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Three Essays on Crime

by

Hernán Botero Degiovanni

Dissertation submitted to the
College of Business and Economics
at West Virginia University
in partial fulfillment of the requirements
for the degree of

Doctor of Philosophy
in
Economics

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Morgantown, West Virginia
2013

Keywords: Crime, Enforcement, Drug Enforcement, Drug War, Durable Goods

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Abstract

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West Virginia University

Stratford Douglas, Ph.D., Chair

In this dissertation, I use the tools of economics to analyze two forms of crime – property and violent crime – in order to investigate three specific incentives that induce them. First, I develop a property crime model with secondary markets for stolen durable goods where agents can be thieves who steal durable goods to consume or exchange them for a profit, and non-thieves who can also demand stolen durable goods in the secondary market. The results indicate that the government must focus their resources to capture thieves on the streets in order to minimize their number in the economy. They also indicate that when the government focuses its efforts to control stolen property traders, the price of a stolen durable good increases, which in turn increases the number of thieves who want to consume the good. Second, I study the relationship between property crime and minimum drug consumption requirements. I use a crime model with an exogenous income distribution to determine the government’s optimal drug supply control in the presence of drug addicts who might be induced to commit property crime to satisfy their minimum requirement of drug consumption. If the government does not have a budget constraint and aims to reduce the percentage of thieves in the economy, the minimum percentage of thieves is reached when the government spends on capturing thieves and not on seizing narcotics. If the government has a budget constraint and intends to minimize its expenditure on enforcement, minimum expenditure requirements make the government spend on both capturing thieves and seizing narcotics. This occurs when the government’s budget is not enough to control the optimal percentage of thieves. Once the government has enough revenue to attain that optimal number, it subsidizes drug consumption. Finally, using the altitude of each municipality and distance from capital cities as sources of exogenous variation, I estimate the effect of drug enforcement on violence in Colombia. To test the latter hypothesis, I use drug and violence information on Colombian municipalities during the period 1999 – 2010. The results seem to indicate that both the Colombian government’s enforcement activities and the war among drug dealers are important sources of violence in the country.

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Chapter 1

Introduction

Crime is a very complex phenomenon that can be manifested in different forms and incentivized in a variety of ways. In this dissertation, I use the tools of economics to analyze two forms of crime – property¹ and violent crime– to investigate three specific incentives that induce them. With regard to property crime, in chapter 2, I develop a model of property crime with secondary markets for stolen durable goods where agents face various decisions at different stages. First, they decide whether to become a criminal or not. Next, criminals decide whether to consume or sell the stolen durable goods in a secondary market, and non-criminals decide whether to buy legal or stolen durable goods. In this scenario, the government can target law enforcement activities to capture criminals *in flagranti* or monitor the illegal transactions that take place in the secondary market. The chapter studies the different types of equilibria that would arise from different combinations of law enforcement activities. Here, property crime arises from intertemporal incentives to consume stolen property.

In chapter 3, I study the relationship between property crime and minimum drug consumption requirements. A crime model with an exogenous income distribution is used to determine the government’s optimal drug supply control in the presence

¹Property crime can also be a violent crime. I am abstracting from this feature of property crime to focus attention on the economic incentives behind this type of crime without explicitly modeling the victims’ costs associated to violence. In spite of the fact that these costs might be very important from a victim’s perspective, they depend on the victim’s valuation of being subject to criminal activities, which might be uncorrelated with the economic incentives behind property crime. As a result, I abstract from these costs to avoid considering these subjective valuations in this initial analysis. The introduction of these costs will be left for future research.

of drug addicts who, in equilibrium, might be induced to commit property crime to satisfy their minimum requirement of drug consumption. This model enables us to interpret a positive percentage of drug control as a tax and a negative percentage as a subsidy. If the government does not have a budget constraint and aims to reduce the percentage of thieves in the economy, the minimum equilibrium percentage of thieves is reached when the government spends on capturing thieves and not on seizing narcotics. If the government has a budget constraint and intends to minimize its expenditure on enforcement, minimum expenditure requirements make the government spend on both capturing thieves and seizing narcotics. This occurs when the government's budget is not enough to control the optimal percentage of thieves. Once the government has enough revenue to attain that optimal number of thieves, it subsidizes drug consumption.

