Use - Inmates</i>	<i>Lifetime</i>	<i>Lifetime - PC</i>	<i>Last Month</i>	<i>Last Month - PC</i>
<i>Heroin</i>	20.27%	19.11%	6.96%	5.27%
<i>Crack</i>	38.64%	36.90%	13.97%	13.01%
<i>Cocaine</i>	46.31%	44.65%	10.56%	9.23%

Table 2.2: Prevalence of Hard Drugs Use - US Inmates, Males 16+ (Source: Survey of Inmates 1996)

As it is clear from the two tables, the most commonly used substance is cocaine, with a prevalence rate in the civilian population much higher than for the other two drugs. Notice also that this gap is less drastic for the inmates, and that in terms of prevalence rates there are no substantial differences between DV criminals and PC ones, the latter category being reported in the columns with the *PC* label. Not surprisingly, there are also major differences between the prevalence rates of the general non-institutional population and that of the convicted criminals. Part of this gap is due precisely to the fact that hard

drugs use is illegal in the US. However, notice that the size of the gap remains almost unchanged when focusing on the property crime felons.

From this set of figures we learn that most American males never use hard drugs, not even once, during their lifetime. They might be doing so for several reasons: 1) they don't like these substances; 2) hard drugs might hurt their employability, partially compromising their investment in human capital; 3) there might be informational problems, i.e. the actual addictive properties of these goods are not known and people abstain from consumption not being able to predict how they would be affected if they were to use them; 4) hard drugs use it's illegal, hence they refrain from consumption in order to avoid the punishment of the criminal justice system.

We also learn that people with the highest prevalence rates might be convicted and that the prevalence rate is decreasing in the potency of the substance.

### **Hard Drugs Use (Age Profile)**

Figure 2.1 plots the age distribution of the respondents who declared to have used at least once a hard drug in 1996, a question included in the NHSDA. This Figure suggests that hard drugs use has a clear age dimension. Virtually all the action seems to take place between the age of 12 and 43. It is interesting to notice that hard drugs use declines as the labor market rewards increase. On the one hand, as outlined in the previous paragraph, people might want to treasure the returns on the accumulated human capital, reducing the likelihood of being fired and/or getting into troubles with the criminal justice system. On the other hand, as people age they also have more money to be spent on consumption; nevertheless, they do not seem to use their economic resources on hard drugs. Notice that with a quantitative equilibrium model it is possible to single out the effect of habit formation vis-a-vis higher wages as people age on the hard drugs consumption.

### **Hard Drugs Use (Age at First Use)**

The NHSDA includes a set of questions related to the age at first use of cocaine, crack and heroin. Figure 2.2 shows its distribution.<sup>5</sup>

---

<sup>5</sup>Notice that if people declared to have used more than one hard drug, we selected the lowest reported age at first use.



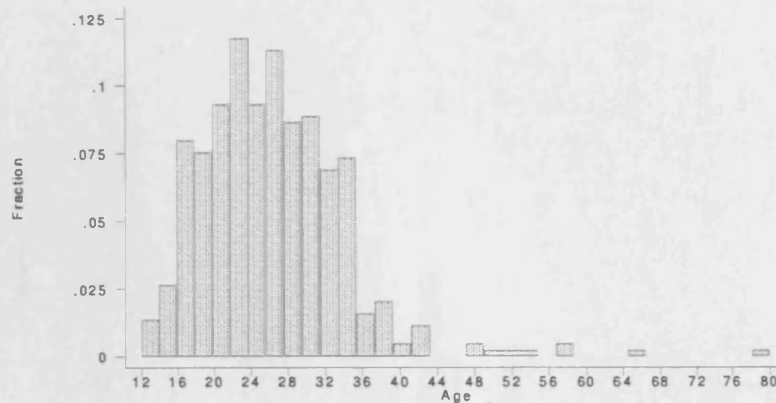


Figure 2.1: Cocaine, Crack and Heroin Use - Age Distribution (Source: NHSDA 1996)

Also this graph conveys a clear message: age is a crucial factor as far as the first contact with hard drugs by American males is concerned. In the civilian population, everything seems to happen between age 12 and 42, with about 90% of the hard drugs users reporting that they tried those substances for the first time between age 16 and 35.

By comparing different waves of the NHSDA, we get to discover quite an interesting fact: the distribution of age at first use seems to be stationary. For the waves carried out between 1979 and 1990, depicted in Figure 2.3, the distributions lie almost one on top of the other, with the only noticeable differences showing up at age 25.<sup>6</sup>

### Hard Drugs Violations (Breakdown by type of violation)

From the criminal justice statistics point of view, what are the main facts related to hard drugs? Figure 2.4 shows two pieces of information that refer to the 1977-2002 period. First, the time series for the number of arrests made (whose most serious mention was either the possession or the sale/manufacturing of hard drugs) is plotted. Second, the time series of the percentages for the two types of drug violations, possession and the sale/manufacturing, are shown. A couple of comments are in order. From the Figure, it

<sup>6</sup> Although available, we dropped the 1982 wave of the NHSDA. For budget reasons, the sample size for that year was extremely small, making some of the estimates based on that sample clearly unreliable.

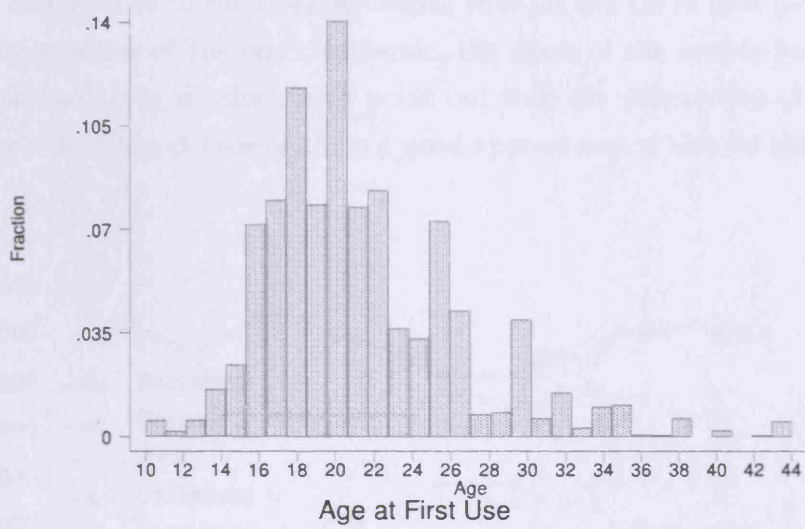


Figure 2.2: Cocaine, Crack and Heroin Age at First Use - Age Distribution (Source: NHSDA 1996)

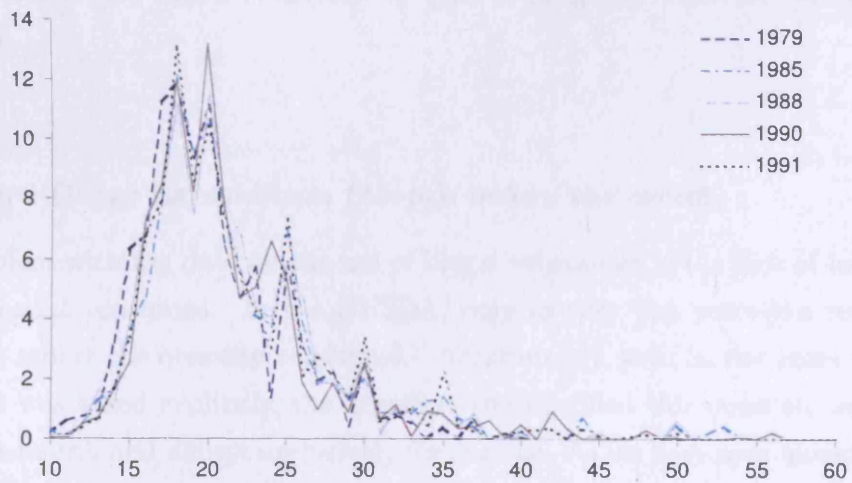


Figure 2.3: Cocaine - Age at First Use (Source: NHSDA, several years)

is clear that the number of arrests rose dramatically between the early and late 80's. This period of time corresponds to the crack epidemic, that hit the US in that period of time. Interestingly, irrespective of the crack epidemic, the share of the arrests has not shown any trend. Moreover, it is worthwhile to point out that the assumption of stationarity that will be made in the model seems to be a good approximation also for this part of the problem.

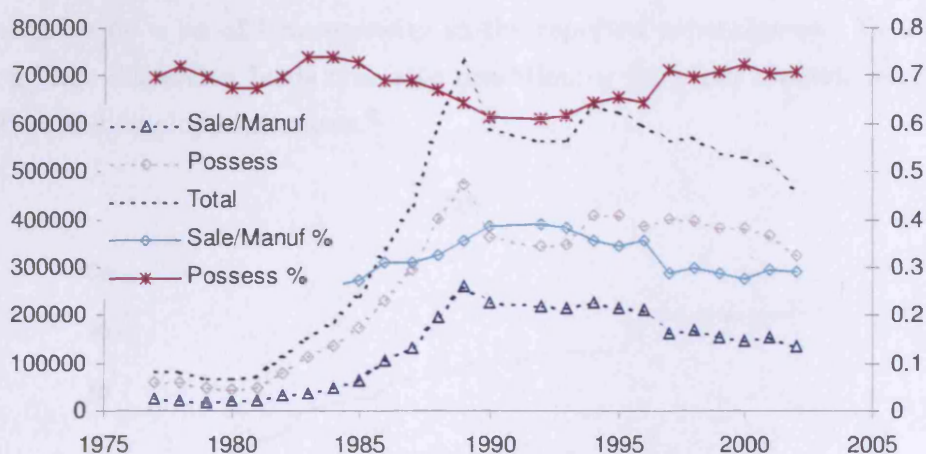


Figure 2.4: Number and shares of arrests, by type of Drug Law Violation (Source: UCR, several years)

### Inmates Hard Drugs Expenditure (Month before the arrest)

A major problem with the data on the use of illegal substances is the lack of information about the amount consumed. In the NHSDA, only in very few years the respondents were asked to report the quantity consumed. Unfortunately, even in the years where the quantity used was asked explicitly, the questionnaire specified this question only for the use in the last month and almost exclusively for cocaine. As we have seen already, quite a limited number of people report to have used hard drugs in the month before the interview took place, making estimates about the quantity used de facto very unreliable.

Luckily, in the 1996 wave of the SI a question was included asking the inmates to report their expenditure on drugs in the month before the arrest. Given that the percentage of

convicted people using hard drugs is high, the number of observations for people reporting positive hard drug expenditures is also relatively large, allowing for a meaningful analysis.<sup>7</sup>

Figure 2.5 plots the Cumulative Distribution Function for the expenditure on hard drugs in the 30 days before the arrest that led to the current conviction took place. A couple of points are worth being stressed: 1) the top quartile spent in a month more than \$2,500, a very large amount of money given the limited economic legal prospects of the people under consideration (young adults, poorly educated and likely to be unemployed); 2) there seems to be a lot of heterogeneity in the reported expenditures. To a certain degree, such large dispersion holds true also conditioning for other observables, such as age, education and employment status.<sup>8</sup>

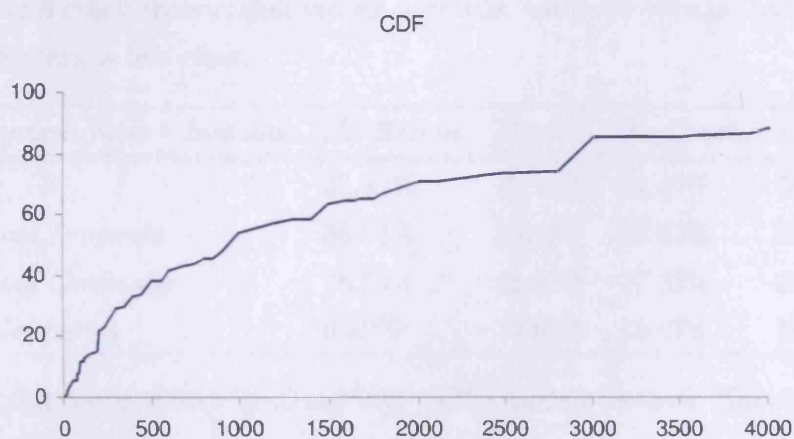


Figure 2.5: Inmates Hard Drugs Expenditure (Source: Survey of Local Jails Inmates 1996)

<sup>7</sup>Notice that the expenditure data is available only for the local jail inmates. However, this does not seem to be a major issue, since a non negligible share of local jail inmates are there only waiting to be relocated to either a state prison or a federal one. To some extent, the fact that the question is asked to local jails inmates is better. This way the problems of recall for state and federal prisoners are reduced somewhat: usually, the criminals who transit to state and federal prisons have been in a local jail for a relatively short period of time, if compared to the average state and federal prison term.

<sup>8</sup>For some unknown reasons, the expenditure question has not been included in the latest wave of the SI, which was released in April 2006 and refers to the year 2002.

### Employment Status by Hard Drugs Use

As seen above, the involvement of American males with hard drugs displays a strong age dimension. One of the possible explanations can be linked to the risk of unemployment related to hard drugs abuse. This issue has already been studied by DeSimone (2002), who finds in the NLSY 1979 sample that cocaine use reduces substantially the likelihood of employment. The following Tables 3 and 4 present additional evidence supporting this claim. Table 3 refers to the inmates, while Table 4 to the general US population. The unemployment spells refer to the month before the arrest for inmates, and to the month before the interview for the NHSDA sample. When comparing the unemployment rates by hard drugs use, we notice a clear jump if the person was using hard drugs. As for inmates, heroin and crack show rather strong patterns, while for cocaine (not reported in the Table) the pattern is less clear.

<i>Unemployment rates - Inmates</i>	<i>No Heroin</i>	<i>Heroin</i>	<i>No Crack</i>	<i>Crack</i>
<i>All</i>	33.30%	48.11%	34.47%	36.83%
<i>High School Dropouts</i>	36.63%	49.12%	37.93%	38.38%
<i>High School Graduates</i>	26.54%	46.07%	27.22%	34.17%
<i>College Graduates</i>	9.82%	42.92%	13.07%	16.69%

Table 2.3: Unemployment Rates by Drug Use - US Inmates (Source: Survey of Inmates 1997)

As displayed in Table 4, in the US non-institutional population the unemployment rates of hard drugs users are more than twice as much as those of people who did not consume any hard drugs in the year 1996. Notice that the gap in the two unemployment rates is present for many age categories, while it seems to decrease for older individuals.

<i>Unemployment rates - Population</i>	<i>No Hard Drugs</i>	<i>Hard Drugs</i>
<i>All</i>	4.15%	11.09%
<i>Age: 16 - 25</i>	7.57%	16.30%
<i>Age: 26 - 35</i>	4.01%	10.38%
<i>Age: 35+</i>	3.12%	4.48%

Table 2.4: Unemployment Rates by Drug Use - US Population (Source: NHSDA 1996)

It is worth mentioning that, for some job categories, it is legal for employers to test their employees for drug use: a worker testing positive constitutes ground for dismissal.

### **Inmates Fired Because of Drug Use**

The previous Table has provided some indirect evidence on the disruptive effects of hard drugs on the employment status of illegal substance users. The following Table reports more direct information on the same phenomenon. A question in the SI asked explicitly if the inmate was fired because of his drug use. Table 5 reports the percentages of people answering affirmatively, by type of drug and frequency of use. We defined "regular" users those who used hard drugs at least once every two days. Notice that the share is increasing in the potency of the drug, which is what one would expect. Moreover, the likelihood of having being fired is higher for people using the substances more often.

<i>Hard Drug</i>	<i>% Fired</i>	<i>% Fired "Regular" Users</i>
<i>Heroin</i>	43.22%	46.54%
<i>Crack</i>	38.85%	43.90%
<i>Cocaine</i>	34.56%	42.36%

Table 2.5: Fired Because of Drug Use (Source: Survey of Local Jails Inmates 1996)

### **Property Crimes and Drug Violations Arrest Rates (Age Profiles)**

Figure 2.6 plots the age profiles of both the property crimes and drug violations arrest rates in the US for males in the year 1996.<sup>9</sup> The arrest rate for the drug violations considers the arrests for both drug selling and possession, the related percentages being 30% and 70%, respectively.

From Figure 2.6 it is evident that the arrest rates for both crime categories peak early, before age 20 and then decline monotonically. Notice that they become virtually zero for people older than 50. Interestingly, the same patterns hold, at least qualitatively, for these age profiles since the 70's.

<sup>9</sup>The arrest rates are computed as the number of people arrested per 100.000 individuals belonging to a specific age category.

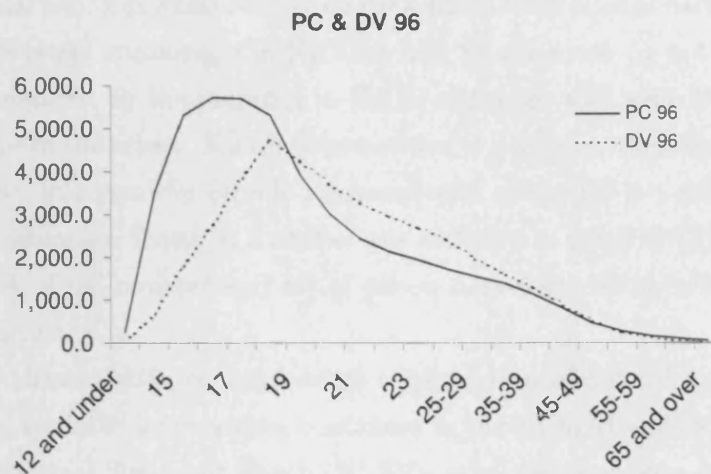


Figure 2.6: Property crime (PC) and Drug abuse violations (DV) arrest rate by age (Source: UCR 1996)

### Data Limitations

We conclude the Section on the empirical evidence with a discussion on the limitations of the data used.

The first caveat refers to the extent of under-reporting. Dealing with illegal behaviors, chances are that some people tend to under-report their participation, while others to over-report it. Notice that the teams in charge of designing these datasets paid a lot of attention to this problem, US Dept of Health and Human Services (1998), US Dept of Justice (1999) and US Dept of Justice (2001). The questionnaires were developed carefully, relying on the ordering and the phrasing of the questions that was thought to induce truth telling, based on the results of previous studies in the field. Notice also that for the most delicate questions the respondents were given the opportunity to answer while being on their own, and that the principal investigators were granted by criminal justice authorities the right for the collected information not to be used as evidence against the respondents. Such special arrangements were told clearly by the interviewer before the surveys were administered. Irrespective of such efforts, it is likely that some under-reporting took place anyway. However, its extent is unknown. As a positive remark, notice that the response rates for the NHSDA are high and almost identical to the CPS ones, while the response rates for the SI are rather impressive and about 95%.

Another potential problem when relying on data taken from several surveys is the issue of comparability. Strictly speaking, the NHSDA and SI universes do not coincide. The discrepancy is represented by the presence in the SI of people who were homeless and on the street at the time of the arrest. For obvious reasons, it is very hard for this demographic group to be included in a random sample representative of the US population. However, notice that: 1) the homeless living in a shelter are included in the NHSDA universe, and 2) in the SI only 7% of jail inmates and 4% of prison ones declared to be homeless in the month before the arrest.

As pointed out already, data on hard drugs consumption in the US are not currently available. The only available information, contained in the NHSDA and to some extent in the National Longitudinal Survey of Youth (NLSY), is on the frequency of consumption, which does not allow to understand what happens both to the individual consumption and to the aggregate one when prices change.

This lack of data is one of the reasons why a theory of drug consumption and addiction is needed, that is a model has to be developed to understand the response of consumption to changes in prices. Such a model will be presented in Section 3.

Notice also that the lack of drug consumption data problem is more severe than it might seem. Unfortunately, there are no representative data for the US on the economic value of drug selling. The only available studies, Reuter, MacCoun and Murphy (1990), Wilson and Abrahamse (1992), Levitt and Venkatesh (2000) and Kinlock, O'Grady and Hanlon (2003), focus on a large city, namely Washington DC, Los Angeles, Chicago or Baltimore, and obtain estimates which are quite different from one another, ranging from few hundred dollars to several thousand a month. If at least the aggregate consumption of drugs were to be known, it would be possible to obtain an estimate of how much the average drug sales are worth, a value which can be computed in our equilibrium model.

Notice also that standard econometric techniques would be inappropriate with the information included in the SI dataset. By construction, the people surveyed are a selected sample, so that it is crucial to take care of the selection issues, in order to draw inferences valid for the general population. The model developed in this paper represents a feasible way to address the selection problem.

The next Section is devoted to discuss a simple economic model of rational drug addiction, drug selling and property crimes.



## 2.3 The Model

In order to study the determinants of hard drugs addiction, drug selling and property crimes, a simple dynamic general equilibrium model is developed. The main features of the framework are discussed briefly in what follows.

Since both crime involvement and hard drugs use are not evenly distributed in the population, Freeman (1999) and Freeman (1996). agents are assumed to be heterogeneous along several dimensions.

First, agents differ with respect to their age, denoted by  $i \in \mathcal{I} = \{1, \dots, I\}$ : every individual goes through a life-cycle, whose main aspects are related to both the legal earnings opportunities and the likelihood of being a hard drugs user. By assumption, the illegal opportunities do not change as the individuals age. This assumption seems to be supported by the relevant empirical evidence presented in Blumstein et al. (1986).

Second, agents differ in their employment status, denoted by  $s \in \mathcal{S} = \{e, u\}$ : in every period of time, some agents are employed ( $e$ ), while others are unemployed ( $u$ ). Becoming unemployed is modeled as an idiosyncratic shock, i.e. the shocks are assumed to be i.i.d. among different individuals.<sup>10</sup>

Data limitations do not allow to consider a time period short enough to model explicitly the labor market dynamics, as for example in Burdett, Lagos and Wright (2003). Alternatively, it is assumed that agents who turn out to be unemployed, will be so only for a fraction of the period.

Third, since the empirical evidence, discussed for example in Lochner (2004), and Lochner and Moretti (2004), shows that the bulk of property crimes are committed by people with poor educational achievements, we assume that agents differ in their educational level. Education is denoted by  $ed \in \mathcal{ED} = \{hsd, hs, col\}$ , the three possible levels being high school dropouts ( $hsd$ ), high school graduate ( $hs$ ), and college graduate ( $col$ ). For tractability, individuals enter the economy with a predetermined educational level, which does not vary over time. This aspect is admittedly a simplification of the analysis, however, allowing for an endogenous educational choice would increase considerably the complexity of the problem. As long as the decisions of dropping out of high school are

---

<sup>10</sup>Notice that allowing for aggregate shocks would complicate the analysis substantially, since the whole distribution of habits would enter the agents' problem. This would make the model no longer tractable, unless limited rationality assumptions are made, in the spirit of Krusell and Smith (1998), or the habits distribution is given an explicit parametric form, in the spirit of den Haan (1997).

not caused by drug addiction and/or crime involvement, our results would not be affected much even if we were to consider education as endogenous.

Fourth, it is assumed that in every period agents receive a taste shock ( $\varepsilon$ ), which shifts the marginal utility of hard drugs.<sup>11</sup> We might think of these shocks as transitory events, such as the divorce of the parents, or the death of a friend, or the relocation in a new city, or some kind of health shock, that are likely to affect the utility attached to the consumption of hard drugs.

By assumption, consumption of drugs is addictive, i.e. it entails the accumulation of a stock of habits, denoted by  $h$ . The more the agents consume of the addictive good, the higher the level of the stock of habits an addict will transfer to the next period. Notice that the agents are assumed to be rational.

An incomplete markets framework is assumed. Agents cannot buy insurances against two risks: the unemployment risk and the taste shock risk.<sup>12</sup> As for the former assumption, it is a well known fact that felons convicted because of a property crime were more likely to be unemployed at the time of the offense. This state dependent outcome suggests that people cannot fully insure against the unemployment risk. As for the latter assumption, it is sufficient to rely on a moral hazard argument to justify the absence of such an insurance scheme.

In order to keep the notation simple, we assume that agents can buy an insurance against the risk of being victim of a property crime. The insurance sector is assumed to be perfectly competitive, hence in equilibrium the price will simply reflect the probability of being victimized and the amount of lost income.

Studies on convicted drug abusers and property crime offenders, e.g. Kinlock, O'Grady and Hanlon (2003) and Wilson and Abrahamse (1992), show a small degree of specialization: criminals tend to be involved in many different income generating felonies, with drug selling being the most lucrative one. Hence, in the analysis every individual can choose whether to be involved in stealing from other agents and in selling drugs.

Finally, notice that by assumption there is no aggregate uncertainty: every random event is idiosyncratic, and given that there is a continuum of individuals in each state,

---

<sup>11</sup>We chose to model unobserved heterogeneity in this way for the following reasons: it gives the agents a high degree of flexibility in the choice of entering and exiting drug use, it helps in generating highly heterogeneous expenditure profiles and it is computationally tractable.

<sup>12</sup>Strictly speaking, also going to prison is a risky event, which is not insurable. However, it is the punishment related to a public policy, and, as such, it is uninsurable by law.

a law of large number applies. As a consequence, the economy at the aggregate level is deterministic.

### 2.3.1 Demographics

As discussed in Section 2, the participation in property crimes, in drug violations and the use of hard drugs are higher for young individuals. It is of paramount importance to consider explicitly in the analysis the age of the offenders. Hence, an overlapping generations structure is assumed. The economy is populated by  $I$  overlapping generations, whose measure is normalized to one. People age deterministically.

### 2.3.2 Preferences

Agents' preferences are defined on both the numeraire good  $c$  and hard drugs  $d$ . Moreover, in each period every individual receives a taste shock  $\varepsilon$ , which is assumed to be normally distributed. Preferences are separable over time in  $c, d$  and  $h$  taken together, with  $h$  being the stock of habits. Due to the habit forming nature of the  $d$  good, they are not when only  $c$  and  $d$  are considered.  $pc$  stands for the number of property crimes and  $ds$  for the amount of drug sold in the drug market.

Each individual solves the following problem:

$$\max_{\{c_i, d_i, h_{i+1}, pc_i, ds_i\}_{i=1}^I} U(c_1, \dots, d_1, \dots, h_1, \dots, \varepsilon_1, \dots) = \max_{\{c_i, d_i, h_{i+1}, pc_i, ds_i\}_{i=1}^I} E_0 \sum_{i=1}^I \beta^{i-1} [u(c_i, d_i, h_i, \varepsilon_i)]$$

where  $E_0$  represents the expectation operator over all the possible histories generated by the employment opportunity shocks ( $s \in \mathcal{S} = \{e, u\}$ ), the distribution of the taste shock  $\varepsilon$ , the probability of being victim of a crime  $\pi_v$ , and the probabilities of apprehension if property crimes or drug abuse violations are committed  $\{\pi_a^{pc}, \pi_a^{ds}, \pi_a^d\}$ ;  $\pi_a^{pc}$  stands for the probability of being apprehended if a property crime is committed,  $\pi_a^{ds}$  stands for the probability of being apprehended if involved in drug selling and  $\pi_a^d$  stands for the probability of being arrested because of drug possession.  $\beta \in (0, 1)$  is the subjective discount factor.

In every period each agent decides on how much to consume of the numeraire consumption good  $c$ , how much to consume of the habit forming good  $d$ , whether to commit property crimes  $pc$  and whether to sell drugs  $ds$ .

Assume that the per period utility is as follows:

$$u(c, d, h, \varepsilon) = \alpha_{cc}c^2 + \alpha_{cc}c + \alpha_{dd}d^2 + (\alpha_d + \varepsilon)d + \alpha_{dh}dh$$

and the parameters are such that they guarantee concavity of the utility function.<sup>13</sup> We chose a quadratic specification because: 1) it is rather flexible, 2) it can allow for zero consumption of both  $d$  and  $c$ , 3) it is customary in the rational addiction framework. We assume  $\alpha_{dh} > 0$ , for the model to be capable of generating a crucial feature of addictive goods, i.e. a reinforcement effect or that drug consumption is increasing in the level of habits. Possession of hard drugs is illegal: with some probability hard drugs consumer are caught and put into prison. For simplicity assume a linear relationship for the probability of apprehension  $\pi_a^d(d) = \pi_a^d d$ , with  $0 \leq \pi_a^d \leq 1$ . This implies that there is an upper bound for drug consumption in a period, since for  $d \geq \frac{1}{\pi_a^d}$  a drug user is caught with certainty.

The taste shock  $\varepsilon$  affects the marginal utility of hard drugs (i.e. the MRS between  $c$  and  $d$ ), by shifting the line up or down. The rationale for the taste shock is twofold: on the one hand, we don't observe all people in a given state making the same hard drugs consumption decisions. Without the taste shock the model would imply counterfactual drug consumption choices. On the other hand, it allows for very rich patterns of drug consumption over the life cycle: withdrawals and relapses are triggered by the interaction between economic incentives and the realization of the taste shock. Such phenomena would be very complicated to get otherwise. Assume that  $\varepsilon \sim N(0, \sigma_\varepsilon^2)$ .

We denote the stock of habits by  $h$ , and we assume that it can take values on a compact set  $\mathcal{H} = [\underline{h}, \bar{h}]$ ,  $\underline{h} \geq 0$ .<sup>14</sup> Habits evolve according to a deterministic law of motion, which depends on the depreciation of the current stock of habits,  $\lambda h$ , and on the current consumption of the addictive good,  $d$ . Following the literature, Becker and

<sup>13</sup>Notice that in this model it would not be appropriate to rely on the usual arguments to justify a "log" utility function. The environment does not allow for savings, making the elasticity of intertemporal substitution a concept not well defined. What is well defined is the risk aversion. Moreover, the part of the utility function related to drugs allows for utility to be bounded when addicted individuals are incarcerated, i.e. when they receive a zero quantity of the good. Finally, the parameters are identified through the variation in the hard drugs expenditure, and the prevalence rates of drug use.

<sup>14</sup>The upper bound for habits  $\bar{h}$  can be easily obtained. More precisely,  $\bar{h}$  is age specific, i.e.  $\bar{h}_i$  and corresponds to the stock of habits when all income is spent on drugs, with the agent committing the maximum number of property crimes and selling the maximum amount of drugs, without being arrested.

Murphy (1988) and Orphanides and Zervos (1995), the specific functional form is assumed to be  $h' = (1 - \lambda)h + d$ .

Addicts are happy, from an ex-ante perspective, in the sense that they make optimal choices, given their budget sets, the criminal opportunities and the characteristics of the criminal justice system. Notice that individuals are rational and use all the information at their disposal in the best possible way. From this perspective, any public policy aimed at reducing consumption would be welfare decreasing for the agents that decide to consume. Public interventions, in the form of constraints to consumption, can be justified only relying on externality arguments, e.g. if hard drug addicts rely on property crimes to finance their consumption. A costly justice system, the income losses, the psychological traumas of the victims and their related health costs are the relevant externalities to be evaluated in the property crimes case.