In the case of violent crime, in chapter 4, the strategy of Mejia and Restrepo, 2011 is used to disentangle the causal relationship between drug enforcement and violence. To test this relationship, I use information on Colombian municipalities during the period 1999 – 2010. Due to technological reasons related to the quality of terrain, climate, and locational characteristics of the Colombian territory, cocaine production is more productive at low altitudes. Using the altitude of each municipality and distance from capital cities as sources of exogenous variation, I estimate the effect of drug enforcement on violence in Colombia. The results seem to indicate that the Colombian government's enforcement activities generate violence and displacements. Yet, the war that take place among drug dealers is also an important source of violence in the country.

This dissertation contributes to the economic literature in at least three aspects. First, it formally determines the conditions under which a durable good is stolen when the economy is inhabited by risk-neutral individuals who can target the good either to consume or sell. This analysis allows us to ascertain which factors affect individuals' decisions to engage in property crime of a durable good and for what purpose. Second, it shows that when the economy is inhabited by individuals with lexicographic preferences with respect to the single composite drug commodity in the

economy, drug control policies operate in an environment of risk-lover individuals who can be induced to crime by their addiction. In this environment, if drug control policies do not generate a sufficiently large equilibrium drug price, it might induce addicts to crime. Finally, it introduces a set of valid exogenous sources of variation to test whether drug enforcement increases violence or not. This analysis also allows us to test whether a policy targeted to reduce an externality might create another one.

Chapter 2

Property Crime and Secondary Markets

2.1 Introduction

The application of choice theory under uncertainty to the analysis of crime has gained wide attention in economics since the seminal paper of Becker, 1968. Traditional models on crime, however, do not consider explicitly the nature of the goods being targeted by criminals nor the existence of secondary markets for stolen goods on individual criminal behavior.

Traditional models of crime assume that individuals make criminal decisions based on three factors: payoff of the activity ¹, risk of the activity ² and the individuals' risk aversion and preference structure, summarized in each individual's utility function. These models are based on three further technical assumptions: first, criminals and non-criminals are matched randomly. Second, payoffs from illegal activities are assumed to be a lump-sum transfer of wealth from non-criminals to criminals.

¹Traditionally, models on this literature assume that any non-monetary payoff has an equivalent, convertible monetary payoff from an individual perspective. These payoffs are net of the monetary costs incurred if a criminal is captured and the dis-utility of imprisonment and/or fine.

²Which is understood as the probability of capture posed by the government on criminals. It is a probability that depends generally on the amount of resources spent by the government on on-street police and prosecution, and the number of thieves. Several functions have been proposed in the literature to capture this functional relationship, but there is not a consensus on which is the best specification(e.g., see the survey by Pyle, 1983 on the discussion around the empirical specification of this technology).

Third, the government maximizes a social welfare function, composed of both criminal and non-criminal individual utilities, subject to the costs of police on the streets, prosecutors, court personnel, plus the harm that criminals cause when they commit a crime, if any. The control variables for the government are a combination of the sanctioning rule (strict or fault-based), form of sanction (monetary vs non-monetary), and magnitude of the sanction with the probability of capture.³

These technical assumptions have been considered in the literature as not representing real life appropriately, so contributions have been focused on improving them.⁴ An assumption that has generally left untouched is monetary illegal payoffs. Despite of the fact that criminals ultimately might desire an amount of money to satisfy their specific preferences, criminals do not always target cash. At least, that is what the definitions of burglary, larceny, and motor vehicle theft indicate and what the international statistical information on these crimes strikingly show.⁵

³For references on applications of the model of Becker, 1968 to a diversity of issues around the combination of sanctioning rules, forms of sanction and its magnitudes, see Allingham and Sandmo, 1972, Ehrlich, 1973, Heineke, 1978, Heineke and Darrough, 1978, Heineke, 1988, Polinsky and Shavell, 1979, Polinsky and Shavell, 1984, Shavell, 1987a, Shavell, 1987b, Polinsky and Shavell, 1991, Kaplow, 1990, Kaplow and Shavell, 1994, Wilde, 1992, among others. For a thorough summary of the deterrence hypothesis and its main results, see Eide, 1994, Garoupa, 2007, Shavell, 2004 and Polinsky and Shavell, 2007

⁴See Fender, 1999 and Garoupa, 2001 on endogenous probability of capture, Hung and Marceau, 1993, Hui-Wen and Png, 1994 and Helsley and Strange, 2005 on private security provision, Lochner, 2004 on human capital and crime, Imrohorglu et al., 2000 and Merlo, 2003 on the political economics of income distribution and crime, Goff and Tollison, 1993 on control policies that induce crime, Deutsch et al., 1987, Chiu and Madden, 1998, Dixit, 2003, Burnham et al., 2004 and Rattner and Portnov, 2007 on criminals choosing spatially their victims, Marceau, 1997 on local government competition and crime deterrence, Calvó-Armengol and Zenou, 2004 on social networks and crime, Burdett et al., 2004 on unemployment and crime, and finally, Fiorentini and Peltzman, 1997 on organized crime.