Notice that we do not allow for agents to die because of their addiction. The most common cause of death is the inability of consumers to assess the purity of the substance they are using. Either the drug being mixed with toxic chemicals or its excessive purity relative to the level of tolerance already developed can cause a deadly reaction. Essentially, the cause of death lies in an asymmetric information problem, which for simplicity we do not model.

### 2.3.3 Endowments

Agents are endowed with exogenously given efficiency units,  $\omega_{i,ed}$ , which vary with age and education level.<sup>15</sup> Notice that the efficiency units only affect the legal income received by the agents, while they do not influence the illegal earnings possibility.

Agents receive every period a stochastic employment opportunity, which depends on age, education, employment status and the stock of habits.

The employment opportunities follow a first order Markov process. The transition function of the employment opportunity state is represented by matrices which depend on age, education and stock of habits  $\Pi_{i,ed}(h; s, s') = [\pi_{i,ed}(h; k, j)]$ , where each element

---

<sup>15</sup>Unlike in Becker and Murphy (1988), the stock of habits does not affect wages. The available empirical evidence on this matter has proven quite elusive: in a study on the effect of cocaine on wages, Kaestner (1991) finds a positive effect. However, his findings could be driven by both sample attrition issues and several potential sources of simultaneity. Also the 2SLS procedure implemented could lead to unsound findings, given the difficulty of finding reliable instruments for the endogenous regressors.

$\pi_{i,ed}(h; k, j)$  is defined as  $\pi_{i,ed}(h; k, j) = \Pr\{s_{t+1} = j | s_t = k\}$ ,  $k, j = \{e, u\}$ . By assumption,  $\frac{d}{dh}\pi_{i,ed}(h) > 0$  and  $\pi_{i,ed}(\cdot)$  has a logistic functional form:

$$\pi_{i,ed}(h) = \frac{\exp(\gamma + \gamma_h h + \gamma_i i + \gamma_{ii} i^2 + \gamma_{ed} ed)}{1 + \exp(\gamma + \gamma_h h + \gamma_i i + \gamma_{ii} i^2 + \gamma_{ed} ed)}$$

where the  $\gamma$ 's are parameters to be (structurally) estimated.<sup>16</sup>

Being the unemployment probability increasing in the stock of habits, the agents face a trade-off between hard drugs consumption and labor market rewards. The higher the current consumption of  $d$ , the higher the probability of being unemployed tomorrow. Given that the efficiency units are increasing over the life-cycle, the opportunity costs of consuming hard drugs increases with the age of the agent. For a given level of the taste shocks, this mechanism generates hard drugs consumption functions which are decreasing in age, a prediction of the model which is consistent with the empirical facts discussed above.

If an agent is unemployed during a period of time, he receives an unemployment benefit, with a given replacement ratio equal to  $\phi$ . Employed agents contribute to the insurance benefits with a proportional tax  $\tau_U$  on their labor earnings. All agents pay for the costs of the criminal justice system with a proportional tax  $\tau_J$  on their legal earnings. To simplify the notation, denote the agents' legal income with  $y_{s,i,ed}$ , with  $y_{e,i,ed} = (1 - \tau_U - \tau_J)\omega_{i,ed}$  and  $y_{u,i,ed} = \phi(1 - \tau_J)\omega_{i,ed}$ .

As a side comment, notice that the relationship between unemployment and crime has been studied extensively in the literature, e.g. Raphael and Winter-Ebmer (2001). Allowing for agents to be unemployed is crucial if we are to explain the crime participation. Agents in the model need to face the appropriate economic incentives, that is they need to compare the benefits and costs of crime, by taking into consideration their current legal income.

### 2.3.4 Criminal Opportunities

As far as the criminal side of the economy is concerned, we extend the framework first proposed by Becker (1968) and implemented in a dynamic environment by Flinn (1986)

---

<sup>16</sup>The  $\gamma$  parameters are identified through the variation in the unemployment rates by age, education, incarceration status and drug use.

and Imrohorglu, Merlo and Rupert (2004). Every agent has access to two types of income generating criminal opportunities: property crimes and drug selling. These are considered in turn.

### Property Crimes

Every agent can engage in property crimes in every period of his life, irrespective of his employment opportunity. The modeling strategy related to this criminal choice generalizes Imrohorglu, Merlo and Rupert (2004). There exists a criminal technology,  $y(pc)$ , that maps the number of crimes into criminal earnings. We chose to allow for multiple crimes because there is evidence in the Rand Inmate surveys, discussed in Wilson and Abrahamse (1992), that the bulk of crimes are committed by a minority of offenders: these observations suggest that the intensive margin is a relevant one. We assume that committing crimes corresponds to stealing a constant fraction  $\eta$  of the average legal income in the economy  $\bar{y}$  times the number of crimes  $pc$ . That is, we assume that  $y(pc) = \eta\bar{y}pc$ . Notice that  $y'(pc) > 0$  and  $y(0) = 0$ , that is the technology is linear and people who decide not to be involved in property crimes get zero illegal income. A crime attempt is always successful. However, with probability  $\pi_a^{pc}(pc)$  criminals are caught and incarcerated for  $T_{pc}$  periods at the beginning of the period, while with probability  $(1 - \pi_a^{pc}(pc))$  they remain free and can use the additional economic resources  $\eta\bar{y}pc$ , obtained through theft. For simplicity assume a linear relationship for the probability of apprehension  $\pi_a^{pc}(pc) = \pi_a^{pc}pc$ , with  $0 \leq \pi_a^{pc} \leq 1$  being a parameter. A nice feature of this formulation is to have an upper bound for the maximum number of crimes in a period, since for  $pc \geq \frac{1}{\pi_a^{pc}}$  a criminal is caught with certainty. This bound, together with the linearity of the criminal earnings technology, allows for a simple sufficient condition for the aggregate feasibility condition of property crimes, i.e. the condition that ensures that criminals do not steal more than what is available in the economy. In our framework this condition boils down to  $\eta \leq \pi_a^{pc}$ .<sup>17</sup>

Notice that committing crimes does not entail any direct cost, neither monetary nor in terms of time; the only cost is the opportunity cost of being apprehended. With endogenous probability  $\pi_v^{pc}$  (which in equilibrium corresponds to the aggregate crime rate) an agent is victim of a crime and loses  $\eta\bar{y}$  units of his disposable income, that is a flat

---

<sup>17</sup>To get this inequality first compute the highest possible crime rate in the economy, which is obtained when every agent commits exactly  $\bar{pc} = \frac{1}{\pi_a^{pc}}$  crimes. Then impose feasibility, or that the stolen income is less than the average legal income, i.e.  $y(\bar{pc}) = \eta\bar{y}\frac{1}{\pi_a^{pc}} \leq \bar{y}$ .

amount.<sup>18</sup> Notice that we assume that an agent can be victimized at most once in a period of time. Moreover, both the criminal earnings function and the apprehension technology are the same for every agent in the economy.<sup>19</sup>

## Drug Selling

Beside property crimes, another income generating illegal opportunity is available: drug selling. We assume that drugs are not produced in the economy, but are imported from another Country.<sup>20</sup> Every drug seller in the economy acts as an atomistic agent, i.e. he is a price taker, and obtains the illegal substance from non resident international drug dealers. Since the focus of the paper is not on international drug dealing, we assume both that the international drug dealers do not have any active role in the domestic economy and that their supply function is perfectly elastic at an exogenously given price  $\underline{p}_d$ .<sup>21</sup> The assumption of perfect competition for the domestic drug sellers is consistent with the actual structure of the US drug selling business at the street level: 92% (86%) of state (federal) drug prisoners reported in the SI that they were not part of any organized criminal group. It is worth stressing that this seems to be compatible also with the gang structure discussed in Levitt and Venkatesh (2000): in the Chicago based gang they analyze, the majority of people involved in selling drugs are not gang members, but they appear only in their ranks, that is they can buy drugs from gang members to be resold in a location different from the gang's turf.

Notice that the returns from drug dealing are endogenous, and depend on the dimension of the market, i.e. on the aggregate drug demand and on the number of people that decide to sell drugs. It is assumed that every person selling drugs decide how many units of hard drugs ( $ds$ ) he is willing to sell. His revenues are given by the amount

---

<sup>18</sup>This assumption is justified from the data contained in the NCVS: somewhat surprisingly, there is a zero correlation between the victim's income and the amount stolen.

<sup>19</sup>Notice that by assumption there is no income loss from fencing the stolen goods. We justify this choice by noting that: 1) there are no data available on this issue, 2) since the mid 90's virtual markets such as E-bay have increased the likelihood of selling a stolen good for its market value.

<sup>20</sup>For hard drugs this assumption is based on the actual characteristics of this phenomenon, as discussed in UNODC (2003). The most important hard drugs producers and exporters to the US are Afghanistan for heroin, and Colombia for cocaine.

<sup>21</sup>Domestic drug sellers are to be interpreted as street-level drug dealers. For a study on the fight against the producers of illegal hard drugs, what we refer to as international or high level drug dealers, see Grossman and Mejia (2005).



sold times the domestic market price  $\bar{p}_d$ , net of the money given to the high level drug dealers to obtain the good, i.e. the net profits are  $(\bar{p}_d - \underline{p}_d) ds$ . Just like for property crimes, there is an exogenous probability  $\pi_a^{ds}$  of being incarcerated for  $T_{ds}$  periods because of drug selling for each unit sold. For simplicity assume a linear relationship for the probability of apprehension  $\pi_a^{ds}(ds) = \pi_a^{ds} ds$ , with  $0 \leq \pi_a^{ds} \leq 1$ . As for the other illegal activities, also in this case there is an upper bound for drug selling in a period, since for  $ds \geq \frac{1}{\pi_a^{ds}}$  a drug seller is caught with certainty. It is worth stressing that this feature allows for an (endogenous) domestic market price  $\bar{p}_d$  which is above the international one  $\underline{p}_d$ , irrespective of the assumption of perfect competition and free entry. Even if the supply function of international drug dealers is flat at  $\underline{p}_d$ , the domestic supply function is positively sloped. The intuition for this result is simple: since individual drug sellers decide not to sell hard drugs in excess of  $\frac{1}{\pi_a^{ds}}$ , in order to satisfy the demand agents with different characteristics (age, employment status, habits, taste shock) enter the drug market as the quantity increases. Since the opportunity costs of being caught for these agents is progressively increasing, they ask for a higher compensation for this risk, making the supply function an increasing function of the price. In this economy every agent can buy hard drugs at the constant price  $\underline{p}_d$  from foreign drug dealers and resell them at the price  $\bar{p}_d$  in the domestic market. For simplicity there are no liquidity constraints or informational frictions on the location of the drug markets.

### 2.3.5 Government

The role of the government in this economy is twofold.

First, it runs the unemployment insurance benefits scheme, by taxing the labor income of the employed workers at rate  $\tau_U$  and subsidizing the unemployed workers at the replacement rate  $\phi$ .  $\phi$  is a policy parameter exogenously given, while  $\tau_U$  is set residually to ensure in equilibrium a self-financing scheme.

Second, the government runs the legal system, providing the costless apprehension technologies that allow to detect and punish a fraction of the crimes committed. Detected criminals are immediately incarcerated: while in prison they all consume a constant level  $\bar{c}_a$ , which is financed through a proportional tax  $\tau_J$  paid by all the agents in the economy. Also  $\tau_J$  is set such that the scheme is self-financing. Notice that drug addicts receive a zero quantity of the drug while in prison.

### 2.3.6 Technology

The production side of the model is kept as simple as possible. There is a 1-to-1 constant returns to scale technology  $F(L)$ , which relies on aggregate labor  $L$  to produce the output.<sup>22</sup> Aggregate labor is defined as the sum of the employed agents' efficiency units: as a consequence, the wage rate per efficiency unit is equal to one,  $w \equiv 1$ , and labor earnings for each individual are equal to their efficiency units endowment.

### 2.3.7 Timing

The timing of the model is assumed to be the following: 1) A random fraction of inmates get out of jail; 2) Both the idiosyncratic unemployment shocks and the taste shock are realized and observed by the agents; 3) Production takes place, with the employed people working for a wage and with the unemployed receiving a subsidy; 4) The crime and consumption decisions are simultaneously taken; 5) A random fraction of agents involved in illegal activities are arrested and incarcerated.

As a final remark, notice that agents cannot save in this framework. It should be noted that a-priori this is not a shortcoming of the model. On the one hand, in an economy with savings agents hit by the unemployment shock could rely on their asset income to smooth consumption, reducing the likelihood of being involved in crimes. However, on the other hand, if debt was allowed, negative asset income would increase the likelihood of either drug selling or property crimes. Hence, the overall effect is ambiguous: unfortunately, the computational burden of allowing for another continuous state variable would increase substantially.

## 2.4 Equilibrium

In this Section we first define the problem of the agents in their recursive representation, then we provide a formal definition of the equilibrium concept used in this model, the recursive competitive equilibrium. Notice that the vector representing the individual state variables is defined as  $x = (i, ed, s, h, \varepsilon, J)$ , whose entries are age  $i \in \mathcal{I}$ , education level  $ed \in \mathcal{ED}$ , employment status  $s \in \mathcal{S}$ , stock of habits  $h \in \mathcal{H}$ , taste shock  $\varepsilon \in \mathfrak{R}$ , and

---

<sup>22</sup>This assumption is made mainly to give the negative endowment shock the interpretation of an unemployment spell.

conviction status  $J \in \mathcal{J} = \{0, 1\}$ . The optimal value functions are defined as  $V_{i,ed}(s, h, \varepsilon)$  for the agents not in prison and  $J_{i,ed}(h, t)$  for the inmates.

### 2.4.1 Problem of the agents

In recursive form the problem of the agents can be represented as follows:<sup>23</sup>

$$\begin{aligned}
V_{i,ed}(s, h, \varepsilon) &= \\
&\max_{c,d,h',pc,ds} \{Eu(c, d, h, \varepsilon) + \beta E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i,ed}(h'; s, s') V_{i+1,ed}(s', h', \varepsilon')\} = \\
&= \max_{d,pc,ds} (1 - \pi_a^{pc} pc) (1 - \pi_a^{ds} ds) (1 - \pi_a^d d) \\
&\{u(y_{s,i,ed} + \eta \bar{y} pc + (\bar{p}_d - \underline{p}_d) ds - \bar{p}_d d, d, h, \varepsilon) \\
&+ \beta E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i+1,ed}((1 - \lambda) h + d; s, s') V_{i+1,ed}(s', (1 - \lambda) h + d, \varepsilon')\} \\
&+ [1 - (1 - \pi_a^{pc} pc) (1 - \pi_a^{ds} ds) (1 - \pi_a^d d)] \{u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}((1 - \lambda) h, 0)\} \\
&s.t. \\
&c + \bar{p}_d d + p_I \leq y_{s,i,ed} + \eta \bar{y} pc + (\bar{p}_d - \underline{p}_d) ds \\
&h' = (1 - \lambda) h + d \\
&\varepsilon \sim N(0, \sigma_\varepsilon^2) \\
&h_1 \text{ given, } c \geq 0, d \geq 0, pc \geq 0, ds \geq 0
\end{aligned} \tag{2.1}$$

$V_{i,ed}(s, h, \varepsilon)$  stands for the optimal value functions of an agent of age  $i$ , education  $ed$ , with employment status  $s$ , with an accumulated stock of habits  $h$  and with a current period taste shock  $\varepsilon$ . Notice that we have substituted the explicit expression for the expectation, the individual budget constraint and the law of motion for the habits.

$J_{i,ed}(h, t)$  is the value function of a convicted felon, who has spent already  $t$  periods in jail. Notice that these agents do not take any decision. The expressions for the inmates value functions are the following.

<sup>23</sup>In order to save on space, in this section only a simplified version of the problem will be presented. We are implicitly assuming that all crimes are punished with the same prison term, or that  $T_j = T, \forall j$ . This implies that there is just one value function for inmates,  $J_{i,ed}(h, t)$ , irrespective of the crime the offender has been caught for. The complete problem is reported in appendix A.

$$J_{i,ed}(h, t) = u(\bar{c}_a, 0, h, 0) + \beta J_{i+1,ed}(h, t + 1)$$

$$J_{i,ed}(h, T - 1) = u(\bar{c}_a, 0, h, 0) + \beta \left\{ \zeta E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i+1,ed}(h'; s, s') V_{i+1,ed}(s', h', \varepsilon') + (1 - \zeta) J_{i+1,ed}(h', T) \right\}$$

$$J_{i,ed}(h, T) = u(\bar{c}_a, 0, h, 0) + \beta E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i+1,ed}(h'; s, s') V_{i+1,ed}(s', h', \varepsilon') \quad (2.2)$$

s.t.

$$h' = (1 - \lambda) h$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2)$$

$T$  stands for the maximum number of periods a felon has to spend in prison because of his criminal charges, while  $\zeta$  represents the probability of being released after  $T - 1$  periods (prison time does not coincide with  $T$  model periods). Notice that  $\varepsilon$  is not a state in the  $J$  value functions, because of the i.i.d. assumption and the specific utility function used.

## 2.4.2 Recursive Stationary Equilibrium

**Definition 1** For a given set of policies  $\{\phi; \bar{c}_a\}$ , apprehension probabilities  $\{\pi_a^{pc}, \pi_a^{ds}, \pi_a^d\}$ , prison time by type of crime  $\{T_j\}$ , hard drugs retail price  $\underline{p}_d$ , and efficiency units  $\{\omega_{i,ed}\}$ , a recursive stationary equilibrium is a set of individual value functions  $\{V_{i,ed}(s, h, \varepsilon), J_{i,ed}(h, t)\}$ , decision rules  $\{c_{i,ed}(s, h, \varepsilon), d_{i,ed}(s, h, \varepsilon), cr_{i,ed}(s, h, \varepsilon), ds_{i,ed}(s, h, \varepsilon)\}$ , prices for hard drugs and the property crime insurance  $\{\bar{p}_d, p_I\}$ , taxes  $\{\tau_U, \tau_J\}$ , average legal income  $\bar{y}$ , aggregate victimization rate  $\pi_i^{pc}$ , and stationary distributions  $\{\mu_{i,ed}(s, h, \varepsilon), \mu_{i,ed}^J(h)\}$  such that:<sup>24</sup>

- Given relative prices  $\{\bar{p}_d, \underline{p}_d, p_I\}$ , government policies  $\{\phi, \bar{c}_a\}$ , taxes  $\{\tau_U, \tau_J\}$  and  $\{\pi_i^{pc}, \pi_a^{pc}, \pi_a^{ds}, \pi_a^d, \bar{y}, \omega_{i,ed}\}$ , the individual policy functions  $\{c_{i,ed}(s, h, \varepsilon), d_{i,ed}(s, h, \varepsilon),$

<sup>24</sup>  $c_{i,ed}(s, h, \varepsilon) : \mathcal{I} \times \mathcal{ED} \times \mathcal{S} \times \mathcal{H} \times \mathcal{R} \rightarrow \mathcal{R}_+$  denote the numeraire consumption functions,  $d_{i,ed}(s, h, \varepsilon) : \mathcal{I} \times \mathcal{ED} \times \mathcal{S} \times \mathcal{H} \times \mathcal{R} \rightarrow \left[0, \frac{1}{\pi_a^d}\right]$  denote the hard drugs consumption functions,  $cr_{i,ed}(s, h, \varepsilon) : \mathcal{I} \times \mathcal{ED} \times \mathcal{S} \times \mathcal{H} \times \mathcal{R} \rightarrow \left[0, \frac{1}{\pi_a^{pc}}\right]$  denote the property crime functions and  $ds_{i,ed}(s, h, \varepsilon) : \mathcal{I} \times \mathcal{ED} \times \mathcal{S} \times \mathcal{H} \times \mathcal{R} \rightarrow \left[0, \frac{1}{\pi_a^{ds}}\right]$  denote the drug selling functions.

$cr_{i,ed}(s, h, \varepsilon)$ ,  $ds_{i,ed}(s, h, \varepsilon)$  solve the households problem (2.1)-(2.2) and  $\{V_{i,ed}(s, h, \varepsilon), J_{i,ed}(h, t)\}$  are the associated value functions.

- The stationary distributions  $\{\mu_{i,ed}(s, h, \varepsilon), \mu_{i,ed}^J(h)\}$  satisfy:

$$\begin{aligned} \mu_{i+1,ed}(s', h', \varepsilon') = \\ \sum_s \int_{h:h'=d_{i,ed}(s,h,\varepsilon)+(1-\lambda)h} (1 - \pi_a^{pc} pc_{i,ed}(s, h, \varepsilon)) (1 - \pi_a^{ds} ds_{i,ed}(s, h, \varepsilon)) \end{aligned} \quad (2.3)$$

$$(1 - \pi_a^d d_{i,ed}(s, h, \varepsilon)) \pi_{i+1,ed}(h'; s, s') d\mu_{i,ed}(s, h, \varepsilon) \mu(\varepsilon') +$$

$$\int_{h:h'=(1-\lambda)h} \zeta d\mu_{i,ed}^J(h) \mu(\varepsilon')$$

$$\mu_{i+1,ed}^J(h') = \int_{h:h'=(1-\lambda)h} (1 - \zeta) d\mu_{i,ed}^J(h) +$$

$$\sum_s \int_{h:h'=d_{i,ed}(s,h,\varepsilon)+(1-\lambda)h \times \mathfrak{R}} [1 - (1 - \pi_a^{pc} pc_{i,ed}(s, h, \varepsilon)) (1 - \pi_a^{ds} ds_{i,ed}(s, h, \varepsilon)) \quad (2.4)$$

$$(1 - \pi_a^d d_{i,ed}(s, h, \varepsilon))] d\mu_{i,ed}(s, h, \varepsilon)$$

In equilibrium the measure of agents in each state and age is time invariant and consistent with individual decisions.<sup>25</sup>

- The aggregate crime rate (i.e. the victimization probability) is given by:

$$\pi_v^{pc} = \sum_{s,i,ed} \int_{H,\mathfrak{R}} cr_{i,ed}(s, h, \varepsilon) \mu_{i,ed}(s, dh, d\varepsilon).$$

- The average legal income  $\bar{y}$  is equal to:

$$\bar{y} = \sum_{s,i,ed} \int_{H,\mathfrak{R}} y_{s,i,ed} \mu_{i,ed}(s, dh, d\varepsilon).$$

- The measure  $\mu_i^d$  of hard drugs consumers by age is given by:

<sup>25</sup>  $\mu(\varepsilon')$  stands for the CDF of  $\varepsilon$ , that is a normal random variable with mean zero and variance  $\sigma_\varepsilon^2$ .

$$\mu_i^d = \sum_{s,i,ed} \int_{H,\mathfrak{R}} \chi [d_{i,ed}(s, h, \varepsilon) > 0] \mu_{i,ed}(s, dh, d\varepsilon).$$

where  $\chi [d_{i,ed}(\cdot) > 0]$  stands for an indicator function equal to 1 if hard drugs consumption  $d_{i,ed}(\cdot)$  is strictly positive and equal to zero otherwise.

- The measure  $\mu^{ds}$  of hard drugs sellers is given by:

$$\mu^{ds} = \sum_{s,i,ed} \int_{H,\mathfrak{R}} \chi [ds_{i,ed}(s, h, \varepsilon) > 0] \mu_{i,ed}(s, dh, d\varepsilon).$$

where  $\chi [ds_{i,ed}(\cdot) > 0]$  stands for an indicator function equal to 1 if hard drugs consumption  $ds_{i,ed}(\cdot)$  is strictly positive and equal to zero otherwise.

- $\bar{p}_d$  is such that there is market clearing in the hard drugs market, i.e. it is such that:

$$\sum_{s,i,ed} \int_{H,\mathfrak{R}} ds_{i,ed}(s, h, \varepsilon) \mu_{i,ed}(s, dh, d\varepsilon) = \sum_{s,i,ed} \int_{H,\mathfrak{R}} d_{i,ed}(s, h, \varepsilon) \mu_{i,ed}(s, dh, d\varepsilon).$$

- The labor market clears:

$$L = \sum_{i,ed} \int_{H,\mathfrak{R}} \omega_{i,ed} \mu_{i,ed}(e, dh, d\varepsilon).$$

- The aggregate resource constraint is equal to:

$$\begin{aligned} F(L) &= \sum_{i,ed} \int_{H,\mathfrak{R}} \omega_{i,ed} \mu_{i,ed}(e, dh, d\varepsilon) = \\ &\sum_{s,i,ed} \int_{H,\mathfrak{R}} [c_{i,ed}(s, h, \varepsilon) + \bar{p}_d ds_{i,ed}(s, h, \varepsilon)] \mu_{i,ed}(s, dh, d\varepsilon). \end{aligned}$$

- The average labor income  $\tilde{y}$  is equal to:

$$\tilde{y} = \sum_{i,ed} \int_{H,\mathfrak{R}} \omega_{i,ed} \mu_{i,ed}(e, dh, d\varepsilon).$$

- The price for the property crime insurance  $p_I$  is equal to:

$$p_I = \eta \bar{y} \pi_v.$$

Since by assumption the insurance sector is competitive, the price  $p_I$  depends only on the probability of being hit by a criminal and the amount of stolen income.

- The unemployment insurance benefits scheme is self-financing:

$$\tau_U = \frac{\sum_{i,ed} \phi y_{e,i,ed} \int_{H,\mathfrak{R}} \mu_{i,ed}(u, dh, d\varepsilon)}{\bar{y}}.$$

that is the proportional tax rate  $\tau_U$  is set such that the total expenditure for unemployment benefits are exactly equal to the revenues from taxation.

- The proportional tax rate  $\tau_J$  is given by:

$$\tau_J = \frac{\bar{c}_a \sum_{i,ed} \int_H \mu_{i,ed}^J(dh)}{\bar{y}}.$$

or the revenues from this tax cover for all the criminal justice expenses.

## 2.5 SMM Estimation and Numerical Solution

The model, even for very simple functional forms, does not possess a closed form solution. As a consequence, it has to be solved numerically and simulated on a computer.

Being the agents finitely lived, the problem can be solved backwards. Starting from age  $I$  and exploiting the assumption that  $V_{I+1}(\cdot, \cdot, \cdot) = J_{I+1}(\cdot) = 0$  the problems of the agents are solved for each point in the state space  $(ed, s, h, \varepsilon)$  at each age  $i$ , until  $i = 1$  is reached.

Once the value functions and the policy functions are computed, the stationary distributions can be obtained, relying on the recursions (2.3) and (2.4).

The policy functions and the stationary distributions are then used to compute all the aggregate statistics of the economy, in particular the property crime rate and the total demand and supply of drugs.

In order to simulate the model, parameter values need to be specified. The parameters are divided into two groups. The first group consists of those parameters that correspond to a variable which has a natural empirical counterpart, hence they can be obtained directly from the data. For the second kind of parameters, the ones which do not map directly into observable variables, we rely on a Simulated Method of Moments estimation procedure. Hansen (1992) and Gourieroux and Monfort (1996). The Simplex method (Nelder-Mead algorithm) is implemented to search for the set of parameters that minimizes the weighted sum of squares of the difference between the moments predicted by the model and the actual ones. Since several datasets are exploited at the same time, choosing the weighting matrix is not an obvious task. For simplicity, the identity matrix is used: under this specification, estimates are consistent, but not necessarily efficient.

- First step - Parameters obtained directly from the data:
  - Number of periods of economic active life.
  - Share of the population in each educational level.
  - Probability of conviction if a property crime is committed.
  - Value of a property crime.
  - Consumption in jail.
  - Unemployment benefit replacement ratio.
  - International price of a unit of hard drugs at the average purity.
  - Age-education profiles for the efficiency units.
  - Prison period length for the various offenses.
  
- Second step - SMM, Moments used in the estimation:
  - Selected percentiles that lie in the interquartile range of the hard drugs expenditure distribution (to decrease the effect of outliers).
  - Prevalence of drug use by age for both the inmates and the non institutional population.
  - Persistence of drug use.
  - Unemployment rates by age, education and drug use.



- Inmates composition by age, education and type of crime.
- Share of population in Prison.

### 2.5.1 Sources of Identification

This Section provides an informal discussion on the identification of the parameters of the model.

As outlined before, the first set of parameters are exogenous to the model and are observable. It follows that they can be recovered directly from the available data. These are reported in Tables 6, 7 and 8.

The model period is one year, there are 50 years of active economic life and the parameter  $\beta$ , the discount factor, is fixed at a standard value of 0.989.<sup>26</sup> The educational shares in the population are computed from the 1996 CPS. In that year, 15.21% of the male population were high school dropouts, 59.15% were high school graduates and 25.64% had at least some years of college education. The policy parameter  $\phi$ , i.e. the unemployment benefit replacement rate, is set to replicate the actual unemployment benefit scheme operating in the US, i.e.  $\phi = 0.5$ . The probability of apprehension for property crimes  $\pi_a^{pc}$  is obtained dividing the number of convicted property crime felons by the number of property crimes reported to the police, and included in the UCR in 1996. We normalize the average disposable legitimate earnings  $\bar{y}$  to 1. This is done by appropriately rescaling the efficiency units  $\omega_{i,ed}$ . The actual value in 1996 was \$28,513. The parameter related to the earnings from crime is set to  $\eta = 0.0439$ , to replicate the value of \$1,253, the average value of a property crime computed from the UCR in 1996.

Following Imrohoroglu, Merlo and Rupert (2000) the exogenous consumption when in jail  $\bar{c}_a$  is set at \$2,600, i.e. this leads to  $\bar{c}_a = 0.0984$ .<sup>27</sup>

For tractability, the model considers only one type of hard drug. As long as the addictive properties of powder cocaine, crack and heroin are similar, an aggregation of the three drugs is a reasonable step. In order to obtain a hard drug price  $\underline{p}_d$  representative of high level transactions, the quantities and prices for the three types of drugs should

---

<sup>26</sup>We chose not to estimate the discount factor, relying on a standard value for OLG models with a one year time period. The reason being that it is hard to argue that this parameter can be separately identified from the depreciation of the habits stock.

<sup>27</sup>Notice that in the economy there are no agents with a legitimate income less than  $\bar{c}_a$ .

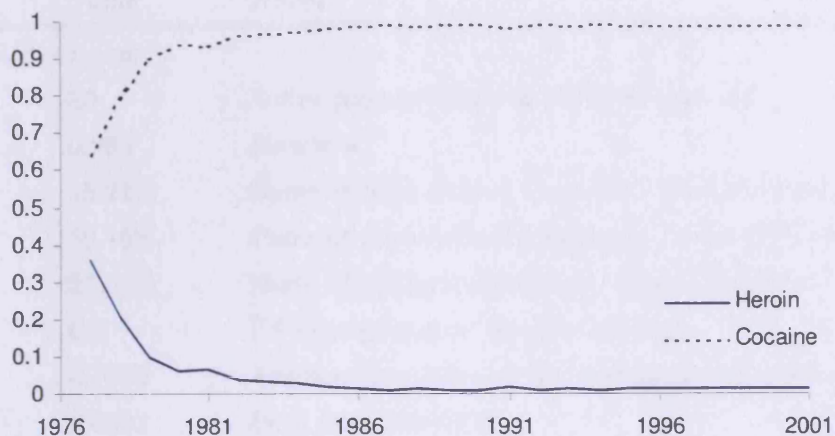


Figure 2.7: Cocaine and Heroin shares in the DEA seizures (Source: US Dept of Justice (2003))

be used. Unfortunately, as stressed also in Section 2, the available data do not allow for such a procedure. A different approach is taken. Thanks to the drug reporting systems managed by the DEA, there exists data on hard drugs seizures by the police. These data provide, for each year, the substance and the quantity seized. For our purposes, as shares of each drug we consider the respective shares in the seizures. This method is valid under the assumption that the drug seizures are a random sample of the actual drug markets. Notice that the shares, as shown in Figure 2.7, have been rather constant since the mid 80's. The values for 1996 are 98.4% for cocaine and 1.6% for heroin. Finally, to get the drug price at the retail level, we proceed as follows. First, for all the transactions included in the STRIDE above 5 grams, we divide the price by the purity. Then we compute separately the average price per pure gram for cocaine, crack and heroin. Next, we multiply the average price of each substance by its average purity. Then, we assume that crack and cocaine have the same market share, and weight cocaine and heroin prices by their respective shares in the DEA seizures. The final retail price for the representative transaction is \$48.68: this is the price per gram of the artificial composed illegal substance sold in the model economy. This implies that the price  $p_d$  at which the domestic dealers can buy the substance to be resold in the street level markets is equal to 0.1532 (for a 100 grams transaction).

<i>Parameter</i>	<i>Value</i>	<i>Target</i>
<i>Model Period</i>	1 year	
$I$	50	Active population from 16 to 65 year old
$\beta$	0.989	Standard
$\mu_{hsd}$	15.21%	Share of High School Dropouts - from CPS data
$\mu_{hs}$	59.15%	Share of High School Graduates - from CPS data
$\mu_{col}$	25.64%	Share of College Graduates - from CPS data
$\phi$	0.5	US unemployment benefits scheme
$\underline{p}_d$	0.1532	Average drug price at the average purity (100 grams)
$\pi_a^{pc}$	0.0492	Data from the UCR
$\eta$	0.0439	One property crime is worth \$1,253
$\bar{c}_a$	0.0984	Inmates consumption = \$2,600
$\omega_{i,ed}$	See Table 7	Predicted values of a wage regression on CPS data
$T_j, \zeta_j$	See Table 8	Actual (mean) time served in prison

Table 2.6: First Stage - Calibration

Table 7 reports the log wage regression from CPS data, which provides the efficiency units by age and educational level. The regressors are a quartic polynomial in age, education dummies (with the high school dropouts being the omitted group) and a constant. Notice that the efficiency units profiles are hump shaped over the life-cycle and increasing in education.<sup>28</sup>

Every illegal activity faces a probability of detection and incarceration. For simplicity, the model abstract from stigma effects on both the labor market and the criminal justice system of previous convictions. Moreover, given the nature of the punishment, it is assumed that arrests per-se do not matter: what matters for the criminal choices are the incarceration probabilities and the level of consumption while in jail. Notice also that an implicit assumption we are making is that every individual knows the true probability of incarceration for every crime.

In the model the police investigations are independent for each crime. Given that there are three illegal activities in the model economy, it follows that there are seven possible combinations of successful detection and incarceration. The prison terms, that is the time

<sup>28</sup>The efficiency units  $\omega_{i,ed}$  are obtained as the predicted values of the OLS regression, and are then rescaled to normalise the average disposable labor income to 1.

<i>Parameter</i>	<i>Log Wage</i>
<i>Age</i>	0.0292 (3.10)
<i>Age</i> <sup>2</sup>	0.00117 (3.33)
<i>Age</i> <sup>3</sup>	-0.000034 (-6.29)
<i>Age</i> <sup>4</sup>	2.11e - 07 (6.99)
<i>High School</i>	0.2303 (43.82)
<i>College</i>	0.3956 (51.15)
<i>Constant</i>	0.8944 (10.21)
<i>N. Obs</i>	45640
<i>Adj. R</i> <sup>2</sup>	0.301

Table 2.7: Log Wage Regression, t statistics in parenthesis (Source: CPS 1996)

<i>Offense Type</i>	<i>Parameter</i>	<i>Time (Months)</i>	<i>Parameter</i>	<i>Probability</i>
<i>Property Crime (PC)</i>	$T_{pc}$	17.8	$\zeta_{pc}$	0.48
<i>Drug Selling (DS)</i>	$T_{ds}$	16.4	$\zeta_{ds}$	0.37
<i>Drug Use (DU)</i>	$T_d$	15.0	$\zeta_d$	0.25
<i>PC &amp; DS</i>	$T_{pc,ds}$	20.5	$\zeta_{pc,ds}$	0.71
<i>DS &amp; DU</i>	$T_{pc,d}$	18.7	$\zeta_{pc,d}$	0.56
<i>PC &amp; DU</i>	$T_{ds,d}$	19.1	$\zeta_{ds,d}$	0.59
<i>PC &amp; DS &amp; DU</i>	$T_{pc,ds,d}$	23.3	$\zeta_{pc,ds,d}$	0.94

Table 2.8: Actual Prison Time and Probability of Leaving Prison After One Period, By Offense Type (Source: NCRP 1996)

a convicted felon has to spend in prison for his charges, are computed using data on actual time spent in correctional institutions in the US. The source is the 1996 wave of the NCRP: for each possible combination of crimes, the prison time by offense type is obtained as the mean time spent by inmates of state prisons released in the year 1996. Table 8 reports the actual time spent in prison. Notice that, quite surprisingly, 1) there is no much variation in time served in prison: all actual served sentences range between 15 and 23.3 months, 2) contrary to what the conventional wisdom and the popular press have been claiming, the actual time served in prison is well below the statutory minimum sentences, 3) the offense punished with the shortest prison term is drug use, with a punishment not very different from the others. Notice also that all prison terms are included between 12 and 24 months, hence  $T_j = 1$  for all  $j \in \tilde{\mathcal{J}} = \{pc, ds, d, (pc, ds), (pc, d), (ds, d), (pc, ds, d)\}$ . From the computed punishments  $T_j$ , it is trivial to get the probabilities  $\zeta_j$ , that is the probability of exiting prison after one period. These are reported in Table 8 as well.

The set of parameters which need to be structurally estimated are the ones related to the taste shock (i.e. its variance), to the law of motion for the habits, to the utility function, to the unemployment probability, and to the conviction probabilities.

The standard deviation of the taste shock  $\sigma_\epsilon$  and the depreciation of habits  $\lambda$  are identified by the prevalence rates of drug use by age, computed from the NHSDA, and the persistence of hard drugs use.<sup>29</sup> The observed values for the prevalence rates and the persistence of use are reported in Table 10.

As for preferences, the parameters  $\alpha$  appearing in the utility function are identified by the moments of the hard drugs expenditure. It is worth stressing that the expenditure refers to the inmates, before their arrest took place. More precisely, the amount consumed  $d$  multiplied by the equilibrium price at the street level  $\bar{p}_d$  is computed for all agents who will eventually be apprehended in the end of the period. Notice that the model and the data are consistent, since we compare statistics obtained from a selected sample, where the model represents the selection mechanism. Agents in the model decide how much hard drugs to consume, hence how much to spend on that good, moreover they decide on their participation on illegal activities. A random fraction of people involved in crime are caught, and for those agents we compute their hard drugs expenditure when still free.

---

<sup>29</sup>As for the latter, there is no information on the persistence of use on a year-to-year basis. We use instead the people in the NHSDA that used hard drugs in the month before the survey divided by the ones who used them in the year before the survey, i.e. the ratio of the values reported in the second and third columns of Table 1.

The moments of the expenditure distribution used in the SMM estimation procedure are the 25th, 40th, 50th, 60th and 75th percentiles (see Figure 2.5 and Table 10). We selected five moments since we have five parameters in the utility function, and we focused on percentiles included in the interquartile range to decrease the importance of outliers.

As for the unemployment probabilities, notice that it is not possible to run a regression of employment status on age, education and drug use for two reasons. First, the CPS does not contain information on hard drugs use, but in the sample there are also individuals who are drug users. Second, the stock of habits is unobservable, and in the model it is endogenous. The parameters in the probability of unemployment are identified by the average unemployment rates by age, education and drug use (i.e. the values reported in Table 4).

As for the conviction probabilities, the only one that can be computed directly from the data is the one related to property crimes. This can be done since there are data on both the number of convicted property criminals and the total number of property crimes. Notice that the second variable is not available for drug selling or drug use: these crimes do not involve a victim, hence there is no one reporting them to the police. The apprehension probabilities for drug possession and drug selling are identified by the inmates composition by type of crimes. Table 9 reports the value of the parameters estimated with SMM and which source of variation in the data allows their identification.

## 2.5.2 Model Fit

In this Section we discuss the fit of the model.

First, in Figure 2.8, the equilibrium decision rules for property crimes are plotted. The graph displays the choices of high school dropouts agents, who are employed and whose current taste shock corresponds to the average of  $\varepsilon$ . To improve the readability of the plot, only some ages were selected, namely ages 16, 20, 25, 37, 40 and 50. A few comments are in order. The property crimes functions are increasing in the stock of habits and are close to linear. This implies that the more intense the level of addiction, the higher the number of crimes that the agents are going to commit. Another interesting feature is the effect of age on the property crimes involvement. The policy functions are decreasing in age. Notice that age 37 is the first age such that if an agent does not have a positive stock of habits, he will not be involved in property crimes. Notice also that at ages 40 and 50 the agents need to have accumulated a strong addiction to steal from the other agents.

<i>Parameter</i>	<i>Value</i>	<i>Source of Identification</i>
<hr/>		
<i>Utility Function</i>		<i>Moments of the Drugs Expenditure</i>
$\alpha_{cc}$	-0.57	
$\alpha_c$	52.12	
$\alpha_{dd}$	-0.35	
$\alpha_d$	16.62	
$\alpha_{dh}$	35.73	
<hr/>		
<i>Taste Shock and Habit Depreciation</i>		
$\sigma_\varepsilon$	3.99	<i>Prevalence Rates of Hard Drugs Use</i>
$\lambda$	0.83	<i>Persistence of Hard Drugs Use</i>
<hr/>		
<i>Unemployment Probability</i>		<i>Unemployment Rate Profiles</i>
$\gamma$	0.27	
$\gamma_h$	1.09	
$\gamma_i$	-0.13	
$\gamma_{ii}$	0.001	
$\gamma_{hs}$	-0.68	
$\gamma_{col}$	-1.41	
<hr/>		
<i>Apprehension Probabilities</i>		<i>Inmates composition by type of crimes</i>
$\pi_a^d$	0.009	
$\pi_a^{ds}$	0.068	

Table 2.9: Second Stage - SMM Estimation

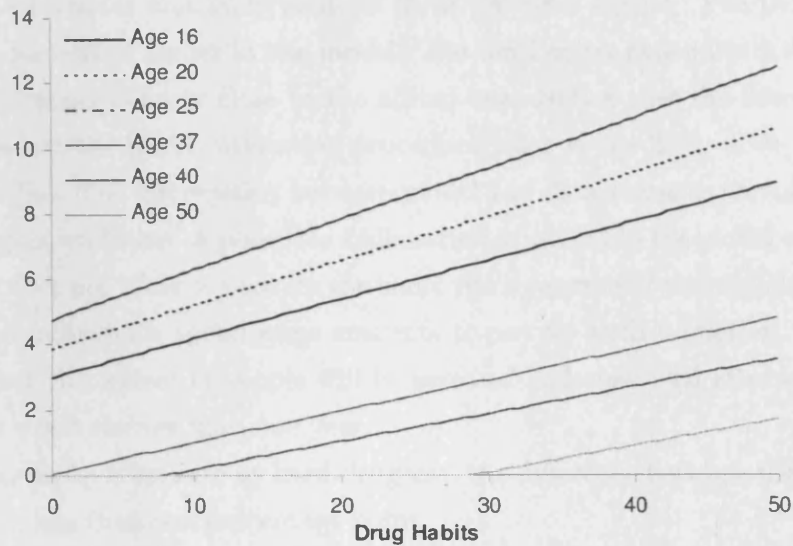


Figure 2.8: Property Crimes - Policy Functions by Age (Employed - Drop Outs - Average Shock)

The main features outlined above are shared also by the decision rules of agents with higher educational levels, with different levels of the taste shock as well as by the unemployed.

Qualitatively, also the decision rules for drug consumption and drug selling behave in a similar way. In the interest of space, we do not report them.

Table 10 reports both the moments obtained by simulating the model and the corresponding moments computed from the data. The simulations are based on 200,000 artificial individuals, behaving according to the optimal decision rules implied by the model. Notice that, in order to maximize the efficiency of the simulations, an oversampling procedure is carried out. We simulate 30,000 individuals that are college graduates, 70,000 that are high school graduates, while the remaining 100,000 are high school dropouts. This is done because the latter group is the most crime prone one, and one wants to compute their crime involvement with some accuracy. Notice that the moments obtained by simulating the model are then weighted, in order to get the appropriate educational shares in the US population.

The model overall delivers a good fit. The model overpredicts the prevalence rates of



hard drugs use for youths and underpredicts them for older agents. The persistence of drug use is also somewhat higher in the model. The hard drugs expenditure distribution predicted by the model is fairly close to the actual one. Notice that the listed moments are the ones used in the SMM estimation procedure, that is the 25th, 40th, 50th, 60th and 75th percentiles. The discrepancy between model and data seems to increase with the value of the drug expenditure. A plausible explanation is related to the model time period. A yearly period does not allow to capture the short run dynamics of the addiction process. Heavily addicted individuals spend large amounts to pay for their addiction, however, it is quite likely that this subset of people will be arrested and convicted after a short time period, possibly much shorter than one year.

As for the unemployment rate by hard drug use, the difference between the model and the data is small, less than one percentage point.

The next set of moments reported in Table 10 refer to the inmates composition by type of crime, considering the most serious offense in case of multiple crime charges. Notice that we are considering drug selling the most serious charge, followed by property crimes and then by drug possession. The model underpredicts the share for this last category of crimes. There are two likely reasons for this result. The first one is related to the criminal justice system, i.e. it stems from a data classification problem. It is quite possible that drug sellers caught with small amounts of illegal substances were convicted for a minor crime, i.e. drug possession, rather than drug selling. This would also explain why the prison time for drug possession does not differ much from the prison time for drug selling. The second explanation is related to the prevalence rates of drug use. If the probability of apprehension for drug possession is sufficiently high, the agents will abstain from using hard drugs. The only way for the model to perform well both in the hard drugs expenditure distribution and in the prevalence rates profiles by age is to have a small probability of apprehension  $\pi_a^d$ . Notice that the two remaining shares, for property crimes offenders and drug dealers, are higher in the model than in the data.

To conclude with. Figure 2.9 depicts the unemployment rates profiles by age and educational achievement. The model replicates successfully the main patterns, with the unemployment rates being very high for the young adults, and decreasing with both age and education.

The mechanism at work in the model is relatively simple and can be summarized as follows. The involvement in crimes is driven by several factors. The first one is the

<i>Variable</i>	<i>Data</i>	<i>Model</i>
<i>Prevalence Rates of Hard Drugs Use:</i>		
<i>Age: 16 - 18</i>	6.5%	8.7%
<i>Age: 19 - 21</i>	5.6%	7.1%
<i>Age: 22 - 24</i>	7.4%	6.0%
<i>Age: 25 - 27</i>	3.9%	5.2%
<i>Age: 28 - 31</i>	5.3%	4.4%
<i>Age: 32 - 35</i>	5.8%	3.7%
<i>Age: 36 - 40</i>	3.5%	3.0%
<i>Age: 40 +</i>	0.4%	1.0%
<i>Persistence of Hard Drugs Use</i>	48.2%	57.1%
<i>Hard Drugs Expenditure Distribution:</i>		
<i>25th percentile</i>	\$250	\$277
<i>40th percentile</i>	\$560	\$503
<i>50th percentile</i>	\$900	\$782
<i>60th percentile</i>	\$1,400	\$1,116
<i>75th percentile</i>	\$2,750	\$2,124
<i>Hard Drugs Users Unemployment Rates</i>	11.09%	10.21%
<i>Inmates Composition:</i>		
<i>Property Crimes</i>	52.6%	56.7%
<i>Drug Selling</i>	34.9%	40.7%
<i>Drug Possession</i>	12.5%	2.6%

Table 2.10: Model Fit - Simulations Vs. Data

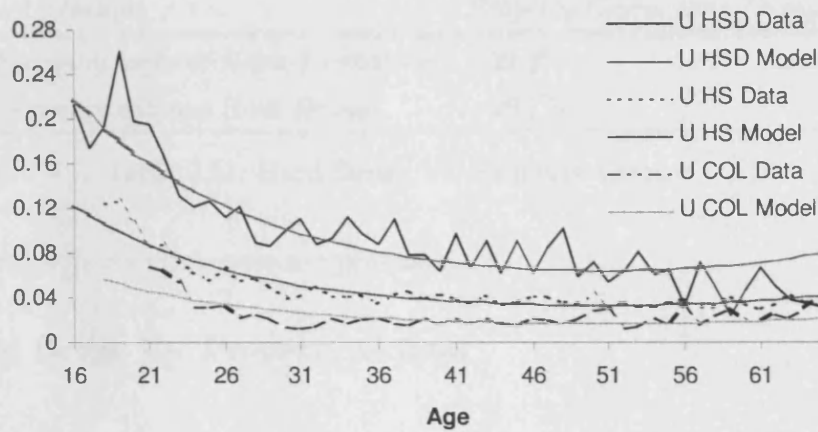


Figure 2.9: Model Fit - Unemployment Rates by Age and Education

life-cycle dimension, which affects the crime decisions in two opposite ways. On the one hand, as people age, the reward to legal activities increases, since the efficiency units are increasing over the life-cycle. This provides an incentive not to commit crimes because of the high opportunity cost of being apprehended and because people with a higher legal income have a lower marginal utility from consumption. The second channel goes through hard drugs consumption. The same comments apply also in this case. The prevalence rate of drug consumption is declining over the life-cycle, because people are deterred by the increased likelihood of being unemployed.

The property crime rate obtained in model is equal to 4.3%, a value which tracks well the actual one for 1996, 4.6%.

Finally, notice that the model implies a price  $\bar{p}_d = 0.187$ , or an equilibrium street level price for hard drugs which is 22% higher than the retail one.

In the following Section a series of counterfactual experiments are carried out, to understand the effect of hard drugs on property crimes.

## 2.6 Results

This Section presents the main results of the paper. First we compute the percentage of property crimes that is accounted for by hard drugs. Then two policy experiments meant

<i>Counterfactual</i>	<i>Property Crime Rate Change</i>
1) <i>Economy without Habit Formation</i>	-22.3%
2) <i>Economy without Hard Drugs</i>	-26.1%

Table 2.11: Hard Drugs Vs. Property Crimes

to decrease the property crime rate are presented.

### 2.6.1 Hard Drugs Vs. Property Crimes

How much of the property crime rate is accounted for by hard drugs addicts stealing in order to pay for their consumption of drugs? Answering this question is not a trivial task. In order to do so we propose two different exercises, based on counterfactual analysis. In the first laboratory economy hard drugs are assumed to be non addictive, that is they are no longer a habit forming good, while in the second economy hard drugs are assumed not to exist. We compute the property crime rates in these two economies and compare them to the baseline one, which is 4.3%.

The results of Table 11 show that a substantial part of property crimes, between 22% and 26%, are accounted for by predatory crime to finance hard drugs addiction.

In the first exercise, hard drugs are assumed to be non addictive: this leaves just the temporary hard drugs demand, leading to a drop in the equilibrium price for hard drugs and in the revenues from drug selling. This general equilibrium effect prevents the property crime rate to fall even further, the drop being equal to 22.3%.

In the second economy we consider another extreme case, that is we assume that hard drugs do not exist. In this economy the property crime rate drops by 26%. In this case agents cannot consume hard drugs and they cannot be involved in drug dealing. The only forces driving their property crime decisions are the poor legitimate opportunities. Young adults in either employment status and unemployed individuals decide to steal some money, because of their high marginal utility of consumption. This channel seems to be the most important one, accounting for no less than 74% of the property crime rate.

The results of this Section suggest that hard drugs play a non negligible role in shaping the US property crime rate. Below we consider two policy experiments aimed at reducing the property crime rate by changing the US drug policy.

<i>Policy Experiment</i>	<i>Property Crime Rate Change</i>
<i>Treatment (for Inmates)</i>	-11.1%

Table 2.12: The Effects of an Ideal Treatment

### 2.6.2 The Effects of an Ideal Treatment Technology

The first policy experiment considers the effect of an ideal treatment technology. Assume that in the economy suddenly a perfect and costless treatment technology capable of eliminating the habit stock of treated individuals becomes available. Assume also that all convicted felons with a positive stock of habits are treated. What would be the indirect effect on the property crime rate of such a treatment?

As shown in Table 12, this policy would decrease the property crime rate by 11.1%. The reduction in the stock of habits reduces both the demand for drugs once the convicted felon is released and increases the likelihood that a taste shock will make this person no longer a drug user in the future.

Notice that in the baseline model economy agents do not have a treatment technology at their disposal, while in the US economy there are several treatment schemes available both for inmates and for the non-institutional population. However, most of the treated people relapse into hard drugs abuse in a very short period of time after having being treated, usually in less than six months. Notice also that it is pretty common for addicted criminals diverted to treatment centers to escape from these institutions, not returning there unless they are arrested again. Furthermore in 1996, the baseline year, the available treatment procedures were still under assessment, with a lot of disagreement among practitioners on which one was most effective.

### 2.6.3 A Legalization Experiment

The last counterfactual we consider is a hard drugs legalization policy. From an a-priori perspective the result of a legalization policy are not clear. Such a policy would make drug consumption legal and, at the same time, it would decrease the price at which hard drugs consumers can purchase these goods. On the one hand, there is a non trivial effect on the reaction of consumption. Both the prevalence rates and the quantity consumed are likely to change, inducing complicated (and hard to forecast) dynamics of addiction. On the other hand, heavily addicted individuals loose the income deriving from selling drugs

<i>Experiment</i>	<i>Property Crime Rate Change</i>
<i>Legalization</i>	-18.6%

Table 2.13: A Hard Drugs Legalization Policy

to casual consumers. Understanding the overall effect is then an empirical question. If the government were to choose a price equal to  $\underline{p}_d$ , that is the price observed for high level transactions, the simulations show that such a policy would decrease the property crime rate by 18.6%, as reported in Table 13.

Legalization of hard drugs might seem to some people a rather extreme measure. However, notice that there have been other places and times where the consumption and the production of some kind of hard drugs were legal. Two such examples are the Opium Regie analyzed in detail by van Ours (1995), and the US experience before the Harrison Act, as discussed in MacCoun and Reuter (2001).

The discussion presented in Friedman (1991) and Miron (2004) shows that many commentators and academics have called for a drastic change in the existing US policy related to illegal drugs. Those in favor of legalization argue that the costs induced by prohibition are large and that the money saved by making drugs legal could be used to set up awareness programs and to improve treatment services. The findings of this policy experiment offer a quantification of the potential benefits of such an alternative policy regime. Freeman (1996) suggests that the direct losses of the victims of crime are about \$3,000, including both the health costs and the lost income. A 18% decrease in the property crime rate would save almost 7 billions to the American households. To this value also the reduced costs of a lighter criminal justice system should be added: if the figure reported in the introduction, 170 billions, is a good approximation, other 90 billions would be saved from the decriminalization of hard drugs possession and from the elimination of drug selling, and other 17 billions would be saved from the decreased conviction rates for property criminals.

Certainly the results are to be taken with some caution. The answers provided in this paper represent a first attempt to tackle this complicated phenomenon and to better inform policy making. Under the specific type of legalization studied here, the government is free to choose to sell hard drugs at any price considered appropriate, according to some principle. We chose the price observed for retail drug purchases, since it is likely that such a price would be enough to eliminate illegal drug dealing. Such a price is pretty

similar to the prices for legal cocaine and heroin that are currently used in the US for medical and scientific purposes, as computed by Miron (2003). However, notice that for even lower prices the response of consumption could be so strong to overcome the effects of a decreased price on the total expenditure and, in turn, on the property crimes. Even if this were not to be the case, under legalization the agents lose one of their income generating activity, i.e. drug selling, which, as discussed above, is not negligible at least for the consumers who are heavily addicted. This other channel might lead some criminals to substitute drug selling with property crimes.

## **2.7 Discussion and Conclusions**

This chapter has contributed to the literature on the economics of crime, furthering our understanding of the determinants of criminal participation. The analysis has looked at property crimes, drug selling and drug abuse through the lens of an equilibrium model, in the spirit of Flinn (1986), Imrohorglu, Merlo and Rupert (2000), and Imrohorglu, Merlo and Rupert (2004).

A striking feature of property crimes, drug selling and illegal substance abuse in the US is the size of these phenomena. Literally millions of people are arrested each year either with a property crime charge or a drug violation one. These are quantitatively relevant both in terms of the number of people involved and in terms of the related economic costs. Not only there are about one and a half million inmates whose most serious charge was either a property crime or a drug violation, but also there is an "army" of probationers and parolees that might easily become convicted felons, if a policy change making the criminal justice system tougher were to be enacted.

In the chapter a model of rational addiction and rational crime participation has been specified, parametrized and solved numerically. In the model, agents can be involved in several illegal behaviors, namely property crimes, hard drugs use and hard drugs selling: this modeling assumption is based on the lessons learned from the RAND inmates survey, studied by Wilson and Abrahamse (1992) among others.

The model is able to generate a declining criminal participation over the life-cycle, as observed in the UCR data. The mechanism that generates this outcome is very simple: the labor market rewards increase as agents age, making the opportunity cost of a prison term higher. This prevents older agents to be involved in income generating illegal activities.

Another interesting feature of the model is the presence of an upward sloping supply of hard drugs at the street level. This is obtained irrespective of the assumptions of perfect competition for street level drug sellers and of a perfectly elastic supply of drugs for the international drug dealers. The supply curve is upward sloping since drug sellers are caught with certainty if they decide to sell drugs above a certain threshold. This assumption allows for drug sellers with different characteristics to participate in the drugs market: as the price of drugs increases, more agents find profitable to enter the market. Since the agents can be ranked in increasing order with respect to their opportunity costs of being apprehended, the supply increases smoothly in the price.

We argued that hard drugs addiction play a significant role in accounting for the observed property crime rate. In the model, agents abusing drugs experience unemployment spells more frequently than people who don't. The unemployment risk, being uninsurable, is the force that induces some agents to abstain from consumption and that increases the likelihood of involvement in crimes for others.

The results show that a substantial part of property crimes, about 26%, is accounted for by predatory crime to finance hard drugs addiction. This value is obtained by comparing the property crime rate of the baseline economy (4.3%) to that of a counterfactual economy where hard drugs do not exist (3.18%). This finding provides a measure of the magnitude of a specific kind of negative externalities: the ones driven by predatory crime. Even if the model is a rational addiction one, there is room for public intervention due to the negative externalities induced by hard drugs addiction.<sup>30</sup>

Given that the number of property crimes accounted for by hard drugs is non negligible, we consider policy interventions alternative to the "War on Drugs" which is currently fought. Namely, the economic consequences of an ideal drug treatment scheme for all arrested felons are computed: such a policy decreases the property crime rate by 11.1%. Finally, with another counterfactual experiment, we assess the effects of a legalization policy: under this new regime, the property crime rate is shown to decrease by 18.6%.

It goes without saying that the findings of this analysis hinge on a number of assumptions: some caveats are in order.

The first caveat is related to the estimation of preferences. It is worth pointing out that the results of the counterfactuals are valid only under the maintained assumption that the primitives of the model are policy invariant. However, a legalization policy might

---

<sup>30</sup>Notice, however, that the analysis focuses on the externalities related to the criminal justice system, while it does not consider other externalities such as the health costs related to drug abuse.



affect also the “forbidden-fruit” type of consumption. If there are people consuming hard drugs mainly for the fact that they are illegal, the structural parameters would violate the policy invariance assumption. To the best of our knowledge, there are no studies assessing the plausibility of the “forbidden-fruit” hypothesis.

Second, the model does not allow for peer effects, which might be an important dimension for drug abuse. However, notice that there is some information contained in the NHSDA that could be exploited to better understand if this channel is a relevant one.

Third, in the legalization experiment the potential indirect costs induced by this policy are neglected. It is likely that phenomena such as Driving While Intoxicated and violent crimes, such as assault and rape, would increase as a consequence of the increase in hard drugs consumption. Admittedly, these costs are potentially very high.

Fourth, the policy experiments are implicitly assuming that the government is rebating the saved criminal justice costs to the households, namely it is not using the resources made available by the policy changes to increase the expenditure on police, affecting the likelihood of an arrest for property crimes. This implies that the results of the counterfactuals are to be considered as lower bounds.

Fifth, in the model the structure of the drug market is very simple. It is reasonable to think that the international supply of drugs is not flat, but positively sloped. Data limitations on the hard drugs expenditure, namely the fact that these data exist only for the year 1996, do not allow to solve the model for more than one year, making the identification of a cost function not possible. As long as the price elasticity is sufficiently high, the results should not be much affected. Furthermore, in the drug markets there are no frictions: there are no fixed costs of drug dealing, such as licensing or buying some weapons, and there is no imperfect information, that is everyone knows where the international drug dealer is and everyone knows where the domestic drug market is located. A question in the NHSDA asked the following *"How difficult do you think it would be for you to get each of the following types of drugs, if you wanted some?"*. The percentage answering that it is almost impossible to get hard drugs is lower for people who already used illegal substances in the past. This might suggest that some people know where the drug market is, while others do not.

To conclude with, an interesting exercise that can be easily implemented in the framework developed here is to search for the “optimal” price under legalization: a sensible value could be the one that minimizes the property crime rate, that is the one minimizing the hard drugs criminal externalities.

## 2.8 Appendix A - The Full Recursive Representation

For the sake of readability, in the text we reported only a simplified version of the Bellman equations and stationary distributions. Their complete formulation follows.