⁵For a thorough statistical report on criminal activities on the world from UNODC, see: *International Statistics on Crime and Justice* at UNITED NATIONS, 2012. The definition used for United Nations Office on Drugs and Crime (UNODC) for burglary: it “means gaining un-authorized access to a part of a building/dwelling or other premises; including by use of force; with the intent to steal goods (breaking and entering)”. UNODC do not present a separate definition and measurement of a variable larceny due to the fact that there are countries such as Norway that provides information on burglary including some cases that could be defined as larceny in some other legislations, and on which there is separate statistical information, such as in U.S.. In this last case, for the Bureau of Justice Statistics larceny means: “the unlawful taking of property other than a motor vehicle from the possession of another, by stealth, without force or deceit. This includes pocketpicking, nonforcible purse snatching, shoplifting, and thefts from motor vehicle”. In turn, for UNODC Motor Vehicle Theft: “means the removal of a motor vehicle without the consent of the owner of the vehicle. ‘Motor Vehicles’ includes all land vehicles with an engine that run on the road, including cars, motorcycles, buses, lorries, construction and agricultural vehicles.(UN-CTS M4.4)”

Several questions arise from the facts presented in the report on crime and justice elaborated by UNODC: Why do criminals steal goods? Which good do they target? Why do they target those goods and not others? Several criminology studies on UK and USA have tried to give an empirical answer to what makes a good attractive to thieves (Cohen and Felson, 1979, Clarke, 1999 and Sutton et al., 2008). This literature has even crafted the acronym CRAVED to refer to six elements that make a product attractive or “hot” to thieves: concealable, removable, available, valuable, enjoyable and disposable.

Enjoyable and disposable refer to the preference structure of both criminals and non-criminals for a specific good, and the potential existence of a secondary market for its illegal trade. Available and concealable pertain to a technical feature of a “hot” good: it must endure on time in order to be able to be stored and then, consumed at a later period. Removable refers to the technology that the security agencies have at hand to combat property crime: if a good can be stolen and re-sold easily, without the security agencies being perfectly effective in controlling these transactions, that good might become a “hot” good. Finally, valuable is related to how costly a new or legal good is relative to its stolen counterpart: if a new good is too expensive relative to the stolen one, that good might also potentially become a “hot” product.

In other words, according to this literature, criminals target highly demanded (by both criminals and non-criminals) and expensive durable goods for which the enforceability of its property rights by the government is imperfect. Despite its insightful conclusions, the authors of these studies recognize that there is not a sound theoretical background on which we can determine the extent to which each of the aforementioned factors influence the likelihood of a good of becoming a “hot” product.

In this paper, I introduce an illegal secondary market for durable goods in a model of property crime. A durable good is a good that does not rapidly depreciate, or equivalently, a good that gives utility to consumer(s) over time. For example, jewelry could be considered a perfectly durable good because it should theoretically never wears out; other goods such as refrigerators, cars, or mobile phones usually continue to be useful for a limited period of time of use. The analysis of durable goods is a

well established topic in industrial organization theory.⁶ A common theme in this literature is that new durable goods always compete with used ones of older vintages of the same kind. This occurs because individuals have economic incentives to demand and supply used durable goods in a secondary market.⁷

In the model constructed in this paper, the secondary market is formed by individuals who rationally decide to become criminals, steal durable goods, and supply them in the market, and by non-criminals that demand stolen goods. By construction, all these decisions are endogenous and take place sequentially. Three aspects are worth noticing of our setup. First, criminal activities take place because individuals target durable goods either for re-selling or for consumption. Second, criminals activities take place because there is a potential demand for stolen property. This demand is composed of individuals buying stolen property willingly. Finally, as part of our contribution to the literature on crime, the government performs two crime control activities: street control and control on illegal transactions taking place in secondary markets⁸.