Bellman equations:

$$\begin{aligned}
V_{i,ed}(s, h, \varepsilon) = & \\
& \max_{c,d,pc,ds} (1 - \pi_a^d d) (1 - \pi_a^{pc} pc) (1 - \pi_a^{ds} ds) \{u(c, d, h, \varepsilon) + \\
& + \beta E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i+1,ed}(h'; s, s') V_{i+1,ed}(s', h', \varepsilon')\} \\
& \pi_a^d d (1 - \pi_a^{pc} pc) (1 - \pi_a^{ds} ds) \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^d((1 - \lambda) h, t = 0) \right\} + \\
& (1 - \pi_a^d d) \pi_a^{pc} pc (1 - \pi_a^{ds} ds) \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^{pc}((1 - \lambda) h, t = 0) \right\} + \\
& (1 - \pi_a^d d) (1 - \pi_a^{pc} pc) \pi_a^{ds} ds \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^{ds}((1 - \lambda) h, t = 0) \right\} + \\
& \pi_a^d d \pi_a^{pc} pc (1 - \pi_a^{ds} ds) \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^{d,pc}((1 - \lambda) h, t = 0) \right\} + \\
& \pi_a^d d (1 - \pi_a^{pc} pc) \pi_a^{ds} ds \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^{d,ds}((1 - \lambda) h, t = 0) \right\} + \\
& (1 - \pi_a^d d) \pi_a^{pc} pc \pi_a^{ds} ds \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^{pc,ds}((1 - \lambda) h, t = 0) \right\} + \\
& \pi_a^d d \pi_a^{pc} pc \pi_a^{ds} ds \left\{ u(\bar{c}_a, 0, h, \varepsilon) + \beta J_{i+1,ed}^{d,pc,ds}((1 - \lambda) h, t = 0) \right\}
\end{aligned}$$

*s.t.*

$$c + \bar{p}_d d + p_I \leq y_{s,i,ed} + \eta \bar{y} pc + (\bar{p}_d - p_d) ds$$

$$h' = (1 - \lambda) h + d$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2), \text{ or more generally } \varepsilon \sim N(\mu(i), \sigma_\varepsilon^2(i))$$

$$h_1 \text{ given, } c \geq 0, d \geq 0, pc \geq 0, ds \geq 0$$

$$J_{i,ed}^j(h, t) = u(\bar{c}_a, 0, h, 0) + \beta J_{i+1,ed}^j(h, t + 1)$$

$$J_{i,ed}^j(h, T_j - 1) = u(\bar{c}_a, 0, h, 0) + \{ \beta \zeta_j E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i+1,ed}(h'; s, s') V_{i+1,ed}(s', h', \varepsilon') + (1 - \zeta_j) J_{i+1,ed}^j(h', T_j) \}$$

$$J_{i,ed}^j(h, T_j) = u(\bar{c}_a, 0, h, 0) + \beta E_{\varepsilon'|\varepsilon} \sum_{s'} \pi_{i+1,ed}(h'; s, s') V_{i+1,ed}(s', h', \varepsilon')$$

s.t.

$$h' = (1 - \lambda) h$$

$$\varepsilon \sim N(0, \sigma_\varepsilon^2)$$

$$j \in \bar{J} = \{d, pc, ds, (d, pc), (d, ds), (pc, ds), (d, pc, ds)\}$$

Where  $J_{i,ed}^j(h)$  stands for the value function of an offender convicted because of crime  $j$ ,  $T_j$  stands for the maximum number of periods a felon has to spend in prison because of the same crime, while  $\zeta_j$  represents the probability of being released at  $T_j - 1$  (prison periods do not coincide with model periods).

Stationary distributions (Non convicted agents):

$$\begin{aligned} \mu_{i+1,ed}(s', h', \varepsilon') &= \sum_s \int_{h:h'=d_{i,ed}(s,h,\varepsilon)+(1-\lambda)h} (1 - \pi_a^{pc} pc_{i,ed}(s, h, \varepsilon)) (1 - \pi_a^{ds} ds_{i,ed}(s, h, \varepsilon)) \cdot \\ &\cdot (1 - \pi_a^d d_{i,ed}(s, h, \varepsilon)) + \pi_{i+1,ed}(h'; s, s') d\mu_{i,ed}(s, h, \varepsilon) \mu(\varepsilon') + \mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_d d\mu_{i,ed}^{J,d}(h) \\ &+ \mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_{pc} d\mu_{i,ed}^{J,pc}(h) + \mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_{ds} d\mu_{i,ed}^{J,ds}(h) \\ &+ \mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_{d,pc} d\mu_{i,ed}^{J,(d,pc)}(h) + \mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_{d,ds} d\mu_{i,ed}^{J,(d,ds)}(h) + \\ &\mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_{pc,ds} d\mu_{i,ed}^{J,(pc,ds)}(h) + \mu(\varepsilon') \int_{h:h'=(1-\lambda)h} \zeta_{d,pc,ds} d\mu_{i,ed}^{J,(d,pc,ds)}(h) \end{aligned}$$

$$\text{with } \mu_{1,ed}(\cdot, \underline{h}, \cdot) = \frac{1}{T\mu_{ed}}, \mu_{1,ed}^{J,j}(h) = 0, \forall j \times ed; j \in \tilde{J}$$

Stationary distributions (Inmates charged with a drug possession offense):

$$\mu_{i+1,ed}^{J,d}(h') = \int_{h:h'=(1-\lambda)h} (1 - \zeta_j) d\mu_{i,ed}^{J,d}(h) + \sum_s \int_{h:h'=d_{i,ed}(s,h,\varepsilon)+(1-\lambda)h \times \mathfrak{R}}$$

$$[\pi_a^d d_{i,ed}(s, h, \varepsilon) (1 - \pi_a^{ds} ds_{i,ed}(s, h, \varepsilon)) (1 - \pi_a^{pc} pc_{i,ed}(s, h, \varepsilon))] d\mu_{i,ed}(s, h, \varepsilon)$$

with  $\mu_{1,ed}^{J,j}(h) = 0, \forall j \times ed; j \in \tilde{\mathcal{J}}$

and similarly for all the other possible criminal charges  $j \in \tilde{\mathcal{J}}$ .

## 2.9 Appendix B - UCR

### Description

The Uniform Crime Rate (UCR): is developed and maintained by the FBI. It can be obtained at <http://149.101.22.40/dataonline/Search/Crime/State/StatebyState.cfm>. The FBI property crime category was amended, excluding Arson and considering robberies as a property crime rather than a violent one. More precise definitions follow.

- Robbery - The taking or attempting to take anything of value from the care, custody, or control of a person or persons by force or threat of force or violence and/or by putting the victim in fear.
- Burglary - breaking or entering - The unlawful entry of a structure to commit a felony or a theft. Attempted forcible entry is included.
- Larceny-theft (except motor vehicle theft) - The unlawful taking, carrying, leading, or riding away of property from the possession or constructive possession of another. Examples are thefts of bicycles or automobile accessories, shoplifting, pocket-picking, or the stealing of any property or article which is not taken by force and violence or by fraud. Attempted larcenies are included. Embezzlement, confidence games, forgery, worthless checks, etc., are excluded.

- Motor vehicle theft - The theft or attempted theft of a motor vehicle. A motor vehicle is self-propelled and runs on the surface and not on rails. Motorboats, construction equipment, airplanes, and farming equipment are specifically excluded from this category.
- Drug abuse violations - State and/or local offenses relating to the unlawful possession, sale, use, growing, and manufacturing of narcotic drugs. The following drug categories are specified: opium or cocaine and their derivatives (morphine, heroin, codeine); marijuana; synthetic narcotics—manufactured narcotics that can cause true addiction (demerol, methadone); and dangerous nonnarcotic drugs (barbiturates, benzedrine).

## 2.10 Appendix C - Solution Algorithm

The computational procedure used to solve and estimate the model can be represented by the following algorithm:

- Guess the vector of parameters  $\Theta_0$ ;
- Generate discrete grids over the state space  $[h_{\min}, \dots, h_{\max}] \times [\varepsilon_{\min}, \dots, \varepsilon_{\max}]$ ;
- Guess the aggregate crime rate  $\pi_{v0}$ ;
- Guess the average legal income  $\bar{y}_0$ ;
- Get the equilibrium tax rate on labor income  $\tau_U$ ;
- Guess the criminal justice tax rate  $\tau_{J0}$ ;
- Compute the insurance price  $p_I = \eta \bar{y}_0 \pi_{v0}$ ;
- Guess on the hard drugs price  $\bar{p}_{d0}$ ;
- Get the:
  - Drug consumption functions  $d_{i,ed}(s, h, \varepsilon)$ ;
  - Property crime functions  $pc_{i,ed}(s, h, \varepsilon)$ ;

- Drug selling functions  $ds_{i,ed}(s, h, \varepsilon)$ ;
- Get the numeraire consumption functions  $c_{i,ed}(s, h, \varepsilon)$ ;
- Get the stationary distributions  $\mu_{i,ed}(s, h, \varepsilon)$  and  $\mu_{i,ed}^J(h)$ ;
- Compute the hard drugs excess demand  $exd = \sum \int [d_{...}(\cdot) - ds_{...}(\cdot)] \mu_{...}(\cdot)$ ;
- Check hard drugs market clearing;
- Update  $\bar{p}_{d1} = (1 + \varpi exd) \bar{p}_{d0}$  (with  $\varpi$  arbitrary weight);
- Iterate until hard drugs market clearing;
- Get the average non criminal income  $\bar{y}_1$ ;
- Update  $\bar{y}'_0 = \kappa \bar{y}_0 + (1 - \kappa) \bar{y}_1$  (with  $\kappa$  arbitrary weight);
- Get the aggregate crime rate  $\pi_{v1}$ ;
- Update  $\pi'_{v0} = \nu \pi_{v0} + (1 - \nu) \pi_{v1}$  (with  $\nu$  arbitrary weight);
- Get the criminal justice tax rate  $\tau_{J1}$ ;
- Update  $\tau'_{J0} = \iota \tau_{J0} + (1 - \iota) \tau_{J1}$  (with  $\iota$  arbitrary weight);
- Iterate until convergence;
- Check numeraire good market clearing;
- Compute the predicted moments and evaluate the sum of squared deviations from the data;
- Update the vector of parameters  $\Theta_1$  with the Nelder/Mead simplex method;
- Iterate until a minimum is found.

## Chapter 3

# Accounting for the Racial Property Crime Gap in the US: A Quantitative Equilibrium Analysis

### 3.1 Introduction

In the US a striking fact about property crimes is the high participation of one minority group: the African American males. For example, in 1996 the property crimes arrest rate (per 1.000 males) was equal to 5,35 for white males and 24,0 for black ones. In the same year 2% of the US white population was under correctional supervision, while the same figure for blacks was 8.9%. Such drastic gaps can be explained in several ways. If, for some reasons, legitimate economic opportunities are correlated with demographic traits, the group facing the worse situation can resort to crime more often, to partially overcome the economic disadvantage, as discussed in Bound and Freeman (1992) and Anderson (1999). Alternatively, peer effects and social interactions among people belonging to the same demographic group can influence heavily criminal choices, as proposed by Sah (1991) and Glaser, Sacerdote and Scheinkman (1996). Finally, it can be claimed that the criminal justice system has practices which are discriminatory with respect to minorities, a hypothesis tested for example in Knowles, Persico and Todd (2001) and Hernandez-Murillo and Knowles (2004).

This paper takes the first point of view, assessing the importance of both labor market conditions and asset poverty in accounting for the observed racial crime gap. In a world

with no peer effects or discriminatory criminal justice, this contribution quantitatively evaluates to what extent worse legal opportunities can be considered responsible for the high crime involvement of black American males. A dynamic general equilibrium model of rational crime participation is developed to study the impact of more diffuse poverty, higher unemployment rates, lower educational achievements, lower wages and lower labor supply on the crime behavior of black males in the US. In order to focus on crimes that are mainly driven by economic forces, violent crimes are neglected altogether. The analysis considers only property crimes, or the class of crimes that are more likely to be motivated by an economic evaluation of the potential gains, i.e. the value of the stolen goods, and costs, i.e. the chances of being apprehended together with the severity of the punishment.<sup>1</sup> The theoretical model extends Becker (1968) framework to a dynamic environment, along the lines of Flinn (1986) and Imrohorglu, Merlo and Rupert (2004). It then exploits the information related to the labor market characteristics to quantitatively assess the differences in crime behaviors between agents facing different legitimate opportunities, namely blacks and whites.

An infinitely lived agents model is developed, allowing for several layers of heterogeneity: race (captured by the labor market opportunities), education, employment status and asset holdings. Each dimension of heterogeneity is a channel that gives different incentives to commit a property crime: these are studied altogether and, by means of counterfactual analysis, one at a time. Given the richness of the model, an analytical solution cannot be obtained: the model is calibrated relying on US data and solved numerically.

Simulation results show that the observed poverty and labor market outcomes account for as much as 90% of the black/white arrest rates ratio. The model captures well relevant dimensions of the crime phenomenon, such as the inmates composition by race, employment status and education. The equilibrium features of the framework allow to perform counterfactual analysis with an endogenous response of the individuals to different public policies. The calibrated model is used to compare two alternative policy experiments aimed at reducing the aggregate crime rate: increasing the expenditure on police seems to be cost effective, when compared to an equally expensive lump-sum subsidy targeted to the high school dropouts.

The following section surveys the literature related to this chapter.

---

<sup>1</sup>Property crimes (defined as the sum of burglaries, larcenies, motor vehicle thefts and robberies) reported to the police and included in the FBI Uniform Crime Reports have historically accounted for more than 90% of total known crimes in the US.



### 3.1.1 Related Literature

This chapter is related to at least two strands of literature, the first one being the studies on the economics of race and the labor market, the second one being the economics literature on crime.

As for the economic analysis of the different labor market conditions according to race, the empirical literature in particular is vast. Here the focus will be on the black-white differentials only.<sup>2</sup> Some of the most relevant contributions are Altonji and Blank (1999), Donohue and Heckman (1991) and Neal and Johnson (1996).<sup>3</sup>

Altonji and Blank (1999) provide a survey of the empirical evidence on the differentials by race in the US labor market in the recent past. They discuss and test the theories of discrimination developed in the literature, suggesting that some discrimination is indeed at work. However, from this survey, it seems safe to conclude that there is no consensus on the magnitude of this phenomenon.

Donohue and Heckman (1991) study how the economic status of blacks relative to whites has been improving from the 40's to the late 60's, eventually stagnating from the mid 70's. The authors explain the more recent lack of convergence in the economic outcomes of the two demographic groups with the decline in the relative wages paid to unskilled versus skilled workers that has occurred in that period of time.

Finally, Neal and Johnson (1996) find that the discrimination in the labor market is very limited, once among the determinants of wages a control for workers' skills (i.e. the AFQT test) is included. They argue that the wage gap reflects mainly a skill gap, in turn determined by different family backgrounds and school environments, that is by premarket factors.

In this respect, notice that the model proposed in this paper will be silent on the origins of the labor market differentials by race. In this sense, it can be considered consistent with both a difference in the quantity of human capital and a discrimination behavior determining the different labor market conditions.

As for the literature on crime, it is possible to distinguish between the mainly empirical contributions and the mainly theoretical ones. From an empirical point of view, there have

---

<sup>2</sup>We can justify this choice by noting that in the US hispanic people show labor market outcomes which are halfway from the blacks and whites. Also their involvement in property crimes is in this middle position. Moreover, blacks and whites account for more than 90% of the prison population.

<sup>3</sup>This list is by no means exhaustive. For a more comprehensive one see the references included in the papers mentioned here.

been several studies assessing the effects of unemployment rates on property crimes. The effect has been found to be consistently positive, even though some studies claim that it is small in size.<sup>4</sup> The empirical evidence discussed in Lochner (2004) and Lochner and Moretti (2004) shows that the bulk of property crimes are committed by people with poor educational achievements, with the high school dropouts being the most crime prone group. As for the role of race as a determinant of property crimes, the findings appear to be more controversial. More in detail, some studies find a significant effect of belonging to a minority, e.g. Grogger (1998) and Witte and Tauchen (1994), some other studies do not find any significant effect, e.g. Lochner (1999), and some others find a significant impact of race on the participation in criminal activities depending on the specification adopted, e.g. Kelly (2000) and Levitt (1996). Notice that a potentially important variable that is missing in all these studies is a measure of wealth.

Both the theoretical and quantitative research on the economics of crime have been particularly active in the recent years. Some contributions of interest are Burdett, Lagos and Wright (2003), Glaser, Sacerdote and Scheinkman (1996), Imrohoroglu, Merlo and Rupert (2000), Imrohoroglu, Merlo and Rupert (2004), Persico (2002) and Verdier and Zenou (2004).

Burdett, Lagos and Wright (2003) extend the standard search theoretic framework to allow for criminal activities. They study the effect of crime on both unemployment and inequality, showing that the possibility of committing a crime has non trivial effects on both variables.

In Glaser, Sacerdote and Scheinkman (1996) social interactions are introduced in order to explain the high variance of crime rates in cities and over time. They specify and estimate a model where agents imitate the behavior of people living close to them. Their estimates suggest the presence of social interactions.

The contribution of Imrohoroglu, Merlo and Rupert (2000) studies the endogenous determination of crime, redistribution and police expenditure in a majority voting political economy framework. They analyze how these variables are affected by changes in the income distribution and the criminal apprehension technology. Their framework accounts for the correlation among redistribution, police expenditure and property crimes observed in the US data.

Imrohoroglu, Merlo and Rupert (2004) study in a OLG model which factors account

---

<sup>4</sup>See for instance the papers by Witte and Tauchen (1994) and Raphael and Winter-Ebmer (2001).

for the oscillating behavior of the US property crime rate observed in the mid 70's to mid 90's years. They show that the aging of the population, the stronger economy and the higher apprehension probability explain the drastic drop in the aggregate crime rate that took place in the 90's.

Persico (2002) studies the effect of racial profiling by police in the search for criminals. This study shows that a fair system, that is a system that audits different racial groups with the same intensity, can lead to a lower amount of crime if compared to an unfair system.

To conclude with, Verdier and Zenou (2004) demonstrate how stereotypical beliefs on crime involvement together with location in a city can lead to a discriminatory equilibrium, with the minority group committing more crimes, living further away from productive activities and earning lower wages. The mechanism at work in this economy is of the self-fulfilling type.

As a final remark, notice that none of these papers deals with race, poverty, labor market conditions and property crimes in a quantitative framework, which is the focus of this paper.

The rest of the chapter is organized as follows. Section 2 discusses some stylized facts related to crime behaviors and labor market conditions for the male population in the US. The theoretical model is presented in section 3, while section 4 is devoted to the definition of the equilibrium concept used in the model: the recursive stationary competitive equilibrium. Section 5 presents the calibration used in the simulations. Section 6 provides the main results and predictions of the baseline model, including the comparison of two policy experiments and the discussion of counterfactual analysis. Section 7 concludes. The algorithm used for the solution of the model is described in the appendix.

## **3.2 Empirical Evidence**

In this section we document and discuss some stylized facts about property crime involvement in the US.

Figure (3.1) plots the time series of the property crimes arrest rates by race from 1965 to 2001. These data are collected by the Federal Bureau of Investigations and are expressed as the number of property crimes arrests for 100.000 individuals belonging to that race. From the figure we can see that both races have shown similar trends over time,

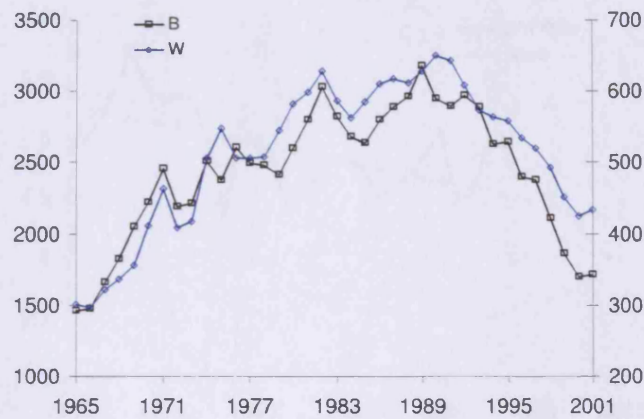


Figure 3.1: Property crimes arrest rates per 100.000 males by race (Whites, blue line and right scale). Source: Uniform Crime Reports, FBI

possibly suggesting that a) the police did not change its apprehension strategy, b) people of different races respond to the same incentives as far as property crimes are concerned. However, the levels are drastically different: for whites, the arrest rate has been oscillating from 300 to 650, while for blacks from 1.464 to 3.180. Even though there seems to be a slow convergence taking place, figure (3.2) tells us that the arrest rate ratio is still above 4.

Figure (3.3) merges data taken from the U.S. Department of Justice, Bureau of Justice Statistics, and the U.S. Census Bureau. This figure plots the property crime rates reported to the police in the year 2000 in each American state versus the share of black people living in those states.<sup>5</sup> This graph can only suggest a positive correlation between the two variables. States with higher black people shares also tend to have higher property crime rates, the sample correlation being equal to 0.49 if Washington DC is included in the sample and to 0.34 if it is excluded.<sup>6</sup> Obviously, this simple plot cannot imply any causal

<sup>5</sup>For a detailed definition of property crimes see appendix B.

<sup>6</sup>This relation appears to be stable over time. See appendix B for the same plot using 1990 data. Moreover, the sample including DC could provide a better representation of this phenomenon, being DC a metropolitan area. Indeed, data from the Bureau of Justice Statistics show that the vast majority of property crimes are perpetrated in metropolitan areas, while data from the Current Population Survey show that in 1996 black households lived mostly in metropolitan areas with at least one million of residents (the precise figure is 60%, versus only 45% of white households). See appendix B for the corresponding

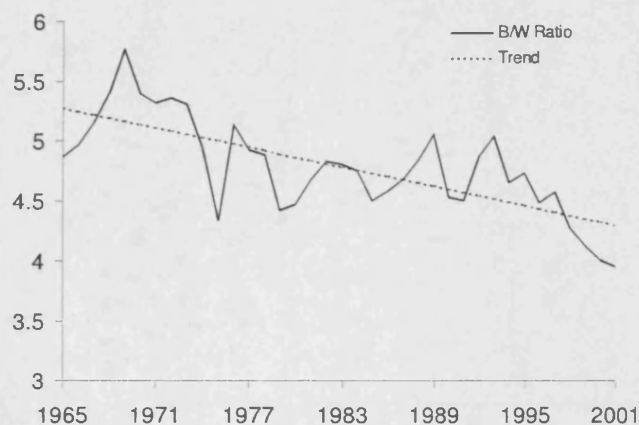


Figure 3.2: FBI Arrest Rates By Race Ratio

link from one variable to the other. One more feature suggested by the plot is the presence of a fairly high degree of non linearity in the data. A linear regression with a common specification in the literature displays an  $R^2$  equal to 0.4, with race being significant across several specifications.<sup>7</sup>

Another source of information on the differentials in crime participation between blacks and whites in the US is the *National Crime Victimization Survey (NCVS)*.<sup>8</sup> Table 1 shows a variable included in the *NCVS*. This provides information about robberies: a sample of persons victim of a robbery were asked to identify the race of the criminals attacking them. Table 1 refers to robberies carried out by a single offender.

The table shows an interesting pattern: irrespective of the decline in the number of total robberies over time, black individuals were recognized to be the offenders in a robbery far more often than people belonging to other races. Moreover, not only these figures do not simply reflect the share of black people in the population (around 12%), but also they represent the highest rate.

So far only indirect evidence of the crime involvement of African Americans has been plot using data from the US cities with a population of at least 200000 people.

<sup>7</sup>The dependent variable is the property crime rate and the regressors are the per capita income, the male unemployment rate, the share of people between 16 and 24 years old, the per capita justice expenditure, the percentage of people below the poverty line, the share of black residents, the percentage of high school dropouts and a constant.

<sup>8</sup>See appendix B for more details on this survey.

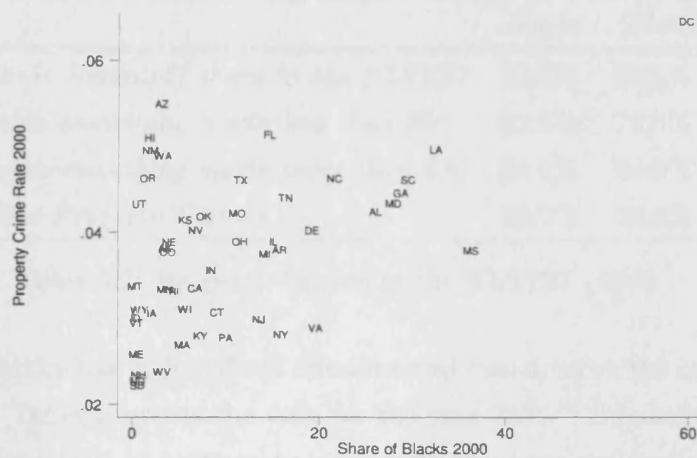


Figure 3.3: Property Crime Rates and Share of Blacks in the US states, 2000.

Year	Robberies	Whites (%)	Blacks (%)	Other	N/A
1996	655800	36.8	51.5	7.5	4.2
1997	565010	38.1	43.0	14.8	4.2
1998	547500	44.3	39.6	10.1	6.0
1999	465430	42.4	46.5	7.0	4.2
2000	407490	37.1	47.7	12.3	2.8
2001	340910	44.9	47.4	6.1	1.6

Table 3.1: Race of Robbery Offenders - NCVS

provided. Two longitudinal studies, the *NLSY79* and the *NLSY97*, represent a source of more direct evidence: the young people randomly selected in the samples were asked whether they participated into criminal activities and, if so, in which crimes.

As for the *NLSY79*, the original sample consisted of 14-22 year-old people and the questionnaire included only in the year 1980 a self administered section with questions on crime involvement. These data show that no clear racial pattern arises. However, subsequent cross validation studies suggested that black respondents underreported their crime participation, Freeman (1999).<sup>9</sup>

As for the *NLSY97*, the original sample consisted of 12-16 year-old people. In each

<sup>9</sup> A detailed description of the criminal activities by race of the *NLSY79* respondents is contained in Grogger (1998), table 2 pag. 769.

	<i>Blacks</i>	<i>Whites</i>
<i>Ethnic (rescaled) share in the NLSY97</i>	33.4%	66.6%
<i>Stolen something worth less than \$50</i>	29.5%	70.5%
<i>Stolen something worth more than \$50</i>	36.0%	64.0%
<i>Other Property Crimes</i>	35.2%	64.8%

Table 3.2: Property Crimes in the NLSY97 - 2001

round the questionnaire has included self administered questions on the crime involvement of the respondent. Table 2 reports the data for the year 2001.<sup>10</sup> Similarly to the *NLSY79* black youths did not report to participate into property crimes strikingly more often than white youths, even though they tend to show a slightly higher involvement, as Table 2 shows.

A possible interpretation of this result calls for the short labor market experience of the youths in the *NLSY97*.

Finally, on a more indirect ground, from the Survey of Inmates in State and Federal Correctional Facilities, 40.4% of the prison population in 1997 convicted because of property crimes consisted of black males, while they represented only 11.4% of the male population.<sup>11</sup> It would be possible to argue that the judicial system is racially biased, as in Donohue and Levitt (2001): this is not the line of research pursued here. In this work it is assumed that the judicial system is fair, or that it is blind to race. Irrespective of his race, every criminal faces the same probability of being caught.

The empirical evidence presented above focuses on the crime involvement of the two main racial groups in the US. Next, some stylized facts about both the economic conditions and the labor market outcomes for the same racial groups are presented.

Figure (3.4) reports the time series for the unemployment rates of white and black males 20 years old and over (data are from the Bureau of labor Statistics) in the period 1976-2003. The top line represents the black unemployment rate. What is striking in the graph is the stable relationship between the two unemployment rates. Black males

<sup>10</sup>The year 2001 was selected in order for all the people in the sample to be old enough to participate in the labor market.

<sup>11</sup>According to the US Bureau of Justice, in 1995 more than 90% of the prison and jail population consisted of males. This suggests to drop women from the relevant population, in order to focus on the main forces driving the decisions of becoming a criminal.

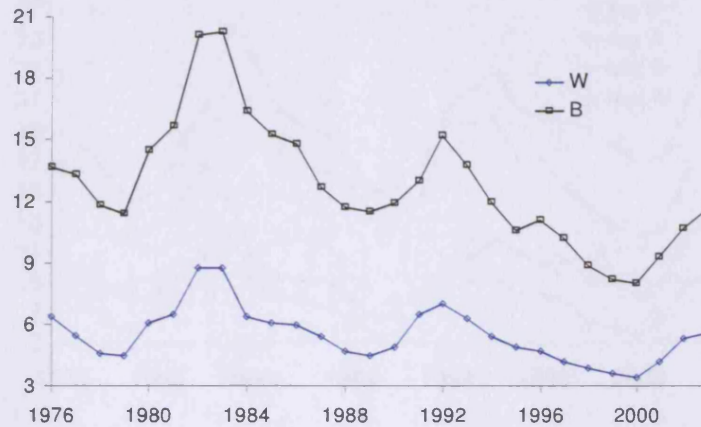


Figure 3.4: Black (top) and White (bottom) Men (16+) Unemployment Rates

have suffered an unemployment rate which has always been at least twice as much as the corresponding figure for white males.<sup>12</sup> Beside the higher incidence of unemployment, black males have consistently had also longer average unemployment spell. Figure (3.5) plots the time series for both the average and median unemployment durations, expressed in weeks. Another sharp difference between blacks and whites is related to the rewards in the labor market. As reported in Altonji and Blank (1999), data from the March 1996 CPS show that there was a substantial gap in annual earnings: white males earned on average \$36,169, while black males earned as little as \$23,645. Obviously, part of these gaps are explained by the different educational achievements of the two groups. In 1996, 14.56% (20.17%) of white (black) males did not have a high school degree, 58.37% (65.14%) had at least a high school degree but did not had a college one and 27.06% (14.68%) had at least a college degree. These facts suggest that black males have experienced worse labor market conditions and outcomes in the recent past. On a different perspective, relying on data from the Survey of Consumer Finances, Wolff (1998) has provided evidence on the racial wealth disparities: the average asset holdings of white households has been around five times higher than the corresponding figure for black households in the last 20 years. Large wealth differentials might be due to differences in inheritances, as studied by Altonji and Doraszelski (2005), or by different rates of entrepreneurship, as discussed in Fairlie and Meyer (1996). Moreover, Wolff (2000) shows that in 1995 31.3% black households had

<sup>12</sup>Notice that considering the unemployment rates by education groups does not alter the picture.