None of these factors have been incorporated in a formal model of crime nor have criminal effects been considered in the literature of durable goods. Based on a simplified assumption of preferences (risk neutrality), I show that, (1) under certain conditions individuals with a low preference for the durable good steal and sell the goods; (2) the preference for the durable good also determines whether consumers will become criminals or not: individuals with a “low-middle” preference for the durable

⁶See Coase, 1972, Swan, 1970, Aghion and Tirole, 1994b and Esteban and Shum, 2007 on durability, secondary markets and optimal monopoly response, Akerlof, 1970, Aghion and Tirole, 1994a and Hendel and Lizzeri, 1999 for adverse selection, durable goods and secondary markets and Pelletiere and Reinart, 2002, Clerides, 2008 and Clerides and Hadjiyiannis, 2008 on international trade and political economy of entry barrier on durable goods, to cite some insightful examples.

⁷See especially Porter and Sattler, 1999 on an analysis on the patterns of demand and supply of used durable goods.

⁸In the real world, there are prosecuting agencies who perform several activities to control crime on durable goods. One such activity is the investigation performed by prosecutors to apprehend and indict criminals. As in this model the government directly performs prosecuting activities without relying on a bureaucracy to do it, the control of illegal transactions incorporate the activities of these agencies. In other words, in order to stop the functioning of illegal markets for stolen property, the government is assumed to perform all kind of activities to accomplish this task. In this sense, I am not formally modelling the activities of the prosecuting bureaucracies to impede criminal activities. This analysis is left for future research.

good will always steal the durable good regardless of what the government does when street control is less than “perfect”; and (3) some non-criminals that are subject to crime and lose their property may have incentives to replace the stolen good by purchasing it in the secondary illegal market.

The paper is organized as follows. Section (2.2) introduces the model and section (2.3) characterizes the equilibrium. Section (2.4) examines different possible scenarios under which the government might operate for different combinations of law enforcement activities and proposes a few policy recommendations. Finally, section (2.5) concludes.

2.2 The Model

The economy is populated by a large number of heterogenous individuals who live one single period. Each individual i is characterized by two parameters $[\alpha_i, w_i]$: w_i determines the productivity of individual i , and will be equal to the individual’s equilibrium wage when employed; α_i measures the preference for quality of a durable good. A higher value of α_i represents a preference for better quality of the good. α_i is assumed to have a uniform probability density function defined on the interval $[0, 1]$. Consequently, α_i also determines the percentage of population with a preference parameter of α_i or less.

There are potentially three goods supplied: a numeraire good, a new durable good, and a stolen durable good. The first two goods are always available, at prices 1 and p_q , respectively, because they are produced legally. The supply of the stolen good in turn depends on the availability of the durable good and on the number of stolen durable goods that are brought successfully to the secondary market. This good, if supplied, will be offered at a price p'_q . Normalizing prices in terms of the numeraire, I say that p and p' are the prices of the new and stolen durable goods, respectively, relative to the price of the numeraire. I also assume that a new durable good is infinitely-elastically supplied at the price p , where p is taken as an exogenous parameter of the model.

Despite the fact that a new and a stolen durable good are in essence the same

good, they have two different qualities which make them different in the consumers' eyes. Let q and q' represent the quality supply by a new and a stolen durable good respectively. I assume that a stolen good is seen by any consumer as being of a lower quality than a new one. I assume that there is an objective reduction in quality of the stolen durable good that is common knowledge to all individuals in the society, both criminals and non-criminals together, and that all agree on the "real" quality of a stolen durable good. Let $q' = \gamma q$, where $\gamma \in [0, 1]$ captures the loss in quality of a new durable good when it is supplied stolen.

Government expenditures on law enforcement determine two types of probabilities: the probability of capturing criminals *in flagranti*, i.e., while committing the crime, π_1 , and the probability of capturing criminals that operate in the illegal market, π_2 . When a criminal is caught *in flagranti*, she is subject to a monetary penalty denoted f_1 , and when the seller of a stolen property is caught, she is subject to a monetary penalty denoted f_2 .

2.2.1 Timing of Events

The timing of the game is as follows⁹:

1. Government expenditures on law enforcement determine π_1 and π_2 .
2. Each individual decides whether to become a criminal or a non-criminal.
3. Non-criminals decide whether to buy a new durable good or not. If a non-criminal decides to buy a new durable good, it will be subject to robbery with a probability λ_{nc}^r . Since the government captures criminal on the street with a probability π_1 , the new durable good is effectively stolen on the street with probability $\lambda_{nc}^r(1 - \pi_1)$, and not stolen with probability $(1 - \lambda_{nc}^r) + \lambda_{nc}^r\pi_1$. Those who become criminals are randomly matched with a non-criminal with probability λ_c^r . A criminal is captured on the street with a probability π_1 . As a result,

⁹This game is based on the extensive form representation presented in figure (A.1)

a criminal will effectively rob a durable good with a probability $\lambda_c^r(1 - \pi_1)$, and will not with a probability $(1 - \lambda_c^r) + \lambda_c^r\pi_1$.

4. Non-criminals who did not get their property stolen or got their property recovered on site enjoy the good, and will make no further decisions. Those who got their property stolen can still consume a durable good. They decide to buy a new durable good, a stolen good, or abstain from consuming the good. When making this decision, they also perfectly know the legal status of the stolen goods.¹⁰ If they buy a new durable good again, they will enjoy it for the rest of the good's lifetime without further risks. However, they can potentially enjoy two durable goods at the same time: if the government returns stolen property to those who already bought a second new durable good, they will enjoy two durable goods instead of one for the remaining of their lifetimes. In turn, if they abstain from buying stolen property, they still can enjoy their property when the government intervenes to recover stolen property in the illegal market. If they do not abstain, individuals can get their property seized by the government. For simplicity, I assume that a non-criminal might both recover her stolen property and get seized her bought stolen property by the government with a probability π_2 . If a non-criminal does not get her bought stolen property seized, she will enjoy its consumption without facing further risks. Criminals who were captured stealing on the street will have to pay a monetary fine f_1 , and will not make further decisions. In contrast, criminals who successfully stole a durable good will further decide whether to sell it or keep it. Those who sell it will further face a probability π_2 of being captured.¹¹ If these criminals are captured, they will have to pay a fine of $f_2 \geq f_1$ for selling stolen property¹²¹³ If they are

¹⁰There is not asymmetric information.

¹¹For simplicity, I assume that criminals sell their own property. The economics of organized crime for this type of crime go beyond the scope of the presence study.

¹² $f_2 \geq f_1$ makes sense as a restriction if we think that stealing and selling property are two compounded activities punishable harsher than performing one of these activities in isolation. As the timing of the game generates that criminals selling stolen property have already committed two felonies, instead of one, it is natural to assume this restriction is true.

¹³I also assume that criminals are captured after they have sold their property to non-criminals. I do not explicitly study what is called in the literature as "sting" operations, in which police officers

not captured, they will make a profit of p' per durable good sold. Any of these individuals make further decisions. Finally, those who keep it will not face any further risks or decisions ¹⁴

2.2.2 Additional Assumptions

A few additional technical assumptions are necessary. First, non-criminals are interested in buying a single unit of the durable good, whether new or stolen. Also, thieves can only steal and supply one unit of the durable good. This assumption is rather common in the industrial organization literature and implies that the distribution of α_i determines the aggregate supply and demand of stolen durable goods and the demand of new ones, as I will explain below.

Second, individuals are all risk neutral and have the following utility function

$$U(.) = c_i + I_i^c I_i^k \alpha_i q'_i + (1 - I_i^c) \alpha_i [I_i^q (I_i^{q,1} q_i + I_i^{q',1} q'_i) + (1 - I_i^q) (I_i^{q,2} q_i + I_i^{q',2} q'_i)] \quad (2.1)$$

where c_i is the amount of numeraire good consumed by individual i , α_i is the preference parameter for quality, q_i is the demand for high quality (new good) of individual i , and q'_i is the demand for low quality (stolen good) of individual i . $I_i^c = 1$ if an individual i becomes a criminal, $I_i^q = 1$ if a non-criminal i consumes a new durable good in the first round of decisions, $I_i^{q,1} = 1$ if a non-criminal i consumes a new durable good in the second round of decisions when she also has bought a new durable good in the first round of decisions, and $I_i^{q,2} = 1$ if a non-criminal i consumes a new durable good in the second round of decisions when she did not buy a new durable good in the first round of decisions, $I_i^{q',1} = 1$ if a non-criminal i consumes a stolen durable

act as buyers of stolen property to capture thieves. This idea is left for further research.

¹⁴There could be a probability of capture for “consuming” stolen property. However, this probability makes sense for some durable goods, such as cars, than for others, such as tv’s or parts of a car. In the case of a car, it is easier for a police officer to ascertain ownership, after it has been either stolen and used by its own thief or bought and used by a non-thief. But, for a part of a car or a tv, it is way more difficult. For these later goods, the police would have to dismantle every car on the street or knock on everybody’s door to ascertain legal ownership of them; a rather expensive and ineffective control activity. Consequently, in the present paper I abstract from it. To analyze the case of the whole car, this model has to be adjusted on this regard. This avenue will be pursued in the future.

good in the second round of decisions when she has bought a new durable good in the first round of decisions, $I_i^{q',2} = 1$ if a non-criminal i consumes a stolen durable good in the second round of decisions when she did not buy a new durable good in the first round of decisions, and 0 otherwise, $I_i^k = 1$ if a criminal i decides to keep the stolen property for their consumption. Note that I assume that only non-criminals can make decisions on whether to buy a durable good or not, whereas criminals can consume a durable good only if they steal it and decide to keep it.