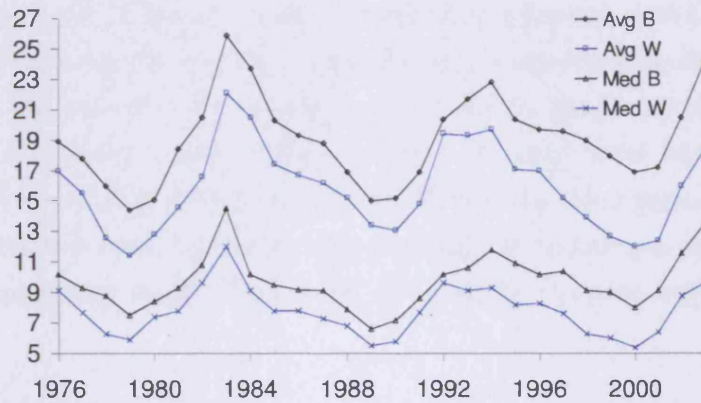


Figure 3.5: Males Average and Median Unemployment Durations

a negative value for the net worth, while the percentage for white households was 15%.

From this set of empirical facts it is possible to argue that African Americans face very different incentives to commit a property crime if compared to the white population. The next section develops a theoretical model aimed both at exploiting these stylized facts and explaining the higher involvement of African Americans in illegitimate activities. Notice that the concept of race adopted is extremely naive. It is a characteristic which is perfectly observable by all economic agents at no costs and relates only to different legitimate opportunities.

### 3.3 The Baseline Model

In this section we propose a dynamic general equilibrium model of crime, along the lines of Imrohoroglu, Merlo and Rupert (2004), with infinitely lived heterogeneous agents.<sup>13</sup> It extends the framework proposed by Huggett (1993) and Aiyagari (1994) to include an endogenous crime choice, agents belonging to two different races (i.e. Blacks/Whites), three levels of education (i.e. high school dropouts, high school degree and college or higher degree), a self-financing unemployment insurance benefits scheme and a self-financing judicial system. The model is framed in an incomplete markets environment. More specifically, agents in the economy face three idiosyncratic risks: 1) being unemployed, 2) being victim

<sup>13</sup>Other GE models of crime are developed in Fender (1999), Furlong (1987), Grossman (1995), Sala-i-Martin (1992). An interesting partial equilibrium contribution is Davis (1988).

of a property crime, and 3) going to jail if involved in property crimes. The former is assumed to be uninsurable, the second is insurable in a competitive market and the latter is not, since it is the outcome of a public policy.<sup>14</sup> As for the former assumption, it is a well know fact that felons convicted because of a property crime were more likely to be unemployed at the time of the offense. Together with the usual arguments motivating incomplete markets, this state dependent outcome suggests that people cannot fully insure against the unemployment risk.<sup>15</sup> Time is discrete and the economy lasts forever.

### 3.3.1 Demographics

The economy is populated by infinitely lived agents whose measure is normalized to one.<sup>16</sup> Agents are ex-ante heterogenous with respect to both their race and their educational achievement. Race is denoted with  $ra \in \mathcal{RA} = \{wh, bl\}$  while education level is denoted with  $ed \in \mathcal{ED} = \{hsd, hs, col\}$ . More in detail, agents of different race/education pairs differ in the probability and duration of employment opportunities, exogenous labor supply  $h_{ra,ed}$  and labor efficiency units  $\varepsilon_{ra,ed}$ . The parameter  $\psi_{ra,ed}$  represents the share of  $(ra, ed)$  workers. Obviously the shares must add up to one, that is  $\sum_{ra,ed} \psi_{ra,ed} = 1$ . There is no population growth and the  $\psi_{ra,ed}$  do not change over time. As mentioned before, in this framework race boils down to exogenous labor market related characteristics and endogenous asset distributions. Notice also that at this stage there is no feedback from the criminal market to the labor market.

---

<sup>14</sup>The assumption of insurability of property crimes is made mainly to keep the notation simple. In previous versions of the model we assumed that alle risks were uninsurable, obtaining results with no relevant differences.

<sup>15</sup>An alternative explanation could be linked to ability. People of low ability could be more likely to be unemployed hence they could self select into criminal activities, showing at the same time high incarceration and unemployment rates. For the latter kind of argument to go through, the concept of ability adopted should be a kind of ability rewarded by the labor market, but not necessarily linked to the criminal ability. Otherwise less able criminals would spend more time in jail, making crime economically less attractive.

<sup>16</sup>The infinitely lived agents assumption is made to give both the wealth distribution and the exogenous borrowing limits a sharper role, without resorting to arbitrary assumptions on the initial wealth distribution, assumptions that would be needed in a standard OLG framework.

### 3.3.2 Preferences

Agents' preferences are assumed to be represented by a time separable utility function  $U(\cdot)$ . Agents' utility is defined over stochastic consumption sequences  $\{c_t\}_{t=0}^{\infty}$ : their aim is to choose how much to consume ( $c_t$ ), how much to save in an interest bearing asset ( $a_{t+1}$ ) and how many property crimes to commit ( $cr_t$ ) in each period of their lives, in order to maximize their objective function.<sup>17</sup> The agents problem can be defined as

$$\max_{\{c_t, a_{t+1}, cr_t\}_{t=0}^{\infty}} U(c_0, c_1, \dots) = \max_{\{c_t, a_{t+1}, cr_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t u(c_t)$$

where  $E_0$  represents the expectation operator over all the possible histories generated by the employment opportunity shocks ( $s \in \mathcal{S} = \{e, u\}$ ), the probability of apprehension if crimes are committed ( $\pi_a$ ) and the probability of being a victim of property crimes carried out by other agents ( $\pi_v$ );  $\beta \in (0, 1)$  is the subjective discount factor. We assume that  $u(\cdot) : \mathcal{C} \rightarrow \mathbb{R}$ , the period utility function, is strictly increasing, strictly concave and satisfies the Inada conditions. Notice that there is no direct disutility neither from work nor from incarceration, hence labor supply is fixed.

### 3.3.3 Endowments

Agents are all born with the same asset endowment  $a_0$ .<sup>18</sup> In every period they can be employed ( $e$ ) or unemployed ( $u$ ). If employed they supply inelastically a constant fraction of their time endowment ( $h_{ra,ed}$ ). The stochastic employment opportunities follow a two state first order Markov process. The transition function of the employment opportunity state is represented by the race/education dependent matrices  $\Pi_{ra,ed}(s, s') = [\pi_{ra,ed}(i, j)]$ , where each element  $\pi_{ra,ed}(i, j)$  is defined as  $\pi_{ra,ed}(i, j) = \Pr\{s_{t+1} = j | s_t = i\}$ ,  $i, j = \{e, u\}$ .<sup>19</sup> Finally, every agent is endowed with exogenous efficiency units denoted as  $\varepsilon_{ra,ed}$ .

---

<sup>17</sup>With some abuse of notation, in the sequential representation of the problem we dropped the history of shocks ( $h^t$ ) as an argument of the choice variables. The process for consumption should read  $\{c_t(h^t)\}_{t=0}^{\infty}$  and similarly for savings and property crimes.

<sup>18</sup>Notice that the specific initial value does not play any role, since the analysis will focus on stationary equilibria, which do not depend on the initial condition.

<sup>19</sup>Hereafter the prime symbol  $\prime$  denotes future variables.

### 3.3.4 Property Crimes

Every agent can engage in property crimes in every period of his life, irrespective of his employment opportunity. The modeling strategy related to the crime choice generalizes Imrohorglu, Merlo and Rupert (2004). There exists a criminal technology,  $y(cr)$ , that maps the number of crimes into criminal earnings. We assume that committing crimes corresponds to stealing a constant fraction  $\eta$  of the average non-asset income in the economy  $\bar{y}$  times the number of crimes  $cr$ . That is, we assume that  $y(cr) = \eta\bar{y}cr$ . Notice that  $y'(cr) > 0$  and  $y(0) = 0$ , that is the technology is linear and people who decide not to be involved in property crimes get zero illegal income. A crime attempt is always successful. However, with probability  $\pi_a(cr)$  criminals are caught and incarcerated at the beginning of the period, while with probability  $(1 - \pi_a(cr))$  they remain free and can use the additional economic resources  $\eta\bar{y}cr$ , obtained through theft. For simplicity assume a linear relationship for the probability of apprehension  $\pi_a(cr) = \pi_a cr$ , with  $0 \leq \pi_a \leq 1$  being a parameter. Notice that committing crimes does not entail any direct cost, neither monetary nor in terms of time; the only cost is the opportunity cost of being apprehended. With endogenous probability  $\pi_v$  (which in equilibrium corresponds to the aggregate crime rate) an agent is victim of a crime and loses  $\eta\bar{y}$  units of his income.<sup>20</sup> Notice that we assume that an agent can be victimized at most once in a period of time. Moreover, both the criminal earnings function and the apprehension technology are the same for every agent in the economy.

### 3.3.5 Government

The role of the government in this economy is twofold.

On the one side it runs the unemployment insurance benefits scheme, by taxing the labor income of the employed workers at rate  $\tau_U$  and subsidizing the unemployed workers at the replacement rate  $\phi$ .  $\phi$  is a policy parameter exogenously given, while  $\tau_U$  is set residually to ensure a self-financing scheme.

On the other side, the government runs the legal system, providing the apprehension technology that allows to detect and punish a fraction  $\pi_a cr$  of the crimes committed. The justice system is costly and we assume that there is a cost  $\bar{J}$  per arrest made.

---

<sup>20</sup>This assumption is justified from the data contained in the NCVS: somewhat surprisingly, there is a zero correlation between the victim's income and the amount stolen.

Detected criminals are immediately incarcerated: while in prison they all consume a constant level  $\bar{c}_a$ .  $\bar{J}$  consists of both inmates consumption and other expenditures (e.g. judicial expenditures), which are financed through a proportional labor income tax  $\tau_J$  paid by all the agents in the economy. Also  $\tau_J$  is set such that the scheme is self-financing.

### 3.3.6 Technology

The production side of the model is extremely simple. There is a constant returns to scale technology of the Cobb-Douglas form, which relies on aggregate capital  $K$  and labor  $L$  to produce the final output  $Y$ .<sup>21</sup>

$$Y = F(K, L) = BK^\alpha L^{1-\alpha}.$$

Capital depreciates at the exogenous rate  $\delta$  and firms hire capital and labor every period from competitive markets. From the first order conditions of the firm we obtain the expression for the net real return to capital  $r$  and the wage rate per efficiency unit  $w$ :

$$r = \alpha B \left( \frac{L}{K} \right)^{1-\alpha} - \delta, \quad (3.1)$$

$$w = (1 - \alpha) B \left( \frac{K}{L} \right)^\alpha. \quad (3.2)$$

### 3.3.7 Other market arrangements

The final good market is competitive. Moreover, every agent must satisfy an exogenous borrowing limit, denoted by  $d \geq b_{ra}$ . Notice that we allow for borrowing limits to be race dependent. Finally, it is not possible to insure against the unemployment shock, while all agents buy a property crime insurance at price  $p_I$ .

---

<sup>21</sup>Since the analysis will focus on steady-states only, time indexes are omitted, for the sake of notational clarity.

### 3.3.8 Timing

The timing of the model is assumed to be the following: 1) The idiosyncratic unemployment shocks are realized and observed by the agents; 2) Production takes place, with the employed people working for a wage and with the unemployed receiving the subsidy; 3) The crime, consumption and saving decisions are taken; 4) A random fraction of criminals are caught and immediately incarcerated; 5) Inmates get out of jail.

Notice that by assumption the implied model period length corresponds to the average time spent in prison by a criminal: hence, the population eligible to work is stationary and equal to 1 in every period.

## 3.4 Equilibrium

In this section we first define the problems of the employed and unemployed workers in their recursive representation, then we provide a formal definition of the equilibrium concept used in this model. Notice that the vector representing the individual state variables is defined as  $x = (ra, ed, a, s)$ , whose entries are race  $ra \in \mathcal{RA} = \{wh, bl\}$ , education level  $ed \in \mathcal{ED} = \{hsd, hs, col\}$ , individual asset holdings  $a \in \mathcal{A} = [d, \infty)$  and employment status  $s \in \mathcal{S} = \{e, u\}$ . The optimal value functions are defined as  $V_i(a, s)$ , where for notational simplicity  $i \in \mathcal{RA} \times \mathcal{ED}$ . The stationary distributions over the vector  $x$  are denoted as  $\mu_i(a, s)$ .

### 3.4.1 Households' Problem

#### Problem of the unemployed workers

The value function for the unemployed workers of a given race/education pair  $i$  and with asset holding equal to  $a$  can be written as:

$$V_i(a, u) = \max_{c, a', cr} \{Eu(c) + \beta E \sum_{s'} \pi_i(u, s') V_i(a', s')\} \quad (3.3)$$

More in detail

$$V_i(a, u) = \max_{a', cr} \{ [1 - \pi_a(cr)] u((1+r)a + (1 - \tau_J) \phi w h_i \varepsilon_i + y(cr) - a' - p_I) +$$

$$\pi_a(cr) u(\bar{c}_a) + \beta \sum_{s'} \pi_i(u, s') \{ [1 - \pi_a(cr)] V_i(a', s') + \pi_a(cr) V_i(a, s') \}$$

*s.t.*

$$a_0 \text{ given, } c \geq 0, a' \geq d, cr \geq 0$$

Notice that we have substituted the explicit expression for the current expected utility  $Eu(c) = [1 - \pi_a(cr)] u(c) + \pi_a(cr) u(\bar{c}_a)$ , the expected continuation values and the individual budget constraint  $c + a' + p_I \leq (1+r)a + (1 - \tau_J) \phi w h_i \varepsilon_i + y(cr)$ .

### Problem of the employed workers

The value function for the employed workers can be written as:

$$V_i(a, e) = \max_{c, a', cr} \{ Eu(c) + \beta \sum_{s'} \pi_i(e, s') V_i(a', s') \} \quad (3.4)$$

More in detail,

$$V_i(a, e) = \max_{a', cr} \{ (1 - \pi_a(cr)) u((1+r)a + (1 - \tau_U - \tau_J) w h_i \varepsilon_i + y(cr) - a' - p_I) +$$

$$\pi_a(cr) u(\bar{c}_a) + \beta \sum_{s'} \pi_i(e, s') \{ [1 - \pi_a(cr)] V_i(a', s') + \pi_a(cr) V_i(a, s') \}$$

*s.t.*

$$a_0 \text{ given, } c \geq 0, a' \geq d, cr \geq 0$$

Notice that the individual budget constraint in this case reads  $c + a' + p_I \leq (1+r)a + (1 - \tau_U - \tau_J) w h_i \varepsilon_i + y(cr)$ .

Is it worth stressing the assumption that if a criminal is detected he is immediately convicted. To avoid prisons to act as a forced savings mechanism, we assume that the

legal resources of a criminal are seized and destroyed by the government. It follows that convicted felons cannot rely on their earned legal income for their consumption/saving plans. More precisely, in this case, savings are equal to the current asset level, or  $a' = a$ .

It is now possible to define the recursive competitive equilibrium. Moreover, the analysis will be restricted to steady-states only, that is to prices, endogenous variables and distributions over the state variables which are stationary over time.

### 3.4.2 Recursive Stationary Equilibrium

**Definition 2** For a given set of policies  $\{\phi; \bar{c}_a\}$ , apprehension probability  $\pi_a$ , cost per arrest  $\bar{J}$ , race/education shares  $\psi_i$ , labor supplies  $h_i$  and efficiency units  $\varepsilon_i$ , a recursive stationary equilibrium is a set of individual decision rules  $\{c_i(a, s), a'_i(a, s), cr_i(a, s)\}$ , value functions  $\{V_i(a, s)\}$ , prices  $\{r, w, p_I\}$ , taxes  $\{\tau_U, \tau_J\}$ , average labor income  $\bar{y}$ , aggregate victimization rate  $\pi_v$ , cost of criminal justice  $J$  and stationary distributions  $\{\mu_i(a, s)\}$  such that:<sup>22</sup>

- Relative factor prices  $\{r, w\}$  solve the firm's problem and satisfy equations (3.1)-(3.2).
- Given relative prices  $\{r, w, p_I\}$ , government policies  $\{\phi; \bar{c}_a\}$ , taxes  $\{\tau_U, \tau_J\}$  and  $\{\pi_a, \pi_v, \bar{y}, J, \psi_i, h_i, \varepsilon_i\}$ , the individual policy functions  $\{c_i(a, s), a'_i(a, s), cr_i(a, s)\}$ , solve the households problem (3.3)-(3.4) and  $\{V_i(a, s)\}$  are the associated value functions.
- The labor market clears:

$$L = \sum_i \psi_i h_i \varepsilon_i \int_A d\mu_i(a, e).$$

- The asset market clears:

$$K = \sum_{i,s} \psi_i \int_A \{[1 - \pi_a cr_i(a, s)] a'_i(a, s) + \pi_a cr_i(a, s) a\} d\mu_i(a, s).$$

---

<sup>22</sup>  $c_i(a, s) : A \times S \rightarrow R_+$  denotes the consumption functions,  $a'_i(a, s) : A \times S \rightarrow A$  denotes the saving functions and  $cr_i(a, s) : A \times S \left[0, \frac{1}{\pi_a} \right] \frac{1}{\pi_a}$  denotes the crime functions.



- The final good market clears:

$$F(K, L) = \sum_{i,s} \psi_i \int_A [1 - \pi_a cr_i(a, s)] c_i(a, s) d\mu_i(a, s) + \delta K + J.$$

- The stationary distributions  $\{\mu_i(a, s)\}$  satisfy:

$$\mu_i(a', s') = \sum_s \pi_i(s, s') \left\{ \int_{a:a'_i(a,s)=a'} [1 - \pi_a cr_i(a, s)] d\mu_i(a, s) + \int_{a:a=a'} \pi_a cr_i(a, s) d\mu_i(a, s) \right\}.$$

In equilibrium the measure of agents of each race in each state is time invariant and consistent with individual decisions.

- The criminal justice expenditure is equal to:

$$J = \bar{J} \sum_{i,s} \psi_i \int_A \pi_a cr_i(a, s) d\mu_i(a, s).$$

- The aggregate crime rate (i.e. the victimization probability) is given by:

$$\pi_v = \sum_{i,s} \psi_i \int_A cr_i(a, s) d\mu_i(a, s).$$

- Average non-asset legitimate income  $\bar{y}$  is equal to:

$$\bar{y} = \sum_{i,s} \psi_i h_i \varepsilon_i \int_A y_s d\mu_i(a, s), \text{ with } y_e = (1 - \tau_U - \tau_J) w, y_u = (1 - \tau_J) \phi w.$$

- The proportional tax rate  $\tau_J$  is given by:

$$\tau_J = \frac{J}{\sum_{i,s} \psi_i h_i \varepsilon_i \int_A y_s d\mu_i(a, s)}, \text{ with } y_e = w, y_u = \phi w.$$

or the revenues from this tax cover for all the criminal justice expenses.

- The unemployment insurance benefits scheme is self-financing:

$$\tau_U = \frac{w \sum_i \psi_i \phi h_i \varepsilon_i \int_A d\mu_i(a, u)}{w \sum_i \psi_i h_i \varepsilon_i \int_A d\mu_i(a, e)}$$

that is the proportional tax rate  $\tau_U$  is set such that the total expenditure for unemployment benefits are exactly equal to the revenues from taxation.

- The price for the property crime insurance  $p_I$  is equal to:

$$p_I = \eta \bar{y} \pi_v$$

Since by assumption the insurance sector is competitive, the price  $p_I$  depends only on the probability of being hit by a criminal and the amount stolen.

### 3.5 Calibration and Computation

The model is calibrated relying on US data, focusing only on males of age 16 and above in the labor force.

One model period corresponds to the average prison term in the baseline year, or 12.3 months in 1996.<sup>23</sup> Notice that the choice of the model period allows for every person in the economy to be eligible to work in every period of time.

As for preferences, the instantaneous utility function is specified as a Constant Relative Risk Aversion:  $u(c_t) = \frac{c_t^{1-\sigma} - 1}{1-\sigma}$ , with  $\sigma = 1.0$ .

In order to pin down the efficiency units parameters  $\varepsilon_{ra,ed}$ , we used the Current Population Survey (CPS) monthly data for 1996. More in detail for each month we run a linear regression with log wages as a dependent variable together with a constant term, a set of education dummies and a dummy for race as regressors.<sup>24</sup> The reference group consisted of the whites high school dropouts. After taking the average of the parameters, from the

<sup>23</sup>The year 1996 was chosen because the observed crime rate was close to the average rate over the period 1970-2000.

<sup>24</sup>Being the model an infinitely lived agents, there is no explicit role for age. However, we estimated an alternative and more common specification which included also age and age squared as regressors. We then computed the efficiency parameters by substituting the relevant average age. The final results were quite similar to the ones in the text.

predicted values of the regression we get the profile for the efficiency units, which is as follows:  $\varepsilon_{wh,hsd}=1.62$ ,  $\varepsilon_{wh,hs}=2.07$ ,  $\varepsilon_{wh,col}=2.42$ ,  $\varepsilon_{bl,hsd}=1.4$ ,  $\varepsilon_{bl,hs}=1.78$  and  $\varepsilon_{bl,col}=2.09$ .

The exogenous labor supply  $h_{ra,ed}$  was computed as follows. From the CPS we obtained the average hours worked for each education/race pair. Following the literature on the time use, the average hours worked in the population was set to match the average share of available time devoted to market activities, that is 0.4. Rescaling the hours worked according to this value gives the following parameters  $h_{wh,hsd}=0.369$ ,  $h_{wh,hs}=0.407$ ,  $h_{wh,col}=0.426$ ,  $h_{bl,hsd}=0.355$ ,  $h_{bl,hs}=0.382$ , and  $h_{bl,col}=0.401$ .

Again from the 1996 CPS, data related to the unemployment rates by race and education category allow to pin down the entries of the transition matrices  $\Pi_{ra,ed}$  for the Markov-chain. We do not allow for state dependence of the unemployment shock, i.e. the probability of future unemployment is the same irrespective of the current occupational status. Figures for unemployment rates in 1996 were  $\pi_{wh,hsd}(\cdot, u')=10.2\%$ ,  $\pi_{wh,hs}(\cdot, u')=4.32\%$ ,  $\pi_{wh,col}(\cdot, u')=2.18\%$ ,  $\pi_{bl,hsd}(\cdot, u')=19.7\%$ ,  $\pi_{bl,hs}(\cdot, u')=10.29\%$  and  $\pi_{bl,col}(\cdot, u')=3.82\%$ .

The race/education shares are obtained from the CPS, which gives the following values  $\psi_{wh,hsd}=12.89\%$ ,  $\psi_{wh,hs}=51.67\%$ ,  $\psi_{wh,col}=23.95\%$ ,  $\psi_{bl,hsd}=2.32\%$ ,  $\psi_{bl,hs}=7.48\%$  and  $\psi_{bl,col}=1.69\%$ .

In the simulations the exogenous borrowing limit  $d$  is set at different levels for the two races. The values are chosen for the model to replicate in equilibrium the share of agents with negative net worth. As reported in Wolff (2000), table 7, in 1995 31.3% black households had a negative value for the net worth, while the percentage for white households was 15%. The values  $b_{bl} = -1.151$  and  $b_{wh} = -0.655$  allow to replicate these figures. This point deserves further discussion. First, even though there is some evidence of racial discrimination in credit markets, there are no definitive answers on the matter. Furthermore, our calibration strategy goes in the opposite direction of a natural borrowing limit concept, as in Aiyagari (1994). Having black agents lower legitimate earnings, relying on a natural borrowing limit would imply a borrowing limit more stringent for black agents than for whites. Notice, however, that the values for the borrowing limits we are imposing are more stringent than the ones implied by the natural borrowing limit concept.

We normalize the average disposable legitimate earnings  $\bar{y}$  to 1. This is done by setting the TFP parameter  $B$  equal to 1.047. The actual value in 1996 was \$28,513.

Following Imrohoroglu, Merlo and Rupert (2000) the exogenous consumption when in jail  $\bar{c}_a$  is set at \$2,600, i.e. this leads to  $\bar{c}_a = 0.0984$ .<sup>25</sup>

<sup>25</sup>Notice that in the calibrated economy there will be no agents with a total legitimate income less than

The policy parameter  $\phi$ , i.e. the replacement rate, is set in order to replicate the actual unemployment benefit scheme operating in the US, i.e.  $\phi=0.5$ .

From the FBI Uniform Crime Reports in 1996 we obtain the number of property crimes cleared with the arrest of the felon. From the NCVS, we compute the total number of property crimes committed in 1996.<sup>26</sup> Accordingly, the apprehension probability per crime is set at  $\pi_a = 0.0492$ . The parameter related to the earnings from crime is set to  $\eta = 0.0439$ , to replicate the value of \$1,253, the average value of a property crime computed from the Uniform Crime Reports in 1996.

The cost of justice  $\bar{J}$  is estimated to be \$10,610, i.e.  $\bar{J} = 0.3721$ . This estimate is obtained as follows. The actual expenditures on judicial, legal activities and corrections for 1996 are weighted by the appropriate percentages of property crimes, i.e. 14.39% for the first two and 31% for the last. This gives a total justice expenditure for property crimes equal to 24 billions. This amount is divided by the total number of property crimes cleared with an arrest in 1996, giving the value of \$10,610.<sup>27</sup>

Both for the capital share parameter and the depreciation one, consensus values are used:  $\alpha = 0.36$  and  $\delta = 0.08$ . Finally, we set the subjective discount rate  $\beta = 0.958$ , to get an equilibrium interest rate in all computations at a value of about 4% on an annual basis.

The complete parameterization of the model is reported in Table 3.

## 3.6 Results

This section starts presenting the optimal policy functions for both black and white agents. Then it moves on to describe the results related to the crime rates.

### 3.6.1 Policy Functions

In this simple model we have only three sets of decision rules: the saving functions, the consumption functions and the crime ones. These are considered in turn.

---

<sup>26</sup> $\bar{c}_a$ . The lowest value of legitimate disposable income is 0.2.

<sup>26</sup>The NCVS is considered to give more reliable estimates for property crime victimisation of the american households.

<sup>27</sup>Notice that  $\bar{c}_a$  is part of  $\bar{J}$ .

<i>Parameter</i>	<i>Value</i>	<i>Target</i>
<i>Model Period</i>	12.3 months	<i>Average Prison term period</i>
$B$	1.047	<i>Average legitimate non-asset income= 1</i>
$\alpha$	0.36	<i>Standard</i>
$\delta$	0.08	<i>Standard</i>
$\beta$	0.958	<i>Standard</i>
$\sigma$	1.0	<i>Standard</i>
$h_{ra,ed}$	<i>See text</i>	<i>Data from CPS</i>
$\varepsilon_{ra,ed}$	<i>See text</i>	<i>From a regression on CPS data</i>
$\psi_{ra,ed}$	<i>See text</i>	<i>Data from CPS</i>
$b_{wh}$	-0.655	<i>15.0% of whites with negative net worth</i>
$b_{bl}$	-1.152	<i>31.3% of blacks with negative net worth</i>
$\bar{c}_a$	0.0984	<i>Inmates consumption = \$2,600</i>
$\eta$	0.0439	<i>One crime is worth \$1,253</i>
$\pi_a$	0.0492	<i>Data from NCVS and UCR</i>
$\bar{J}$	0.3721	<i>Expenditure per arrest = \$10,610</i>
$\phi$	0.5	<i>US unemployment benefits legislation</i>
$\pi_{ra,ed}(\cdot, u')$	<i>See text</i>	<i>Data from CPS</i>

Table 3.3: Calibration

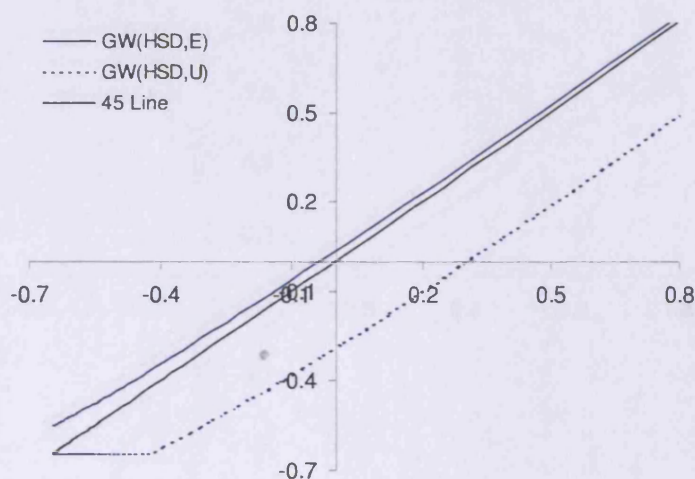


Figure 3.6: Saving Functions (Whites - Dropouts)

### Saving Functions

Figures (3.6) and (3.7) show the saving decisions and the 45-degree line for both blacks and whites high school dropouts. One property of these functions is worth noticing: sufficiently poor unemployed individuals are borrowing constrained, while employed ones are not. Another property worth stressing is that these functions are non-decreasing. Unlike in simpler models, this is not guaranteed to hold. Actually, for quite extreme parameterizations, the saving functions become non monotone: they first decrease and then start to increase again. This pattern is due to the interaction between the saving choice and the crime one. The intuition is simple. In the model only individuals with low asset levels choose to commit crimes. This decision provides them with additional resources: part of these are spent to buy the consumption good, part of them are saved. As the individuals get richer, they need to resort less and less on stealing, explaining the decreasing part of the function. As the crime involvement vanishes, a more standard behavior is restored.

An interesting comment can be framed in a standard precautionary savings argument. For a given educational level, black individuals know that they will experience bad labor market conditions, as represented by the high unemployment rate. Since they are risk averse, they tend to accumulate assets, in order to smooth consumption over the possible

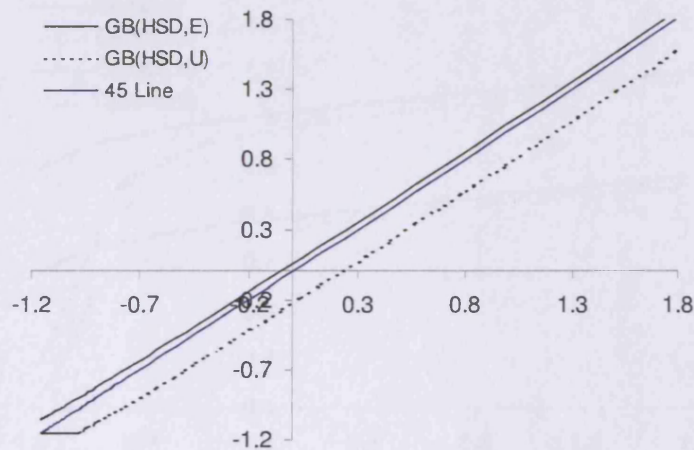


Figure 3.7: Saving Functions (Blacks - Dropouts)

states of the world: by doing this, when a bad shock is realized, they have enough resources to keep the consumption profile sufficiently stable and avoid the borrowing constraint. This buffer stock strategy can lead some blacks to consume less and save more than the whites. However, at the same time, black individuals receive an extremely low labor income that do not allow them to save much. If on the one hand higher unemployment rates increase the incentive to commit a property crime for black individuals, on the other hand they tend to reduce the likelihood of this choice, since agents are induced to save a higher proportion of their income.

It is important to recall that the intersection between the 45-degree line and the saving function for employed agents gives the highest level of assets that in equilibrium the individuals will hold. These intersections occur in regions of the asset space that are not reported in the graphs: this was done only to make the figures visually clear.

Notice that the saving functions qualitative behavior is the same for all education levels, hence we avoid to report them.

### Consumption Functions

Figure (3.8) plots the consumption functions for black individuals who are either high school dropouts or college graduate, for both occupational possibilities. Two things are interesting in this graph. First, for a given educational level, the consumption function of

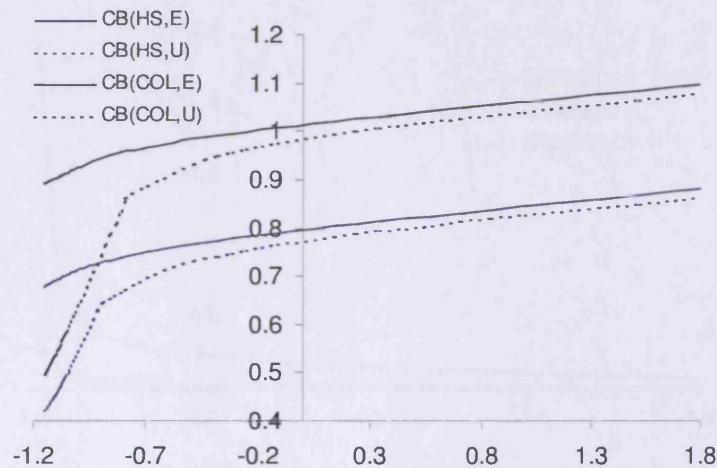


Figure 3.8: Consumption Functions (Blacks - Dropouts and College)

the unemployed is below the employed one, with the distance decreasing in the level of assets. Second, by comparing the consumption functions of the agents with different education, they are unsurprisingly increasing in the education level. What is less obvious is that, for low level of assets, the distance between consumption when employed and unemployed is lower for the high school dropouts. This is again due to the higher involvement in crime of people with a low educational attainment.

### Crime Functions

In this subsection we move to consider the criminal behaviors implied by the model economy. Figure (3.9) plots the crime decision rules for black unemployed agents. The number of crimes depends heavily on both the educational level and the degree of poverty. Higher educational achievements and higher asset levels imply less crimes. Consider in more detail the most crime prone group: black high school dropouts. Figure (3.10) depicts their choices. It is interesting to notice that for this demographic group also employed agents resort to crime relatively often.

By comparing figures (3.10) and (3.11) we can appreciate some positive predictions of the model. If compared to the whites, black agents do commit more crimes, that is for the



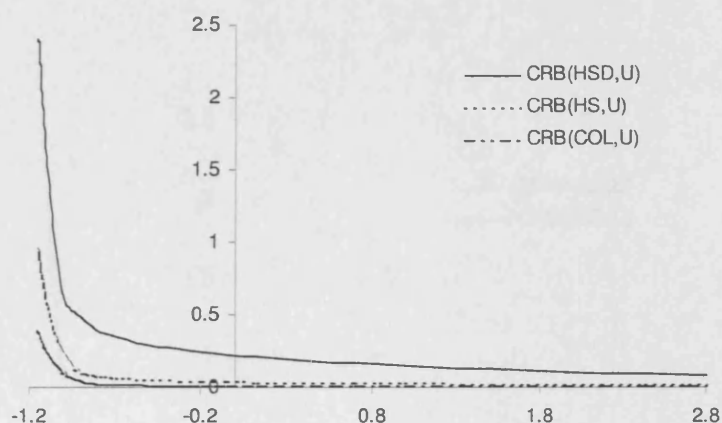


Figure 3.9: Crime Functions (Blacks - Unemployed)

same asset level they perpetrate more crimes, and they decide to do so more often, that is their crime functions decrease more slowly.<sup>28</sup>

### 3.6.2 Who Commits Crimes?

Given the optimal policy functions and the stationary distributions we can discuss the predictions of the model as far as the crime rates are concerned. First, we compute the percentage of agents that steal at least \$50 dollars in a period, that is whose income from illegitimate activities is at least 0.00189. As for the black population, almost every high school dropout is involved in property crimes, defined as above. The precise figures are 89.0% for employed people and 90.3% for the unemployed. As for the white high school dropouts, these values are somewhat different, being 68.3% for the employed and 75.7% for the unemployed. In comparison, as for the high school graduates, 8.0% of the black employed and 22.6% of the unemployed are involved in property crimes, while no white employed and 1.7% of the unemployed are. Finally, only 2.0% of black college graduates

<sup>28</sup>Notice that, as far as crime is concerned, the presence of the *wh* workers in the economy is perceived as a positive externality by the *bl* workers, since *wh* workers receive a higher labour income in equilibrium. This rises the incentives for the *bl* agents to commit crimes. This is why it is crucial to include explicitly different races in the model rather than running separately the model calibrated in turn for the two races. The same comments apply for agents with low education levels when compared to people with higher ones.

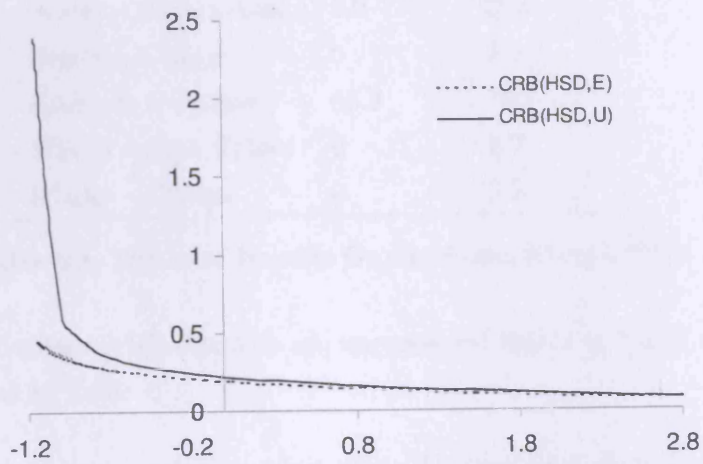


Figure 3.10: Crime Functions (Blacks - Dropouts)

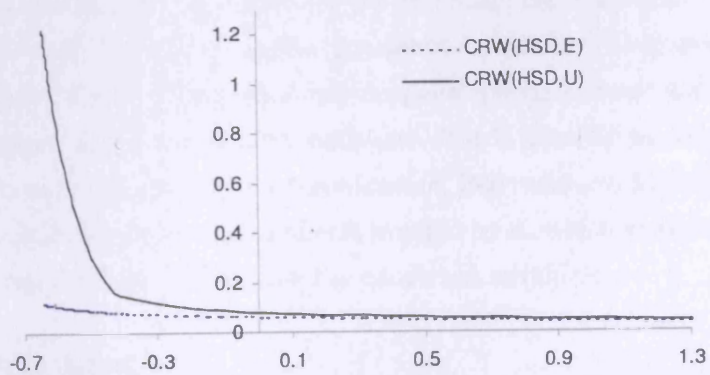


Figure 3.11: Crime Functions (Whites - Dropouts)

<i>% Committing Crime</i>	<i>Employed</i>	<i>Unemployed</i>
<i>Blacks - Dropouts</i>	89.0	90.3
<i>Blacks - High School</i>	8.0	22.6
<i>Blacks - College</i>	0	2.0
<i>Whites - Dropouts</i>	68.3	75.7
<i>Whites - High School</i>	0	1.7
<i>Whites - College</i>	0	0.7

Table 3.4: Shares of Specific Groups Committing Crimes

and 0.7% of white college graduates who are unemployed decide to resort to crime. These results are reported in Table 4.

These results deserve some further discussion. The numbers above highlight how bad labor market conditions and poverty can make criminal activities more appealing, leading black individuals to resort to stealing to overcome the economic disadvantage they are facing in the legitimate activities. This result is consistent with the stylized facts described before, which showed a definitely higher crime involvement for the black population. Moreover, this model shows that is possible to get big differences in criminal behaviors according to race even without relying on a social interaction framework. The combination of the dynamic set-up, the limited legitimate rewards for the dropouts and the temptation induced by well paid workers are the basic ingredients that allow for this result. First, agents with poor labor market prospects accumulate little assets: this is due both to their low income and to the relatively frequent unemployment spells they experience. Poverty is then driving the stealing decisions. If it is possible to name the different labor market conditions with the term *discrimination*, Bertrand and Mullainathan (2004), then it is clear how bad are the dynamic effects implied by it, which would be even greater if we were to introduce a stigma effect for the convicted criminals.

### 3.6.3 Model Vs. Data

In order to assess the performance of the model, we compare four variables of interest to the corresponding figures in the FBI and BJS data for 1996. Namely, we consider the ratio of the arrest rates by race, the percentage of inmates by education, the percentage of inmates by employment at the time of the arrest and the percentage of inmates by race.

<i>Variable</i>	<i>Model</i>	<i>Data</i>
<i>Arrest Rates Ratio (B/W)</i>	4.04	4.48
<i>Inmates Dropouts</i>	54.6%	57.5%
<i>Inmates High School</i>	39.9%	36.3%
<i>Inmates College</i>	5.5%	6.2%
<i>Inmates Employed</i>	86.8%	71.3%
<i>Inmates Unemployed</i>	13.2%	28.7%
<i>Inmates Blacks</i>	44.3%	40.4%
<i>Inmates Whites</i>	55.7%	59.6%

Table 3.5: Model Vs. Data

Table 5 reports these variables.

As for the arrest rates by race ratio, the model implies a number very close to the data provided by the FBI: 4.04 versus 4.48. It is worth stressing that the large race crime gap is obtained only from the differences in labor market conditions and asset holding, that is without resorting to any imitation mechanism among agents. The different legitimate conditions account for 90% of the race crime gap observed in the data.

As for the inmates composition by education, the model tracks the data very well. The discrepancies between the model and the data are modest.

Finally, the model performs fairly well in accounting for both the employment status at the time of the arrest and the race of the 1997 prison population.

### 3.6.4 Experiments

This section is devoted to discuss some counterfactual experiments. First, some conceptual exercises are performed, where the heterogeneity between the two races is reduced. Then, two policies implying the same costs are compared.

As for the first set of exercises, the results are found in Table 6. The table reports both the race arrest ratio implied by the model under consideration and the percent change in the crime rate with respect to either the baseline model or a model where the two races are identical in every dimension. The exercises are divided into two groups. First, in the top part of the table, we report the results of making the two demographic groups equal in just one aspect. These are the models from 2 to 6. Then, in the bottom part of the table,

we report the results of making the two demographic groups identical in every aspect but one. These are the models from 8 to 12.

In both types of exercise, the strongest effect on the criminal behavior is found to be due to the difference in efficiency units. Moreover, the results related to the change in the probability of unemployment are a bit misleading. In these cases the percentage of people with negative assets varies dramatically with respect to the benchmark case, explaining such big responses of the crime rate and the sign of the change.

It is useful to compare our findings to those in Grogger (1998). Relying on an Oaxaca-type decomposition applied to the *NLSY79* data, Grogger (1998) finds that 26% of the racial differential in crime participation rates is due to the black-white wage gap. We find an even stronger effect, since model 9 accounts for 49% of the racial arrest ratio. As seen, the difference in efficiency units directly maps to earnings differential and affects heavily the crime decision. Understanding the determinants of the wage gap is of paramount importance. As remarked before, there are many competing explanations in the literature: the role of pre-market factors, taste discrimination, statistical discrimination and specialization into jobs with lower wage growth. In this version of the model we assumed the efficiency units gap to be exogenous. Considering explicitly the feedbacks from the labor market to the crime one and viceversa seems to be an appropriate way to endogenise the wage differences.

The second set of counterfactuals is aimed at understanding which public policy is more effective in reducing the aggregate crime rate. More precisely, a comparison between two policies implying the same cost is carried out. The first policy involves an increase in the income for the high school dropouts, that is an improvement for the group with the worst economic condition. In contrast, the second policy increases the likelihood of the punishment through an increase in the police expenditure. Notice that for the policy comparisons to be more informative, the most crime prone groups need to be modeled in a rather detailed way. This is one of reasons why it is very important to consider race explicitly. The results of such experiments are reported in Table 7.

For the first case, starting from the benchmark calibration, we compute the value of the high school dropouts non asset income. Then we give a lump-sum subsidy to all dropouts worth 2.5% of this value. Considering the number of people involved and the monetary value of the subsidy (\$481), this policy would imply a cost in per capita terms of \$73. Then we solve the model under this new specification. The new model economy implies a

<i>Model</i>	<i>Arrest Ratio</i>	<i>Crime Rate Change</i>
1) <i>Baseline</i>	4.04	-
2) <i>Equal Borrowing Limit</i>	3.43	-5.15%
3) <i>Equal Efficiency Units</i>	1.75	-13.38%
4) <i>Equal labor Supplies</i>	3.09	-5.45%
5) <i>Equal Unemployment</i>	4.16	+2.17%
6) <i>Equal Education</i>	3.28	-4.27%
7) <i>Everything Equal</i>	1	-
8) <i>Different Borrowing Limit</i>	1.14	+1.57%
9) <i>Different Efficiency Units</i>	2.22	+4.93%
10) <i>Different labor Supplies</i>	1.31	-0.07%
11) <i>Different Unemployment</i>	0.96	-1.69%
12) <i>Different Education</i>	1.23	-0.07%

Table 3.6: Counterfactual Experiments

decrease in the crime rate equal to 6.8%.

Given the cost of the first policy, we consider another policy opposite in spirit to the first one, i.e. a policy which increases the likelihood of the punishment. Following Imrohorglu, Merlo and Rupert (2000), we specify an apprehension technology of the form  $\pi_a = 1 - G^{-\gamma}$ , with  $G$  being the public expenditure on police. To use this function, we need to estimate  $\gamma$ . In order to do so, we consider the time series of the real per capita police expenditure and the time series of the property crimes clearance rates.<sup>29</sup> For the clearance rate, as before, we take the number of crimes cleared with an arrest from the UCR and the total number of crimes from the NCVS. Then we rewrite the equation above as  $1 - \pi_a = G^{-\gamma} \rightarrow \ln(1 - \pi_{at}) = -\gamma \ln G_t$ . Since both series are non stationary, we take first differences and estimate with OLS this equation in growth rates, i.e.  $\Delta \ln(1 - \pi_{at}) = -\gamma \Delta \ln G_t$ .

The point estimate for  $\gamma$  is 0.04. Finally, increasing the police expenditure in 1996 by \$73, from a starting value of \$127, we get the new value for  $\pi_a=0.052$ . Then we solve the model with this higher apprehension probability: the crime rate drops by 18.6%.

The table has an immediate interpretation. In terms of decreasing the aggregate crime

<sup>29</sup>This series is readily available from 1980 to 1999, see table 1.2 of the 2002 Sourcebook of Criminal Justice Statistics, US Dept of Justice.

<i>Experiment</i>	<i>Crime Rate Change</i>
<i>Lump-sum subsidy to dropouts</i>	-6.8%
<i>Increased apprehension probability</i>	-18.6%

Table 3.7: Policy Experiments

rate, the most effective policy is the one that increases the expenditure on police, making a prison term more likely for the criminals.

### 3.7 Discussion and Conclusions

In this chapter a model able to explain the observed differences in crime involvement between black and white American males has been discussed. A dynamic general equilibrium model presenting racial differences in legitimate opportunities has been developed.

The overall assessment of the model suggests that it succeeds in generating the race crime gap, or the higher involvement in crime of black versus white individuals. Blacks do commit disproportionately more crime in the model: the model accounts for 90% of the race arrest ratio observed in 1996. In addition, on the basis of counterfactual analysis, the race wage gap seems to be the most important factor in shaping the crime differential, a channel already discussed by Grogger (1998) and Machin and Meghir (2003). This chapter has argued that if we are to understand the race crime gap it is of paramount importance to understand what forces drive the observed differentials in the labor market.

The next step in the research is to obtain endogenously the labor market differences according to race. It is reasonable to think that, given the dimension of the crime phenomenon in the US, there are significant feedback effects going from the labor market to the crime market and viceversa. This kind of considerations are potentially very important for agents with low educational levels, whose criminal participation is particularly high. If training and hiring costs are non-negligible and if on the job learning is an important component of the worker's productivity, employers will accurately screen the workforce trying to form a match only with those workers that maximize the expected profits of the relationship, with duration playing an important role. Obviously, the incarceration of a worker represents an interruption of the employer/employee relationship. In the hiring process, given the high historical race crime gap, employers could use race as a signal, that is they could statistically discriminate among applicants on the basis of race. According

to this story, unemployment, wage and crime differences by race should be persistent. However, this explanation begs for a question: where do the initial differences between races come from?

It goes without saying that the simple firms structure assumed in the current version of the model cannot accommodate such an extension. First, the value of a firm must be non-zero in order for the future to play a non trivial role on the current decisions. Second, the labor market should provide a wage per worker type, rather than a wage per efficiency units.

Furthermore, the model considered here cannot take into consideration some crucial aspects of the crime phenomenon. In first instance, crime is primarily committed by people of young age, Leung (1994), while our framework does not give age any role in determining the crime decisions. A feasible extension, in order to capture in a parsimonious way the life-cycle dimension of the property crime participation, is to specify a perpetual youth model. This way the framework could allow easily for two different and important aspects: 1) temporary stigma effects in the labor market for convicted criminals: 2) changing labor market conditions over the life-cycle.

### 3.8 Appendix A - Solution Algorithm

The computational procedure used to solve the baseline model can be represented by the following algorithm:

- Generate discrete grids over the asset space  $[b_{ra}, \dots, a_{\max}]$ :
- Get the invariant distributions over  $s$  associated with  $\Pi_{ra.ed}$ :
- Get the equilibrium tax rate on labor income  $\tau_U$ :
- Get the aggregate labor supply  $L$ :
- Guess the aggregate crime rate  $\pi_{i0}$ :
- Guess the criminal justice tax rate  $\tau_{J0}$ :
- Compute the insurance price  $p_I = \eta \bar{y} \pi_{i0}$ :
- Guess on the interest rate  $r_0$ :



- Get the capital demand and the wage rate  $w$ :
- Get the average non asset legitimate income  $\bar{y}$ :
- Get the crime functions  $cr_{ra,ed}(a, s)$ :
- Get the saving functions  $a'_{ra,ed}(a, s)$ :
- Get the stationary distributions  $\mu_{ra,ed}(a, s)$ :
- Check asset market clearing; Get  $r_1$ :
- Update  $r'_0 = \varpi r_0 + (1 - \varpi) r_1$  (with  $\varpi$  arbitrary weight);
- Iterate until market clearing;
- Check final good market clearing;
- Get the aggregate crime rate  $\pi_{\iota 1}$ :
- Update  $\pi'_{\iota 0} = \xi \pi_{\iota 0} + (1 - \xi) \pi_{\iota 1}$  (with  $\xi$  arbitrary weight);
- Get the criminal justice tax rate  $\tau_{J1}$ :
- Update  $\tau'_{J0} = \zeta \tau_{J0} + (1 - \zeta) \tau_{J1}$  (with  $\zeta$  arbitrary weight);
- Iterate until convergence.

## Chapter 4

# Severance Payments: Equilibrium Welfare Effects in a Model with Heterogeneous Workers

### 4.1 Introduction

Several labor market institutions are designed to provide insurance to workers facing shocks to their labor earnings, their employment status or their specific and general human capital. In this paper we consider a particular form of employment protection legislation (EPL), namely severance payments. Our contribution focuses on the equilibrium welfare effects arising from their introduction in a labor market with costly mobility and heterogeneous workers.

Severance payments represent a direct transfer from the employer to the employee, paid when an employer initiated separation takes place. In several European Countries government-mandated severance payments have been a long lasting and distinctive feature of their labor markets. For the period 1956-1984, Lazear (1990) finds that, for a worker with ten years of tenure, the value of the severance payments in Italy, Spain, Norway and France was considerably high, being equal to 15.9, 13.6, 12 and 5.2 months of wages, respectively.

The debate on EPL is a long lived and rather extensive one. Several contributions, starting from the seminal paper by Lazear (1990), find large and negative effects of EPL. More in detail, he finds that stricter EPL is responsible for lower employment level and

higher unemployment rates. His estimates suggest that an increase from zero to three months of severance pay would raise the unemployment rate by 5.5 percent in the United States.

Garibaldi and Violante (2005) argue that the most suitable conceptual framework to model firing costs is not a firing tax and, at the same time, provide evidence that the direct transfer component of EPL is quantitatively important. Garibaldi and Violante (2005) show, in the context of a search model with insider and outsider workers, the different results obtained when modeling the EPL as a firing tax as opposed to severance payments. They stress how the impact of severance payments on unemployment is qualitatively different from that of firing taxes, and find that it varies according to the bite of the wage rigidity.

A recent contribution, Ljungqvist (2002), analyses how lay-off costs affect employment in three prototype frameworks: a search model, a matching model and a model with employment lotteries. The aim of the paper is to single out the common economic forces at work in these general equilibrium models. The employment outcomes differ, depending on the specific framework used: search and matching models show a positive employment effect, while with employment lotteries lay-off costs tend to be detrimental. However, notice that: 1) welfare effects are not taken into consideration, 2) lay-off costs are specified as firing taxes.

This chapter studies the equilibrium welfare effects of introducing mandated severance payments in a labor market with costly mobility, where self-insurance through a riskless asset is the only way to smooth fluctuations in labour income due to unemployment shocks. A similar set up has been analysed by Alvarez and Veracierto (2001).<sup>1</sup> Alvarez-Veracierto assumed that there is only one market clearing wage for all types of workers in the economy, i.e. independently of their productivity. In their set-up, the SP has an insurance role for unemployed workers and important general-equilibrium effects: it reduces labor demand and wages, and since it insures workers it reduces precautionary savings with a further effect on the capital stock and wages. The novelty of our analysis is to allow for wage flexibility at the level of the individual firm-worker match. More precisely, wages vary with both tenure and productivity of the workers. When severance payments are introduced, the firm can potentially undo their effect by modifying the wage profile. The introduction of severance payments is equivalent to the introduction of a compulsory actuarially fair

---

<sup>1</sup>Though in their model severance payments are a priori non-neutral in so far as a unique market wage applies for both new hires and workers in surviving jobs.

insurance scheme. Workers entry wages fall by the expected present value of the future payment. However, because of incomplete markets, workers are unlikely to be indifferent about the slope of the wage profile. In particular, young workers in an economy with long unemployment durations and long tenures could be adversely affected because they spend a long period unemployed before finding a job, so they are likely to be constrained. Moreover, once they find a job, for an initial period their wage will remain low as they are pre-paying a large expected severance payment, so their borrowing constraint might remain binding. For this group of agents the welfare costs of severance payments are potentially high. The model is solved numerically and calibrated to the US economy. The measure of welfare we rely on is the change in consumption needed to equate the expected lifetime utilities in the stationary equilibria of several economies: the baseline economy, i.e. without severance payments, and a series of counterfactual economies where the severance payments are introduced at increasing levels. Non trivial general equilibrium effects are also present, since the capital stock in the various economies varies. On the one hand, the precautionary motive for savings is reduced by the introduction of severance payments, since agents are better insured. On the other hand, the change in the wage profile is likely to reduce the savings of young individuals and increase that of older ones.

The rest of the chapter is organized as follows. Section 2 presents the theoretical model. Section 3 is devoted to the definition of the equilibrium concept used in the model. Section 4 presents the calibration procedure. Section 5 provides the main results and predictions of the model, while Section 6 concludes.

## 4.2 The Economy

### 4.2.1 Demographics

The economy is populated by a measure one of agents (workers). With probability  $(1 - \lambda)$ , constant across individuals, an agent dies and is immediately replaced by an offspring of working age who starts life as an unemployed.

### 4.2.2 Preferences

Agents' intraperiod utility function is defined over consumption  $c$  and search effort  $\psi$  as

$$U(c_t, \psi_t) = u(c_t) - v(\psi_t) \quad (4.1)$$

and the future is discounted at factor  $\beta = \hat{\beta}\lambda$  where  $\hat{\beta} \in (0, 1)$  is the discount factor. We assume that  $u(\cdot)$  is strictly increasing, strictly concave, and satisfies the Inada conditions, and  $v(\cdot)$  is strictly increasing, strictly convex. Effort choices are defined over the set  $\Psi \equiv [0, 1]$ , with  $v(0) = 0$  and  $v(1) = +\infty$ . Agents do not value their offsprings' welfare.

### 4.2.3 Endowments

Agents can be employed ( $e$ ) or unemployed ( $u$ ). If employed they supply labor inelastically. Newly born agents are endowed with  $a_0$  units of the consumption good. Every employed agent of working age goes through a life cycle of  $I$  labor productivity shocks  $i \in \mathcal{I} = \{1, 2, \dots, I\}$ .<sup>2</sup> Let  $\pi_i^e$  be the transition probability between productivity level  $i$  and  $i + 1$  of employed workers. We only allow jumps between successive productivity levels until  $i = I - 1$ , thus  $\pi_I^e = 0$ . We index job tenure of an employed worker by  $t$ , with  $t \in \mathcal{T} = \{0, 1, \dots, T\}$ . Tenure increases with probability  $\tau_t = \tau$  between successive tenure levels for all employed workers until  $t = T - 1$ , and let  $\tau_T = 0$ . Denote the productivity level of a  $(i, t)$ -type worker as  $\varepsilon_{it}$ , where the pair stands for the agent's current age-tenure levels. The set of (labour augmenting) productivity levels is denoted as  $\mathcal{E} = \{\varepsilon_{10}, \varepsilon_{20}, \dots, \varepsilon_{I0}, \varepsilon_{11}, \dots, \varepsilon_{it}, \dots, \varepsilon_{IT}\}$ . Unemployed workers have zero tenure and transit between productivity levels  $i$  and  $i - 1$  (i.e. lose some of their skills) with probability  $\pi_i^u$  until level  $i = 2$ , or  $\pi_1^u = 0$ .

### 4.2.4 Technology

Each firm uses one worker and capital to produce output according to a common, constant returns to scale technology. The output of a firm employing a worker of productivity  $\varepsilon_{it}$  and  $K_{it}$  units of capital is  $Y_{it} = F(K_{it}, \varepsilon_{it})$ . The same production function in intensive units is  $y_{it} = f(k_{it})$ , with  $k_{it} = K_{it}/\varepsilon_{it}$ . Capital depreciates at the exogenous rate  $\delta$ .

---

<sup>2</sup>With some abuse of language, we are going to refer to  $i$  as the productivity or age of the agents. Since the model is a version of the perpetual youth model, and given the assumptions on the stochastic evolution of  $i$ , an individual can see her  $i$  decrease during an unemployment spell. Strictly speaking,  $i$  does not represent either concept.

### 4.2.5 Search frictions and labor markets

Every period unemployed workers of experience  $i$  meet a firm with an unfilled vacancy with probability  $\phi_i(\psi)$ .<sup>3</sup> Keeping an open vacancy is costless. In every period, after production has taken place, employed workers of type  $(i, t)$  may be separated from their employer and enter the unemployment pool with exogenous probability  $\sigma_{it} > 0$ . Or, we can think of a competitive labor market with free entry of firms and workers who become unproductive with probability  $\sigma_{it}$  and productive again with probability  $\phi_i(\psi)$ , with  $\phi_i(0) = 0$ ,  $\phi_i(1) = 1$ , and  $\frac{d\phi_i(\psi)}{d\psi} > 0$ .

The value of a firm with a filled vacancy, whose worker is of type  $(i, t)$ , is denoted with  $J(i, t)$ . Notice that the worker's type fully characterizes the firms' state space: once the employee's "age"-tenure pair is known, also the value of the firm can be computed.

The considerations above related to the free entry of firms justify the condition  $J(i, 0) = 0, \forall i$ . This set of equations imposes that the value of a firm who has just started an employment relationship with a worker of productivity  $i$  is equal to zero, irrespective of the labor market experience of the agent.

Tenure evolves stochastically and once the worker becomes an insider (i.e. has positive tenure) the firm is locked in: the SP needs to be paid to get rid of the worker. Job security legislation insulates insiders from competition from outsiders.

The value function of an employed agent of type  $(i, t)$ , whose current asset holdings are equal to  $a$  is denoted with  $V(i, a, t)$ . In general, the SP will depend both on the age of the worker and on his tenure with the firm he is working for. We denote the SP with  $\theta(i, t)$ . Since SP are unconditional and a worker that quits is still productive, an insider has threat point  $V(i, a + \theta(i, t), 0)$  as she can quit, receive the severance payment and obtain a new job with zero tenure immediately. On the other hand the shadow value of a worker cannot fall below  $J(i, t) = -\theta(i, t)$  since the firm would optimally fire the worker otherwise. Any wage such that both the worker and the firm receive a payoff strictly above their respective threat points is compatible with the survival of the match. We assume that wages will be determined by bilateral ex-post bargaining over the value of the match.

For tractability, we assume that the worker has all the bargaining power.<sup>4</sup>

As a final note, notice that, in the absence of the SP, the value of each firm is equal

---

<sup>3</sup>In the benchmark model we assume that the search effort is a constant, i.e.  $\psi = \bar{\psi}$ , and that "age" does not affect the shape of the  $\phi_i(\psi)$  functions. It follows that the job finding probability  $\phi_i(\psi) = \phi(\bar{\psi}) = \phi(\bar{\psi})$  is exogenous.

<sup>4</sup>See the discussion below.

to zero irrespective of the worker's tenure level. In particular, wages in this economy correspond to the competitive ones.

#### 4.2.6 Mutual Fund

Since the SP are set by the government, there is nothing that prevents them to be higher than the output produced by a worker. It follows that, upon separation, a firm could incur some losses, determined by the size of the severance payment. In order to deal with this aspect of the problem, we assume the existence of a mutual fund (*MF*) that owns all the firms, covers their losses, pays out the severance payment upon separation and reinvests the flow profits into the asset market.

#### 4.2.7 Other market arrangements

The final good market is competitive. Firms hire capital every period from a competitive market. Capital is supplied by rental firms that borrow from workers and the mutual fund at the risk-free rate  $r$  and invest in physical capital.

There are no state-contingent markets to insure against unemployment and income risk, but workers can self-insure by saving into the risk-free asset. The agents also face a borrowing limit, denoted as  $d \geq 0$ . There are perfect annuity markets where workers share their mortality risk.

#### 4.2.8 Government

The government enforces an unconditional severance payment from the firm to those workers who enter unemployment. The severance payment is a lump sum payment specified as a function  $\theta(i, t) = \gamma_t w_{it}$ .<sup>5</sup> Such specification allows the severance payment to depend both on productivity  $\varepsilon_{it}$  and on tenure lengths  $t$ . We assume  $\gamma_0 = 0$ , or that a worker with zero tenure is not entitled to a severance payment.

---

<sup>5</sup>In reality severance payments are usually proportional to the last wage. Our formulation makes the severance payment a function of the wage a worker would receive in the *current* period. The wage in the current period differs from the last wage whenever a state transition has taken place in the previous period. Making the severance payment proportional to the last wage would complicate notation substantially and require us to keep track of when the last state transition took place.

### 4.2.9 Wage setting

Wages are determined in every period before capital is rented. The wages of workers with zero tenure (outsiders) are determined competitively. We assume that workers with positive tenure (insiders) have all the bargaining power and make firms a take-it-or-leave-it offer.<sup>6</sup> Therefore workers are going to extract all the surplus and the value of a firm employing a worker of productivity  $\varepsilon_{it}$  and tenure  $t$  is  $J(i, t) = -\theta(i, t)$ .

## 4.3 Stationary Equilibrium

We first define the problem of an employed and unemployed worker and the problem of the firm. The individual state variables are the employment status  $s \in \mathcal{S} = \{e, u\}$ , experience  $i \in \mathcal{I}$ , asset holdings  $a \in \mathcal{A} = [-d, \bar{a}]$  and tenure  $t \in \mathcal{T}$ .<sup>7</sup> The stationary distribution of employed agents is denoted by  $\mu_e(i, a, t)$  whereas the distribution of unemployed agents is  $\mu_u(i, a)$ .

### 4.3.1 Problem of the agents

In this Section we first define the problem of the agents in their recursive representation. then we provide a formal definition of the equilibrium concept used in this model, the recursive competitive equilibrium.

#### Problem of the unemployed worker

The value function of an unemployed agent of type  $(i, t = 0)$  whose current asset holdings are equal to  $a$  is denoted with  $U(i, a)$ . The problem of these agents can be represented as follows:

---

<sup>6</sup>This assumptions implies that wages are determined only by productivity and severance payments. If firms had positive bargaining power wages would depend on workers' marginal utility of consumption and wealth. This would not only substantially complicate the problem but also imply that saving decisions have a strategic element in so far as they affect workers' future bargaining power and wages.

<sup>7</sup>A formal argument proving that  $\bar{a} < \infty$  appears for a similar economy in Huggett (1993).



$$U(i, a) = \max_{c, a'} \{u(c) - v(\bar{\psi}) + \beta \phi_i V(i, a', 0) \quad (4.2)$$

$$+ \beta (1 - \phi_i) [\pi_i^u U(i - 1, a') + (1 - \pi_i^u) U(i, a')]\}$$

*s.t.*

$$c + a' = \frac{(1 + r)}{\lambda} a + b(i)$$

$$a_0 \text{ given, } c \geq 0, \quad -a' > d$$

Unemployed agents enjoy utility from consumption, have some disutility from searching for a job, and face some uncertain events in the future. In the next period they can still be unemployed, and if so they might lose part of their skills, or they can find a job and be employed. We interpret  $b(i)$  as an unemployment benefit scheme depending on productivity (alternatively, we could interpret it as home production). Notice that the gross interest rate  $(1 + r)$  is divided by the survival probability  $\lambda$  to "adjust" the returns from investing in the risk-free asset for the probability of death. This ensures that at the aggregate level there are no incidental bequests to be distributed: in steady state the average value of the asset holdings of people that die is zero.<sup>8</sup>

### Problem of the employed worker

The recursive representation of the problem of the employed worker is as follows:

$$V(i, a, t) = \max_{c, a'} \{u(c) + \beta (1 - \sigma_{it}) [\pi_i^\epsilon \tau_t V(i + 1, a', t + 1) + \pi_i^\epsilon (1 - \tau_t) V(i + 1, a', t) +$$

$$(1 - \pi_i^\epsilon) \tau_t V(i, a', t + 1) + (1 - \pi_i^\epsilon) (1 - \tau_t) V(i, a', t)] + \beta \sigma_{it} U(i, a' + \theta(i, t))\}$$

(4.3)

*s.t.*

$$c + a' + l = \frac{(1 + r)}{\lambda} a + w_{it}$$

$$c \geq 0, \quad -a' > d$$

Employed agents enjoy utility from consumption and face several uncertain events in the future. In the next period they can still be employed, and if so they might see

---

<sup>8</sup>Notice that the Bellman equations need to be appropriately adjusted when productivity reaches its minimum value. When  $i = 1$ , the object  $U(i - 1, a')$  is not well defined. A similar comment applies for both the employed workers' and firms' value functions. The equations are trivially modified when tenure and/or productivity are at their boundaries. We do not report them in order to save on space.

an increase in their tenure and/or their age. or they can be fired, receive the severance payments and be unemployed. Notice that in case a separation occurs, the SP is paid to the worker at the end of the period: the amount of resources that she brings into the following period is equal to  $a' + \theta(i, t)$ , the sum of accumulated wealth and the severance payment. Finally, notice that  $l$  stands for a lump-sum tax paid by the agents currently employed to finance the unemployment benefit scheme.

### Problem of the firms

We assume that establishments are risk neutral. In every period, after wages have been set, an establishment matched to a worker of type  $(i, t)$  rents the amount of capital solving

$$J(i, t) = \max_{k_{it}} \left\{ f(k_{it})\varepsilon_{it} - w_{it} - (r + \delta)k_{it}\varepsilon_{it} + \frac{\lambda(1 - \sigma_{it})}{1 + r} [\pi_i^\varepsilon \tau_t J(i + 1, t + 1) + \right. \quad (4.4)$$

$$\left. \pi_i^\varepsilon (1 - \tau_t) J(i + 1, t) + (1 - \pi_i^\varepsilon) \tau_t J(i, t + 1) + (1 - \pi_i^\varepsilon) (1 - \tau_t) J(i, t)] \right.$$

$$\left. - \frac{\lambda\sigma_{it}}{1 + r} \theta(i, t) \right\}$$

where  $k_{it} = K_{it}/\varepsilon_{it}$ . In the firm's Bellman equation we need to take into account all possible transitions the worker currently employed could go through. Beside the transitions outlined above, we also need to take into consideration the death of the agent, which would destroy the match, with no SP paid to the worker.  $J(i, t)$  represent the expected present discounted stream of the firm's revenues and costs.

### Wage determination

Since the workers have all the bargaining power and make a take-it-or-leave-it offer to the firm, the wage  $w_{it}$  leaves the firm indifferent between continuing and terminating the employment relationship; i.e.  $J(i, t) = -\theta(i, t)$  for any pair  $(i, t)$ . Hence,  $w_{it}$  satisfies

$$-\theta(i, t) = f(k_{it})\varepsilon_{it} - w_{it} - (r + \delta)k_{it}\varepsilon_{it}$$

$$- \frac{\lambda}{1 + r} \{ (1 - \sigma_{it}) [\pi_i^\varepsilon \tau_t \theta(i + 1, t + 1) + \pi_i^\varepsilon (1 - \tau_t) \theta(i + 1, t)]$$

$$+ (1 - \pi_i^\varepsilon) \tau_t \theta(i, t + 1) + (1 - \pi_i^\varepsilon) (1 - \tau_t) \theta(i, t) \} + \sigma_{it} \theta(i, t)$$

To understand better how the wage determination (and their actual computation) works in our framework, consider a simplified example. In this illustration, severance payments do not depend on wages, that is  $\theta(i, t) = \theta_t$ , and productivity is a constant,

that is  $\varepsilon_{it} = \varepsilon, \forall (i, t)$ . By imposing the equilibrium conditions  $J(i, 0) = 0, \forall i$  and  $J(i, t) = -\theta_i, \forall (i, t \neq 0)$ , and rearranging the firms' value functions we are able to derive the equilibrium expressions for wages:

$$\begin{aligned} w_{i0} &= f(k)\varepsilon - (r + \delta)k\varepsilon - \frac{\lambda}{1+r} (1 - \sigma_{i0}) \tau_0 \theta_1 \\ w_{i1} &= f(k)\varepsilon - (r + \delta)k\varepsilon + \theta_1 - \frac{\lambda}{1+r} \{ (1 - \sigma_{i1}) [\tau_1 \theta_2 + (1 - \tau_1) \theta_1] + \sigma_{i1} \theta_1 \} \\ &\dots \text{ and similarly } \forall t \end{aligned}$$

This example is interesting since it shows that every period the worker pre-pays the severance payment that she will receive next period if laid off, so that the expected present value of the wage bill does not depend on  $\theta(i, t)$  at all, as expected. Only the time-profile of wages is affected.

If we consider a more general specification for the severance payments, namely  $\theta(i, t) = \gamma_t w_{it}$ . and we let productivity vary by type, then repeating the same steps gets a set of equations that the bargained wages need to satisfy:

$$\begin{aligned} -\gamma_t w_{it} &= f(k_{it})\varepsilon_{it} - w_{it} - (r + \delta)k_{it}\varepsilon_{it} \\ &- \frac{\lambda}{1+r} \{ (1 - \sigma_{it}) [\pi_i^e \tau_t \gamma_{t+1} w_{i+1,t+1} + \pi_i^e (1 - \tau_t) \gamma_t w_{i+1,t} \\ &+ (1 - \pi_i^e) \tau_t \gamma_{t+1} w_{i,t+1} + (1 - \pi_i^e) (1 - \tau_t) \gamma_t w_{it}] + \sigma_{it} \gamma_t w_{it} \} \end{aligned} \quad (4.5)$$

From (4.5) a system of  $T \times I$  equations is originated, whose unknown are the  $T \times I$  wages. Notice however that the system is: 1) recursive, thanks to the fact that  $I$  and  $T$  are the maximum values of  $(i, t)$ , and 2) linear in  $w_{it}$ , hence it admits a unique solution. Notice that in general  $w_{it} = W(w_{i,t+1}, w_{i+1,t}, w_{i+1,t+1})$ . In the actual solution one can start solving  $w_{IT} = W(w_{IT}, w_{IT}, w_{IT})$ . next  $w_{I-1,T} = W(w_{I-1,T}, w_{IT}, w_{IT})$ . and  $w_{I,T-1} = W(w_{IT}, w_{I,T-1}, w_{IT})$ . Then, it is possible to obtain, recursively, the whole sequence of  $\{w_{it}\}$ . The consequence is that one never has to deal with a system of equations to get the equilibrium wages, which is computationally simple and efficient.

### The mutual fund

The intertemporal budget constraint of the mutual fund is

$$\int (1 - \lambda)\theta(i, t) \sigma_{it} d\mu_e(i, a, t) + MF' = (1 + r)MF + \int p(i, t) d\mu_e(i, a, t) \quad (4.6)$$

where  $p(i, t)$  denotes the profit of a production unit of type  $(i, t)$  and  $MF$  denotes the asset-value of the fund. The quantity  $\int p(i, t) d\mu_e(i, a, t)$  represents the aggregate value of profits in steady state. The quantity  $\int (1 - \lambda)\theta(i, t) \sigma_{it} d\mu_e(i, a, t)$  represents the aggregate value of the severance payments paid to the workers who got separated in the current period. In steady state,  $MF = MF'$  so the fund has an amount of assets  $MF$  that guarantees a return which is large enough to cover the operating losses. A natural question arises: "Where do these funds come from?" The intuition is the following: a job has initially positive profits, then possibly negative profits, but ex-ante it has zero value when the present value of profits are discounted at rate  $r$ . It follows that if the fund reinvests the initial profits in the risk-free asset, it will be able to repay, in expected terms, all the future losses. Basically,  $MF$  is the cumulated value of the reinvested initial profits for each job in the stationary distribution  $\mu_e(i, a, t)$ .

### 4.3.2 Recursive Stationary Equilibrium

**Definition 3** For given policies  $\theta(i, t), b(i)$  a recursive stationary equilibrium is a set of decision rules  $\{c_e(i, a, t), c_u(i, a), a'_e(i, a, t), a'_u(i, a), k_{it}\}$ , value functions  $\{V(i, a, t), U(i, a), J(i, t)\}$ , a value of the mutual fund  $MF$ , prices  $\{r, w_{it}\}$ , a lump-sum tax  $l$  and a pair of stationary distributions  $\{\mu_e(i, a, t), \mu_u(i, a)\}$  such that:

- Given relative prices  $\{r, w_{it}\}$ , severance payments  $\theta(i, t)$ , lump-sum tax  $l$ , and unemployment benefits  $b(i)$ , the individual policy functions  $\{c_e(i, a, t), c_u(i, a), a'_e(i, a, t), a'_u(i, a)\}$  solve the household problems (4.2)-(4.3) and  $\{V(i, a, t), U(i, a)\}$  are the associated value functions.
- Given relative prices  $\{r, w_{it}\}$ , and severance payments  $\theta(i, t)$ ,  $k_{it}$  solves the firm's problem (4.4) and satisfies

$$r + \delta = f'(k_{it}) \quad (4.7)$$

Since the LHS of equation (4.7) is equal for every firm in the economy, it follows that  $k_{it}$  (the capital stock per efficiency unit of labor) is the same across establishments, or  $k_{it} = k$  for any pair  $(i, t)$ .

- The wage  $w_{it}$  leaves the firm indifferent between continuing and terminating the employment relationship; i.e.  $J(i, t) = -\theta(i, t)$  for any pair  $(i, t)$ . Hence,  $w_{it}$  satisfies the recursive system of equations (4.5).

- The stationary value of the mutual fund  $MF$  satisfies

$$rMF = (1 - \lambda) \int \theta(i, t) \sigma_{it} d\mu_e(i, a, t) - \int p(i, t) d\mu_e(i, a, t)$$

which highlights how the operating losses are paid for with the asset income.

- The labor market is in flow equilibrium

$$\begin{aligned} & \int_{I \times A \times T} \lambda \sigma_{it} d\mu_e(i, a, t) + \int_{I \times A \times T} (1 - \lambda) d\mu_e(i, a, t) \\ &= \int_{I \times A} \lambda \phi_i d\mu_u(i, a) \end{aligned}$$

notice that we need to take into consideration that some people die and are substituted by the flow of newborns, who enter the job market as unemployed.

- The asset market clears

$$k \int_{I \times A \times T} \varepsilon_{it} d\mu_e(i, a, t) = \int_{I \times A \times T} a'_e(i, a, t) d\mu_e(i, a, t) + \int_{I \times A} a'_u(i, a) d\mu_u(i, a) + MF$$

notice that here we need to add the supply of capital of the mutual fund.

- The goods market clears

$$\begin{aligned} & [f(k) - \delta k] \int_{I \times A \times T} \varepsilon_{it} d\mu_e(i, a, t) + \int_{I \times A} b(i) d\mu_u(i, a) = \\ & \int_{I \times A \times T} c_e(i, a, t) d\mu_e(i, a, t) + \int_{I \times A} c_u(i, a) d\mu_u(i, a) \end{aligned}$$

- For  $b(i) = bw_{i0}$  the lump-sum tax satisfies

$$l = \frac{\int_{I \times A} bw_{i0} d\mu_u(i, a)}{\int_{I \times A \times T} d\mu_e(i, a, t)}$$

- The stationary distributions  $\{\mu_e(i, a, t), \mu_u(i, a)\}$  satisfy

$$\begin{aligned} \mu_u(i, a') &= \lambda \left[ (1 - \pi_i^u) \int_{a: a'_u(i, a) = a'} (1 - \phi_i) d\mu_u(i, a) \right. \\ & \left. + \pi_i^u \int_{a: a'_u(i, a) = a'} (1 - \phi_{i+1}) d\mu_u(i+1, a) + \int_{T \times \{a: a'_e(i, a, t) = a'\}} \sigma_{it} d\mu_e(i, a, t) \right] \\ & + (1 - \lambda) \chi(i=1) \chi(a' = a_0) \left[ \int_{I \times A \times T} d\mu_e(i, a, t) + \int_{I \times A} d\mu_u(i, a) \right] \end{aligned} \quad (4.8)$$

and

$$\begin{aligned}
\mu_e(i, a', t) = & \lambda \left[ \int_{a: a'_e(i, a, t) = a'} (1 - \sigma_{it}) (1 - \pi_i) (1 - \tau_t) d\mu_e(i, a, t) \right. \\
& + \left. \int_{a: a'_e(i-1, a, t) = a'} (1 - \sigma_{i-1t}) \pi_{i-1} (1 - \tau_t) d\mu_e(i-1, a, t) \right] \\
& + \lambda \left[ \int_{a: a'_e(i, a, t-1) = a'} (1 - \sigma_{it-1}) (1 - \pi_i) \tau_{t-1} d\mu_e(i, a, t-1) \right. \\
& + \int_{a: a'_e(i-1, a, t-1) = a'} (1 - \sigma_{i-1t-1}) \pi_{i-1} \tau_{t-1} d\mu_e(i-1, a, t-1) \\
& \left. + \chi(t=1) \int_{a: a'_u(i, a) = a'} \mathcal{O}_i d\mu_u(i, a) \right]
\end{aligned} \tag{4.9}$$

where  $\chi(\cdot)$  is an indicator function taking the value one if the condition in parenthesis is satisfied and zero otherwise.

In equilibrium the measure of agents in each state is time invariant and consistent with individual decisions, as given by the above two equations (4.8) and (4.9).

## 4.4 Parameterization

The complete parameterization of the model is reported in Table 1. We calibrate the model to the US, where severance packages are in place only for few categories of workers.

In order to properly capture the labor market dynamics, we need to work with a short time period: one model period corresponds to two months. The survival probability is calibrated for the agents to have on average an active working life of 40 years. The concavity of the utility function is pinned down by the CRRA coefficient  $\eta$ , which is set to 2.0, a common value in the literature. The borrowing limit  $d$  is endogenous to the model, and we stick to the Natural Borrowing Limit concept proposed by Aiyagari (1994). In the benchmark economy  $d = 0.16$ . We assume that the newborns enter the economy without any asset endowment, or  $a_0 = 0$ . We allow for 11 points in the age/productivity grid. People enter the economy at age 20 and reach at most age 60. The grid is evenly spaced, that is we allow for a jump in age occurring on average every 4 years. It follows that  $\pi_i^e = 0.038$ . As for the probability of losing skills while unemployed  $\pi_i^u$ , we choose a value

Parameter	Value	Target
Model Period	Bimonthly	
$\lambda$ - Survival prob	$1 - \frac{1}{40.6} = 0.9958$	40 years of active working life
$\eta$ - CRRA	2.0	Standard
$d$ - Borrowing limit	0.16	Natural Borrowing Limit
$a_0$ - Newborn asset endowment	0	
$I$ - Productivity levels	11; {20, 24, ..., 60}	Working age between 20 and 60
$\varepsilon_{it}$ - Productivity values	See Table 2	From a regression on CPS data
$\pi_i^e$ - Prob of increasing productivity	$\frac{8}{4.52} = 0.038$	A jump every 4 years
$\pi_i^u$ - Prob of decreasing productivity	0.1	
$T - T + 1$ Tenure levels	10; {0, 2, ..., 20}	Maximum Tenure=20 years
$\tau_t$ - Prob of increasing tenure	$\frac{8}{2.52} = 0.077$	A jump every 2 years
$\phi_i$ - Job finding prob	0.66	Average unemployment duration
$\sigma_{it}$ - Job losing prob	$\frac{8}{8.52} = 0.019$	A separation every 8 years
$\gamma_t$ - Severance Payment	0	Competitive Labor Market
$\delta$ - Capital depreciation rate	0.012	Investment/Output ratio $\approx 20\%$
$\alpha$ - Capital share	0.3	Labor Share
$\hat{\beta}$ - Rate of time preference	0.9962	Annual interest rate=5%

Table 4.1: Calibration

equal to 10%. This implies that there is a 10% probability that an unemployed worker will see her efficiency units decreased of four years. Given the estimated parameters of the log wage regression, this implies an average wage loss equal to approximately 6%. Notice that we use this value only for  $i \leq 8$ . Since the estimated profiles are concave in age, the efficiency units peak at (model) age  $i = 8$ , and start declining afterwards. If we were to allow for a positive  $\pi_i^u$  for the ages between 9 and 11, unemployed workers facing a negative shock would acquire skills rather than losing them. To avoid this problem, we set  $\pi_i^u = 0$  for  $i = 9, \dots, 11$ . As with the age/productivity grid, we allow for 11 points in the tenure grid, which starts at zero and reaches at most 20 years. The grid is evenly spaced, that is on average people experience an increase in tenure every 2 years. It follows that  $\tau_t = 0.019$ . The job finding probability  $\phi_i$  is pinned down by the average unemployment duration. This is approximately 12 weeks in the data, which dictates a value for  $\phi_i = 0.66$ . At this stage of the analysis, we allow for a constant separation probability, equal to  $\sigma_{it} = 0.019$ .

This implies that on average a worker gets separated every 8 years. For the benchmark economy  $\gamma_t = 0$  because it is meant to capture the US economy where SP are limited to few occupations. The depreciation of capital is set to replicate an investment/output share of 20% on an annual basis. This is achieved when  $\delta = 0.012$ . We assume a Cobb-Douglas production function, hence the capital share is captured by the parameter  $\alpha = 0.3$ . The rate of time preference  $\hat{\beta}$  is calibrated to get an equilibrium interest rate equal to 5%, on an annual basis.

The computation of the efficiency units profile for each  $(i, t)$  type is no trivial task for this model. If one were to interpret literally the  $(i, t)$  pairs, the  $\varepsilon_{it}$  should be estimated in equilibrium. Since we are allowing for human capital depreciation during an unemployment spell (captured by a decrease in  $i$ ), the variable  $i$  could not be taken to the data as being age. However, structurally estimating  $(I \times T)$  efficiency units would represent an intractable problem. To reduce the dimensionality of the exercise, one could rely on additional parametric assumptions on how  $\varepsilon_{it}$  is related to  $i$  and  $t$ . However, here we take a pragmatical approach: we neglect for the moment the logical inconsistency between the variable  $i$  in the model and calendar age in the data.

In order to get estimates for the efficiency units, we need to rely on data that provide information on both age and tenure with the current employer. Both the NLSY and the February CPS include such information. We decided to use the CPS data, because they represent a random sample of the whole US labor force, unlike the NLSY that contains information on only one cohort.

We estimate a simple linear regression with OLS, where the dependent variable is the natural logarithm of earnings and the set of explanatory variables are the constant, and two third-degree polynomials in age and tenure.

As for the returns to tenure, given the pervasive selection and endogeneity problems, there is no consensus in the literature on their magnitude. Here we take a stand which is consistent with the model we are working with. In the model an increase in tenure with the current employer is a random event, which neither the firm or the worker can affect. It follows that tenure is strongly exogenous and can be included in the right hand side of a log wage regression like the one in Table 2. The estimated returns to tenure on the February 1996 CPS data are approximately 2% on a yearly basis. This value seems to be on the high end of the estimated returns to tenure.

Once we have the OLS estimates, we retrieve the  $\{\varepsilon_{it}\}$  by simply considering the fitted values of the econometric model at all the  $(i, t)$  pairs implied by their grids.



Notice that in order to preserve consistency between the theoretical model and the data, we transformed the dependent variable and the explanatory ones to the same time period of the model, that is we estimated log wages on a bi-monthly basis. Table 2 reports the results of the OLS regression.

<i>Parameter</i>	<i>Log Wage</i>
<i>Age</i>	0.04747 (0.00245)
<i>Age</i> <sup>2</sup>	-0.00012 (8.15e - 06)
<i>Age</i> <sup>3</sup>	9.47e - 08 (8.56e - 09)
<i>Tenure</i>	0.00395 (0.00069)
<i>Tenure</i> <sup>2</sup>	-0.00001 (7.01e - 06)
<i>Tenure</i> <sup>3</sup>	1.83e - 08 (1.82e - 08)
<i>Constant</i>	0.25533 (0.23070)
<i>N. Obs</i>	6160
<i>Adj. R</i> <sup>2</sup>	0.332

Table 4.2: Log Earnings Regression, t statistics in parenthesis (Source: CPS Feb 1996)

## 4.5 Results

This Section presents the main results. First we show how the equilibrium wage profiles are affected by the introduction of severance payments. Then we discuss the prediction of the model. Finally, we compute the welfare effects induced by the severance payments. We consider the benchmark economy as the one without SP, and a series of counterfactual economies where the SP is set at an increasing level. More in detail, we consider five values for SP, that is in the five experiments we set  $\gamma_t$  at 3, 6, 9, 12, and 15 monthly wages.

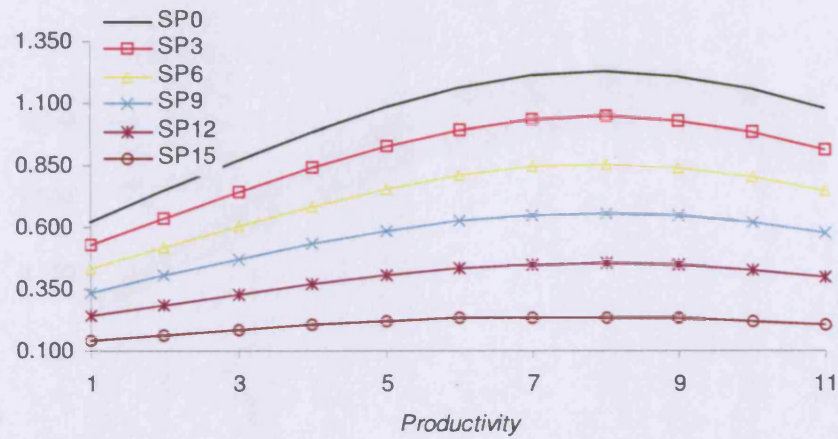


Figure 4.1: The effects of SP on the Wage Profile (No Tenure)

#### 4.5.1 Wage profiles

Figure (4.1) plots the equilibrium effects on wages derived by introducing the severance payments at different levels. As discussed above, the workers pre-pay the SP with a low entry wage. This graph shows how untenured workers see their wage profile change during their life-cycle. These plots take into consideration also the General Equilibrium effects, since the wage profiles associated to different severance payments are compared for the equilibrium interest rate  $r$ . From the figure, it is possible to appreciate that untenured workers suffer a large wage loss for every productivity level they might have. The effect is smooth in the level of the SP: for SP equal to 15 monthly wages the drop is substantial and wages in the competitive environment are six times higher than in the counterfactual economy with SP. Another aspect of the introduction of SP is the present value of wages which remains unaltered. Another way of interpreting this result is to say that higher SP imply faster wage growth in the first years of a job match. This effect is captured in Figure (4.2), which plots the wage profiles for tenured workers with tenure equal to two years. It is possible to appreciate how the SP have now the opposite effect on wages if compared to before. Wages of tenured workers rise with  $\gamma_t$  and the rise tends to get amplified during the life cycle. For SP equal to 15 monthly wages rises up to 22% when compared to the benchmark economy.

Closely linked to the wage profile is the SP the workers are entitled to if a separation

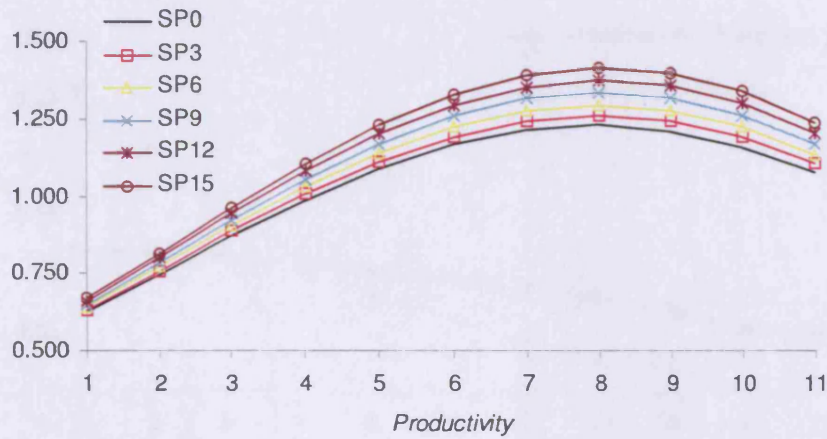


Figure 4.2: The effects of SP on the Wage Profile (Tenure=1)

takes place. Since  $\theta(i, t) = \gamma_t w_{it}$  their behaviour is similar to Figure (4.2), which is only rescaled by the factor  $\gamma_t$ .

One of the endogenous outcomes of the model is the stationary distribution of worker types by employment status, age and tenure. Figure (4.3) reports the equilibrium marginal distributions over tenure and productivity. As for the former, the share of workers employed decreases smoothly with tenure and captures the main features of the data, qualitatively and, for low tenure values, quantitatively as well. The results related to the latter are somewhat less satisfactory: the model predicts that young workers have the highest shares in the pool of employment, which is not a feature of the data. These results were obtained on the basis of a simple and parsimonious calibration strategy, which imposed a constant value for  $\pi_i^e$ ,  $\pi_i^u$ ,  $\tau_t$ ,  $\phi_i$  and  $\sigma_{it}$ . A feasible alternative is to estimate the transition probabilities with a simulated method of moments. More in detail, once we "integrate out" the asset level, the stationary distributions over tenure and productivity can be obtained without solving the model, since they depend only on a set of exogenous shocks. The corresponding distributions in the data are easily computed, and it would be possible to iterate on the parameters values until the squared deviations are minimized.<sup>9</sup>

<sup>9</sup>However, this procedure might suffer from some identification issues. Unless we are able to pin down some of the parameters directly from the data, the same stationary distributions might be obtained with different combinations of shocks, in particular the ones related to the increase and decrease in productivity tend to offset each other.

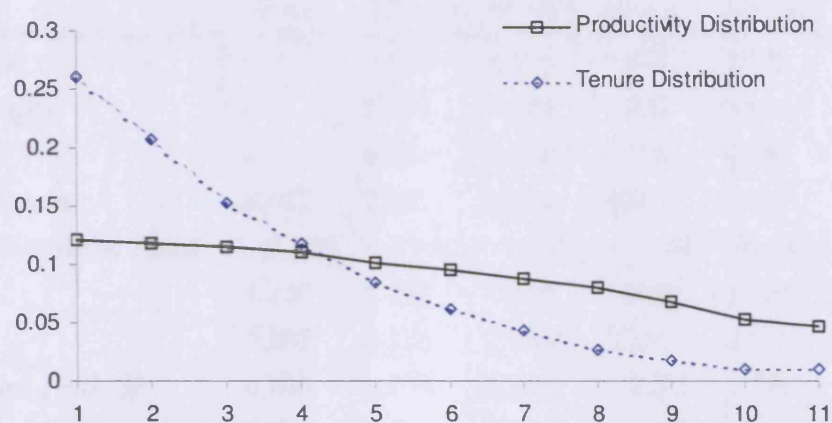


Figure 4.3: Workers Marginal Distributions over Productivity and Tenure

#### 4.5.2 Equilibrium Effects

This section is devoted to discuss the equilibrium effects of SP on a set of relevant endogenous variables. Tables 3 and 4 present the same results in two different formats. Each column presents the results related to the economy with a level of the SP indicated in the top of the table. In Table 3 we report the values of the endogenous variables of the model in levels, while Table 4 reports the subset of endogenous variables that are not a share themselves divided by the value of output in the benchmark economy.

In Table 3 there several interesting findings. First, as expected, the values of the mutual fund, of the average profits and of the average disbursement in SP are all monotonically increasing in the level of SP. The equilibrium lump-sum tax is quantitatively small, and decreases in SP, both because output is increasing, but also because the average wage is falling, and the cost of the unemployment benefit scheme is decreasing. The same effect is driving the behaviour of the borrowing limit. Since the lowest possible income is the unemployment benefit, and this is a fraction of the untenured wage, the borrowing limit becomes more stringent for higher SP, exactly because those wages are decreasing. A more stringent borrowing limit, on the other hand, influences the agents' saving behaviour, strenghtening the precautionary saving motive and increasing the asset supply in the economy.

<i>Variable</i>	<i>SP=0</i>	<i>SP=3</i>	<i>SP=6</i>	<i>SP=9</i>	<i>SP=12</i>	<i>SP=15</i>
<i>Mutual Fund</i>	0	0.248	0.481	0.672	0.743	0.888
<i>Average Profits</i>	0	0.028	0.059	0.093	0.134	0.179
<i>Average SP</i>	0	0.034	0.069	0.106	0.146	0.187
<i>TAX (lump-sum)</i>	0.017	0.015	0.012	0.009	0.006	0.004
<i>(Natural) Borrowing Limit</i>	-0.162	-0.142	-0.123	-0.103	-0.083	-0.056
<i>Output</i>	1.220	1.229	1.242	1.260	1.286	1.314
<i>I/Y Ratio</i>	0.205	0.208	0.213	0.221	0.231	0.244
<i>Labour Share (with SP)</i>	0.700	0.709	0.716	0.722	0.726	0.727
<i>Labour Share (without SP)</i>	0.700	0.681	0.660	0.638	0.612	0.585
<i>Borrowing Constrained (%)</i>	0.0	0.0	0.0	0.0	0.0	0.0

Table 4.3: Equilibrium

<i>Variable</i>	<i>SP=0</i>	<i>SP=3</i>	<i>SP=6</i>	<i>SP=9</i>	<i>SP=12</i>	<i>SP=15</i>
<i>Mutual Fund</i>	0.0	20.3	39.4	55.1	60.9	72.8
<i>Average Profits</i>	0.0	2.3	4.8	7.6	11.0	14.7
<i>Average SP</i>	0.0	2.8	5.7	8.7	11.9	15.3
<i>TAX (lump-sum)</i>	1.4	1.2	1.0	0.8	0.5	0.3
<i>(Natural) Borrowing Limit</i>	-13.3	-11.7	-10.1	-8.5	-6.8	-4.6
<i>Output</i>	100.0	100.7	101.8	103.2	105.4	107.7
<i>Average wage</i>	70.0	68.6	67.2	65.8	64.5	63.0

Table 4.4: Equilibrium normalized by output in the benchmark economy

An interesting result is related to output. With respect to the benchmark economy, output increases monotonically in the SP, with a 7.7% change for SP equal to 15 monthly wages. The increase in output stems from the additional supply of capital, which drives the interest rate down and expands the stock of physical capital.

As for the labor share, we can think of two different definitions, depending on how we consider the SP. If SP are included in the computation of the labor share, this increases monotonically in the level of SP, passing from 70% to 72.7%. Notice also the concavity of this relationship. Differently, if SP are excluded in the definition of labor share, this decreases considerably, falling to 58.5%. This is due mainly to the increase in output.

To conclude with, as in many models with incomplete markets, the percentage of agents

that are at the borrowing limit is zero in all the economies considered. This is somewhat surprising, especially given the extremely low labor income of the untenured workers when the SP is high.

### 4.5.3 Welfare Effects

As shown by the previous results, the introduction of SP has important allocative effects, with several non trivial General Equilibrium forces being present at the same time. Here we present the results related to a measure of the equilibrium welfare effects of SP. More precisely, we first compute the welfare in the steady state of the benchmark economy using the equilibrium consumption functions. In order to compute the average welfare, we assume the existence of a utilitarian social welfare function. Then we consider as our measure of welfare cost/gain the percentage change in consumption that would equate the social welfare of the counterfactual economy to that of the benchmark one. The equilibrium welfare effects are reported in Table 5.

<i>Severance Payments</i>	<i>Average Welfare Change</i>
<i>SP=3</i>	0.4%
<i>SP=6</i>	1.22%
<i>SP=9</i>	2.98%
<i>SP=12</i>	6.77%
<i>SP=15</i>	16.79%

Table 4.5: Welfare Effects of the SP

The first result is that the average welfare is always higher in the counterfactual economies. For relatively low values of SP, the average welfare change is small. More precisely, for values of the severance payment equal to three and six monthly wages, we need to decrease consumption in each possible state of the world by 0.4% and 1.22%, respectively. However, the effects of SP is highly non linear and increases exponentially. The average results hides different effects for different groups of workers. In each of these simulation, because of the wage cut, the untenured workers suffer a large welfare loss, which in the aggregate is more than compensated by the welfare gains of the tenured workers.

When the is SP equal to 12 and 15 monthly wages, the percentage decrease in consumption that equates the welfare to the competitive labor market is equal to 6.77% and

16.79%, which are extremely high. However, regarding to the plausibility of these welfare gains some caveats are in order. It is worth stressing that the simple formulation for SP we are working with might over-estimate substantially their effects. More in detail, we are assuming that the number of monthly wages is the same for every worker that faces a separation, *irrespective* of their actual tenure with their employer. In reality the severance payments tend to be capped and, more importantly, they do depend on the level of the tenure. For example, the value reported for Italy, 15 monthly wages, refers to worker with a tenure level of ten years (which is also very different from the corresponding figure in the US and hard to reconcile also if considering the likely equilibrium effect on the average duration of a match induced by a more restrictive EPL). On the contrary, the model implies a very large expenditure in SP. If we compare the average SP paid in the economy with  $\gamma_t=15$  to the one in the economy with  $\gamma_t=3$ , the first is 6.38 times higher than the latter. This implies that, in order for the Mutual Fund to be able to cover the operating losses, its equilibrium value has to increase by a factor of 3.58. This leads to an excess supply of capital, the interest rates falls substantially, leading to a large increase in the capital stock. This in turn tends to mitigate the fall in wages caused by the higher SP. To conclude with, severance payments have important allocative effects; their welfare effects are quantitatively small for plausible values of the SP, while they get large for high values of the SP.

## 4.6 Discussion and Conclusions

In this chapter we proposed a quantitative framework to study the equilibrium effects of severance payments. These are an important labor market feature of several OECD Countries and have been proposed as a possible explanation of their high unemployment rates.

The results show that the introduction of severance payments influences positively the average welfare. However, restricting the attention to this aggregate measure hides large losses for the untenured workers, but also large gains for the tenured ones.

This paper has focused on stationary equilibria. It would be interesting to study the welfare effects of SP out of the steady-state, in a model with aggregate uncertainty. A recent contribution, Veracierto (2008), presents an analysis along those lines. Notice, however, that the techniques used to tackle the current problem would need to be amended

since the whole distribution of assets would become a state variable. A feasible solution might be to rely on the approximation methods proposed by den Haan (1997) and Krusell and Smith (1998).

For future work we plan to endogenize the job finding probability, by including a search effort decision in the agents' problem. This extension complicates the solution of the model, but endogenizes a crucial margin. This extension would allow to make quantitative statements on the equilibrium effect of SP on the unemployment rate. Notice also that the current framework does not allow for search/matching externalities in the spirit of Mortensen-Pissarides and included, for example, by Alonso-Borrego, Fernandez-Villaverde and Galdon-Sanchez (2006) in a model of temporary Vs. permanent contracts.

In order to give the Mutual Fund a less extreme role in our counterfactuals, the introduction of a retirement stage could prove helpful. The saving behaviour would reflect also the desire for consumption smoothing during retirement, possibly leading to changes in the equilibrium value of the Mutual Fund which would affect less drastically the interest rate and the accumulation of physical capital.

Finally, there is a large body of evidence showing that the retention probability of a worker is heavily affected by some observables, such as age, and tenure. We could exploit this information to calibrate the separation probabilities and obtain a different response on the wage profiles, because this would reflect the different risks of separation. We leave these extensions and modifications for future work.

## 4.7 Appendix A - Computation

In the actual solution of the model, we need to discretize the continuous state variable  $a$  ( $i, t$  and employment status are already discrete). We rely on an unevenly spaced grid, with the distance between two consecutive points increasing geometrically. This is done to allow for a high precision of the policy rules at low values of  $a$ , that is where the change in curvature is more pronounced.

The model with exogenous search effort is solved with a 'time iteration' procedure on the set of euler equations. In order to keep the computational burden manageable, we use 150 grid points on the asset space, the lowest value being the borrowing constraint and the highest one being a value high enough for the saving functions to cut the 45 degree line. Notice that we do not restrict the agents' asset holding to belong to a discrete set. As for



the approximation method, we rely on a linear approximation scheme for the saving and consumption functions, for values of  $a$  falling outside the grid.

A collocation method is implemented, that is we look for the policy functions such that the residuals of the Euler equations are (close to) zero at the collocation points (which correspond to the asset grid). It follows that for all possible combinations of state variables we need to solve a non linear equation. A time iteration scheme is applied to get the policy functions, i.e. we compute the first order conditions with respect to  $a'$  and through the envelope condition we obtain a set of euler equations, whose unknowns are the policy functions,  $a'_\epsilon(i, a, t), a'_u(i, a)$ .

We start from a set of guesses,  $a'_\epsilon(i, a, t)_0$  and  $a'_u(i, a)_0$ , and keep on iterating until a fixed point is reached, i.e. until two successive iterations satisfy:

$$\begin{aligned} \sup_a |a'_\epsilon(i, a, t)_{n+1} - a'_\epsilon(i, a, t)_n| &< 10^{-6}, \forall i \text{ and } \forall t, \text{ and} \\ \sup_a |a'_u(i, a)_{n+1} - a'_u(i, a)_n| &< 10^{-6}, \forall i. \end{aligned}$$

The model with endogenous search effort is solved with a 'successive approximation' procedure on the set of value functions.

We start from a set of guesses,  $V(i, a, t)_0$  and  $U(i, a)_0$ . We compute the vector of parameters  $\Omega$  representing the Schumaker spline approximations of the value functions. We solve the constrained maximization problems and retrieve the policy functions,  $a'_\epsilon(i, a, t), a'_u(i, a), \psi(i, a)$ . Notice that we do not restrict either the agents' asset holding or the search effort to belong to a discrete set. As for the approximation method, we rely on a linear approximation scheme for the saving, consumption and search effort functions, for values of  $a$  falling outside the grid.

We keep on iterating until a fixed point is reached, i.e. until two successive iterations satisfy:

$$\begin{aligned} \sup_a |V(i, a, t)_{n+1} - V(i, a, t)_n| &< 10^{-6}, \forall i \text{ and } \forall t, \text{ and} \\ \sup_a |U(i, a)_{n+1} - U(i, a)_n| &< 10^{-6}, \forall i. \end{aligned}$$

The stationary distributions are computed either relying on iterating on their definition, using a linear approximation of the distribution functions between grid-points, or by simulating a large sample of 100,000 individuals for 2,000 periods, which ensure that the statistics of interest are stationary processes.

## 4.8 Appendix B - Solution Algorithm

The computational procedure used to solve the baseline model can be represented by the following algorithm:

- Guess  $Min \{b(i)\}_0$  and compute the borrowing limit  $d$ ;
- Generate discrete grids over the asset space  $[-d, \dots, a_{\max}]$ ;
- Guess on the interest rate  $r_0$ ;
- Get the individual firms' capital demand  $k_{it}$ ;
- Guess on the lump-sum tax  $l_0$ ;
- Get the wages  $w_{it}$ ;
- Get the consumption and saving functions  $c_e(i, a, t), c_u(i, a), a'_e(i, a, t), a'_u(i, a)$ ;
- Get the stationary distributions  $\mu_e(i, a, t), \mu_u(i, a)$ ;
- Get the value of the mutual fund  $MF$ ;
- Get the aggregate capital demand;
- Check asset market clearing; Get  $r_1$ ;
- Update  $r'_0 = \varpi r_0 + (1 - \varpi) r_1$  (with  $\varpi$  arbitrary weight);
- Update  $l_1$ ;
- Update  $Min \{b(i)\}_1$ ;
- Iterate until market clearing;
- Check final good market clearing.

# Bibliography

Adda, J. and V. Lechene. (2001) "Smoking and Endogenous Mortality: Does Heterogeneity in Life Expectancy Explain Differences in Smoking Behavior?," mimeo, UCL.

Aiyagari, R. (1994). "Uninsured Idiosyncratic Risk and Aggregate Saving," *Quarterly Journal of Economics*, Vol. 109 (3), 659-684.

Alonso-Borrego, C., J. Fernandez-Villaverde and J. E. Galdon-Sanchez. (2006). "Evaluating Labor Market Reforms: A General Equilibrium Approach," Working Paper, University of Pennsylvania.

Altonji, J. and R. Blank. (1999). "Race and Gender in the labor Market," chapter 48 in *Handbook of labor Economics, Volume 3*, edited by O. Ashenfelter and D. Card. Amsterdam: North Holland.

Altonji, J. and U. Doraszelski. (2005). "The Role of Permanent Income and Demographics in Black/White Differences in Wealth," *Journal of Human Resources*, Vol. 40 (1). 1-30.

Alvarez, F. and M. Veracierto. (2001). "Severance Payments in an Economy with Frictions", *Journal of Monetary Economics*, Vol. 47 (3), 477-98.

Anderson. E. (1999). *The Code Of The Street: Decency, Violence, And The Moral Life Of The Inner City*, New York: W.W. Norton.

Becker, G. (1968). "Crime and Punishment: An Economic Approach," *Journal of Political Economy*, Vol. 76, 169-217.

Becker, G., K. Murphy and M. Grossman. (2006). "The Economic Theory of Illegal Goods: The Case of Drugs," *Journal of Political Economy*, Vol. 114 (1), 38-60.

Becker, G., M. Grossman and K. Murphy. (1994). "An Empirical Analysis of Cigarette Addiction," *American Economic Review*, , Vol. 84 (3), pp. 396-418.

- Becker, G., M. Grossman and K. Murphy. (1991). "Rational Addiction and the Effect of Price on Consumption." *American Economic Review*, Vol. 81 (2), 237-241.
- Becker, G. and K. Murphy. (1988). "A Theory of Rational Addiction," *Journal of Political Economy*, Vol. 96 (4), 675-700.
- Bertrand, M. and S. Mullainathan. (2004). "Are Emily and Brendan More Employable than Latoya and Tyrone? Evidence on Racial Discrimination in the Labor Market from a Large Randomized Experiment," *American Economic Review*, Vol. 94 (4), 991-1013.
- Bound, J. and R. Freeman. (1992). "What Went Wrong? The Erosion of Relative Earnings and Employment among Young Black Men in the 1980s," *Quarterly Journal of Economics*, Vol. 107, 202-232.
- Burdett, K., R. Lagos and R. Wright. (2003). "Crime, Inequality and Unemployment," *American Economic Review*, Vol. 93, 1764-1777.
- Burdett, K., R. Lagos and R. Wright. (2004). "An On-the-job Search Model of Crime, Inequality, and Unemployment," *International Economic Review*, Vol. 45 (3), 681-706.
- Bernheim, D. and A. Rangel. (2004). "Addiction and Cue-Triggered Decision Processes," *American Economic Review*, Vol. 94 (5), 1558-1590.
- Blumstein, A., J. Cohen, J. Roth, and C. Visher. (1986). "Participation in Criminal Careers," chapter 2 in *Criminal Careers and Career Criminals*, Volume 1. Washington, D.C.: National Academy Press.
- Caulkins, J., P. Reuter and L. Taylor. (2006). "Can Supply Restrictions Lower Price? Violence, Drug Dealing and Positional Advantage," *B.E. Journals in Economic Analysis & Policy*, Contributions to Economic Analysis & Policy, Vol. 5 (1), 1-18.
- Caulkins, J. and Padman, R. (1993). "Quantity discounts and quality premia for illicit drugs", *Journal of the American Statistical Association*, Vol. 88, 748-757.
- Chaiken, J., and M. Chaiken. (1990). *Drugs and predatory crime*. In: M. Tonry, J.Q. Wilson (Eds.), *Drugs and crime: Vol. 13. Crime and justice: A review of research* (pp. 203-239). Chicago: University of Chicago Press.
- Corman, H. and N. Mocan. (2000). "A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City," *American Economic Review*, Vol. 90 (3), 584-604.

Dave, D. (2004). "Illicit Drug Use Among Arrestees and Drug Prices," *NBER Working Paper No. w10648*.

Davis, M. (1988). "Time and Punishment: An Intertemporal Model of Crime," *Journal of Political Economy*, Vol. 96 (2), 383-90.

den Haan, W. (1997). "Solving Dynamic Models with Aggregate Shocks and Heterogenous Agents," *Macroeconomic Dynamics*, Vol. 1, 355-386.

DeSimone, J. (2002). "Illegal Drug Use and Employment", *Journal of Labor Economics*, Vol.20 (4), 952-977.

DiIulio, J. (1996). "Help Wanted: Economists, Crime and Public Policy," *Journal of Economic Perspectives*, Vol.10 (1), 3-24.

Donohue, J. and J. Heckman. (1991). "Continuous Versus Episodic Change: the Impact of Civil Rights Policy on the Economic Status of Blacks," *Journal of Economic Literature*, Vol. 29 (4), 1603-1643.

Donohue, J. and S. Levitt. (2001). "The Impact of Race on Policing, Arrest Patterns and Crime," *Journal of Law and Economics*, Vol. 44 (2), 367-394.

Edwards, G. and M. Lader. (1991). *The Nature of Drug Dependence*, Oxford, Oxford University Press.

Ehrlich, I. (1996). "Crime, Punishment, and the Market for Offenses," *Journal of Economic Perspectives*, Vol. 10 (1), 43-67.

Fairlie, R. and B. Meyer. (1996). "Ethnic and Racial Self-Employment Differences and Possible Explanations," *Journal of Human Resources*, Vol. 31 (4), 757-793.

Fender, J. (1999). "A General Equilibrium Model of Crime and Punishment," *Journal of Economic Behavior and Organisation*, Vol. 39 (4), 437-453.

Flinn, C. (1986). "Dynamic Models of Criminal Careers," chapter 9 in *Criminal Careers and Career Criminals*, Volume 2, edited by Blumstein et al. Washington, D.C.: National Academy Press.

Freeman, R. (1999). "The Economics of Crime," chapter 52 in *Handbook of labor Economics*, Volume 3, edited by O. Ashenfelter and D. Card. Amsterdam: North Holland.

- Freeman, R. (1996). "Why Do So Many Young American Men Commit Crimes and What Might We Do About It?," *Journal of Economic Perspectives*, Vol. 10 (1), 25-42.
- Friedman, M. (1991). "The War We Are Losing," in *Searching for Alternatives: Drug-Control Policy in the United States*, edited by M. B. Krauss and E. P. Lazear. Stanford, CA: Hoover Institution Press.
- Furlong, W. (1987). "A General Equilibrium Model of Crime Commission and Prevention," *Journal of Public Economics*, Vol. 34, 87-103.
- Garibaldi, P. and G. Violante. (2005). "The Employment Effects of Severance Payments with Wage Rigidities," *Economic Journal*, Vol. 115, 799-832.
- Glaser, E., B. Sacerdote and J. Scheinkman. (1996). "Crime and Social Interactions," *Quarterly Journal of Economics*, Vol.111 (2), 507-548.
- Gourieroux, C. and A. Monfort. (1996). *Simulation-Based Econometric Methods*, Oxford University Press.
- Grogger, J. (1998). "Market Wages and Youth Crime," *Journal of Labor Economics*, Vol. 16 (4), 756-791.
- Grogger, J. and M. Willis. (2000). "The Emergence of Crack Cocaine and the Rise in Urban Crime Rates." *Review of Economics and Statistics*, Vol. 82 (4), 519-529.
- Grossman, H. (1995). "Robin Hood and the Redistribution of Property Income," *European Journal of Political Economy*, Vol. 11(3), 399-410.
- Grossman, H. and D. Mejia. (2005). "The War Against Drug Producers." *NBER Working Paper*, No. W11141.
- Gruber, J. and B. Koszegi. (2001). "Is Addiction 'Rational'? Theory and Evidence." *Quarterly Journal of Economics*, Vol. 116 (4) , 1261-1303.
- Gruber, J. (2001). "Risky Behavior Among Youths: an Economic Analysis," chapter 1 in *Risky Behavior Among Youths: an Economic Analysis*, edited by J. Gruber. Chicago, IL: University of Chicago Press.
- Gul, F. and W. Pesendorfer. (2006). "Harmful Addiction," *Review of Economic Studies*, Forthcoming.

- Hansen, L. P. (1982). "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, Vol. 50 (4), 1029-54.
- Hernandez-Murillo, R. and J. Knowles. (2004). "Racial Profiling or Racist Policing? Bounds Tests in Aggregate Data," *International Economic Review*, Vol. 45 (3), 959-989.
- Hopenhayn, H. and R. Rogerson. (1993). "Job Turnover and Policy Evaluation: A General Equilibrium Analysis," *Journal of Political Economy*, Vol. 101 (5), pp. 915-38.
- Horowitz, J. (2001). "Should the DEA's STRIDE Data Be Used for Economic Analysis of Markets for Illegal Drugs?," *Journal of the American Statistical Association*, Vol. 96, 1254-1271.
- Huggett, M. (1993). "The Risk-free Rate in Heterogeneous-agent Incomplete-insurance Economies," *Journal of Economic Dynamics and Control*, Vol. 17, 953-969.
- Imrohoroğlu, A., A. Merlo and P. Rupert. (2004). "What Account for the Decline in Crime?," *International Economic Review*, Vol. 45 (3), 707-729.
- Imrohoroğlu, A., A. Merlo and P. Rupert. (2000). "On the Political Economy of Income Redistribution and Crime," *International Economic Review*, Vol. 41 (1), 1-25.
- Kaestner, R. (1991). "The Effect of Illicit Drug Use on the Wages of Young Adults," *Journal of Labor Economics*, Vol.9 (4), 381-412.
- Kaplan, J. (1985). *The Hardest Drug: Heroin and Public Policy*. Chicago, University of Chicago Press.
- Kelly, M. (2000). "Inequality and Crime," *Review of Economics and Statistics*, Vol. 82 (4), 530-539.
- Kinlock, T., K. O'Grady, and T. Hanlon. (2003). "Prediction of the Criminal Activity of Incarcerated Drug-Abusing Offenders," *Journal of Drug Issues*, Vol. 33 (4), 897-920.
- Knowles, J., N. Persico and P. Todd. (2001). "Racial Bias in Motor-Vehicle Searches: Theory and Evidence," *Journal of Political Economy*, Vol. 109 (1), 203-229.
- Krusell, P. and A. Smith. (1998). "Income and Wealth Heterogeneity in the Macroeconomy," *Journal of Political Economy*, Vol. 106, 867-896.

- Kuziemko, I. and S. Levitt. (2004). "An Empirical Analysis of Imprisoning Drug Offenders." *Journal of Public Economics*, Vol. 88 (9-10), 2043-2066.
- Lazear, E. (1990). "Job Security Provisions and Employment." *The Quarterly Journal of Economics*, Vol. 105 (3), pp. 699-726.
- Ljungqvist, L. (2002). "How Do Layoff Costs Affect Employment?" *Economic Journal*, Vol. 112, pp. 829-853.
- Leshner, A. (1997). "Addiction is a Brain Disease and it Matters," *Science*, New Series, Vol. 278, 45-47.
- Leung, S. F. (1994). "An Economic Analysis of the Age-Crime Profile," *Journal of Economic Dynamics and Control*, Vol. 18, 481-497.
- Levitt, S. (1996). "The Effect of Prison Population Size on Crime Rates: Evidence from Prison Overcrowding Litigation," *Quarterly Journal of Economics*, Vol. 111 (2), 319-351.
- Levitt, S. and S. Venkatesh. (2000). "An Economic Analysis of a Drug-Selling Gang's Finances." *Quarterly Journal of Economics*, Vol. 115, 755-789.
- Lochner, L. (1999). "Education, Work, and Crime: Theory and Evidence," RCER Working Paper No. 465, 1999.
- Lochner, L. (2004). "Education, Work, and Crime: A Human Capital Approach," *International Economic Review*, Vol. 45 (3), 811-843.
- Lochner, L. and E. Moretti. (2004). "The Effect of Education on Crime: Evidence from Prison Inmates, Arrests, and Self-Reports," *American Economic Review*, Vol. 94 (1), 155-189.
- MacCoun, R. and P. Reuter. (2001). *Drug War Heresies: Learning from other vices, times, and places*. Cambridge, Cambridge University Press.
- Machin, S and C. Meghir. (2003). "Crime and Economic Incentives," *Journal of Human Resources*, 39(4): 958-979.
- Miron, J. (2004). *Drug War Crimes. The Consequences of Prohibition*. The Independent Institute. Oakland, CA.



Miron, J. (2003). "The Effect of Drug Prohibition on Drug Prices: Evidence from the Markets for Cocaine and Heroin," *Review of Economics and Statistics*, Vol. 85 (3), 522-530.

National Research Council. (2001). *Informing America's Policy on Illegal Drugs: What We Don't Know Keep Hurting Us*. Washington, DC: National Academy Press.

Neal, D. and W. Johnson. (1996). "The Role of Premarket Factors in Black-White Wage Differences," *Journal of Political Economy*, Vol. 104(5), 869-895.

Office of National Drug Control Policy. (2004). *The Price and Purity of Illicit Drugs: 1981 Through the Second Quarter of 2003*. Washington DC: Executive Office of the President (Publication Number NCJ 207768)

Orphanides, A. and D. Zervos. (1998). "Myopia and Addictive Behavior." *The Economic Journal*, Vol. 108, 75-91.

Orphanides, A. and D. Zervos. (1995). "Rational Addiction with Learning and Regret," *Journal of Political Economy*, Vol. 103 (4), 739-758.

Orphanides, A. and D. Zervos. (1994). "Optimal Consumption Dynamics with Non-Concave Habit-Forming Utility," *Economic Letters*, Vol. 44, 67-72

van Ours, J. (1995). "The Price Elasticity of Hard Drugs; The Case of Opium in the Dutch East Indies (1923-1938)," *Journal of Political Economy*, Vol. 103, 261-279.

Persico, N. (2002). "Racial Profiling, Fairness and Effectiveness of Policing," *American Economic Review*, Vol. 92 (5), 1472-1497.

Pudney, S. (2003). "The Road to Ruin? Sequences of Initiation to Drugs and Crime in Britain," *The Economic Journal*, Vol. 113, C182-C198.

Raphael, S. and Rudolf Winter-Ebmer. (2001). "Identifying the Effect of Unemployment on Crime," *Journal of Law and Economics*, 44(1), 259-284.

Reuter, P. MacCoun, R. and Murphy, P. (1990). *Money from crime: A study of the economics of drug dealing in Washington, DC*. Santa Monica, CA: RAND.

Sah, R. (1991). "Social Osmosis and Patterns of Crime," *Journal of Political Economy*, Vol. 99 (6), 1272-1295.

Sala-i-Martin. (1997). "Transfers, Social Safety Nets, and Economic Growth," *International Monetary Fund Staff Papers*, Vol. 44 (1), 81-102.

United Nations Office on Drugs and Crime. (2003). *Global Illicit Drug Trends*.

U.S. Dept. of Justice, Bureau of Justice Statistics. NATIONAL CORRECTIONS REPORTING PROGRAM, 1996: [UNITED STATES] [Computer file]. Conducted by U.S. Dept. of Commerce, Bureau of the Census. ICPSR02448-v1. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 1998.

U.S. Dept. of Justice, Bureau of Justice Statistics. SURVEY OF INMATES OF LOCAL JAILS, 1996: [UNITED STATES] [Computer file]. Conducted by U.S. Dept. of Commerce, Bureau of the Census. ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 1999.

U.S. Dept. of Justice, Bureau of Justice Statistics, and U.S. Dept. of Justice, Federal Bureau of Prisons. SURVEY OF INMATES IN STATE AND FEDERAL CORRECTIONAL FACILITIES, 1997 [Computer file]. Compiled by U.S. Dept. of Commerce, Bureau of the Census. ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 2001.

U.S. Dept. of Justice, Bureau of Justice Statistics. (2003). *Sourcebook of Criminal Justice Statistics 2002*.

U.S. Dept. of Health and Human Services, Substance Abuse and Mental Health Services Administration, Office of Applied Studies. NATIONAL HOUSEHOLD SURVEY ON DRUG ABUSE, 1996 [Computer file]. ICPSR version. Research Triangle Park, NC: Research Triangle Institute/Chicago, IL: National Opinion Research Center [producers], 1997. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 1998.

Veracierto, M. (2008). "Firing Costs and Business Cycle Fluctuations," *International Economic Review*, forthcoming.

Verdier, T. and Y. Zenou. (2004). "Racial Beliefs, Location and the Causes of Crime," *International Economic Review*, Vol. 45 (3), 731-760.

Wilson, J. and A. Abrahamse. (1992). "Does Crime Pay?," *Justice Quarterly*, Volume 9, 359-377.

Wish, E. and B. Johnson. (1986). "The Impact of Substance Abuse on Criminal Careers," chapter 2 in *Criminal Careers and Career Criminals*. Volume 2. edited by Blumstein et al. Washington, D.C.: National Academy Press.

Witte, A. D. and H. Tauchen. (1994). "Work and Crime: An Exploration Using Panel Data," *Public Finance*, Suppl., Vol. 49 (0), 155-67.

Wolff, E. (2000). "Recent trends in wealth ownership, 1983-1998." *Working Paper No. 300*, Jerome Levy Economics Institute.

Wolff, E. (1998). "Recent Trends in the Size Distribution of Household Wealth," *Journal of Economic Perspectives*, Vol.12 (3), 131-150.