Our third assumption refers to the durability of the good. I assume that a durable good, irrespective of its quality, lasts one period as opposed to the numeraire which is consumed at the beginning of the period completely.¹⁵ Let $\beta_i \in [0, 1]$ capture the portion of the durable good enjoyed by a non-criminal i who buys it at the beginning of the period. Consequently, at time β_i the non-criminal derives a level of satisfaction $\beta_i q$. If a non-criminal i gets her new property stolen at time $\beta_i^{t_0}$, she consumes $q_i = \beta_i^{t_0} q$ of her new property. If later on this individual decides to consume a durable good, she can either buy a new durable good instantly, and enjoys $q_i = \beta_i^{t_0} q + (1 - \beta_i^{t_0}) q = q$, or wait until period $\beta_i^{t_1}$, moment at which the secondary illegal market opens for her and purchase a stolen good at a risk. If the stolen good purchased in the secondary market is not seized, she obtains the utility $q_i + q'_i = \beta_i^{t_0} q + (1 - \beta_i^{t_1}) q'$. If her property is returned once the illegal market opens, she will consume $q_i = \beta_i^{t_0} q + (1 - \beta_i^{t_1}) q = q + (\beta_i^{t_0} - \beta_i^{t_1}) q$.

To avoid keeping track of individual β s for criminals and non-criminals, our final assumption is that both criminals activities and the operation of the illegal market happen at the same inframarginal moment β . Consequently, $\beta_i = \beta$ for all non-criminals i . Additionally, all criminals will steal and supply their stolen merchandize at the same inframarginal moment β . The choice of this inframarginal moment is exogenous to both criminals and non-criminals, and it is assumed to be one of the parameters of the model.

¹⁵In this sense, a non-criminal who buys a new durable good at the beginning of her life, and does not get her property stolen effectively, enjoys her durable good until it naturally scrapes itself at the end of period. At this moment, both the owner and the good “die”.

With all these assumptions in place, an individual i 's maximization problem is:

$$\begin{aligned} \max_{\{X_i\}} \quad & c_i + I_i^c I_i^k \alpha_i q'_i + (1 - I_i^c) \alpha_i [I_i^q (I_i^{q,1} q_i + I_i^{q',1} q'_i) + (1 - I_i^q) (I_i^{q,2} q_i + I_i^{q',2} q'_i)] \\ \text{s.t.} \quad & \end{aligned}$$

$$\text{If } I_i^c = 1; \quad \forall I_i^k = 0, 1.$$

$$c_i = w_i - f_1; \quad q_i = 0; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_c^r \pi_1$$

$$c_i = w_i; \quad q_i = 0; \quad q'_i = 0 \quad \text{with prob.} \quad (1 - \lambda_c^r)$$

$$\text{If } I_i^c = 1; \quad I_i^k = 1.$$

$$c_i = w_i; \quad q_i = 0; \quad q'_i = (1 - \beta)q' \quad \text{with prob.} \quad \lambda_c^r (1 - \pi_1) \quad (2.2)$$

$$\text{If } I_i^c = 1; \quad I_i^k = 0.$$

$$c_i = w_i - f_2; \quad q_i = 0; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_c^r (1 - \pi_1) \pi_2$$

$$c_i = w_i + p'; \quad q_i = 0; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_c^r (1 - \pi_1) (1 - \pi_2)$$

$$\text{If } I_i^c = 0; \quad I_i^q = 1; \quad \forall I_i^{q,1} = 0, 1; \quad I_i^{q',1} = 0, 1$$

$$c_i = w_i - p; \quad q_i = q; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_{nc}^r \pi_1 + (1 - \lambda_{nc}^r)$$

$$\text{If } I_i^c = 0; \quad I_i^q = 1; \quad I_i^{q,1} = 1; \quad I_i^{q',1} = 0$$

$$c_i = w_i - 2p; \quad q_i = (2 - \beta)q; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_{nc}^r (1 - \pi_1) \pi_2$$

$$c_i = w_i - p; \quad q_i = q; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2)$$

$$\text{If } I_i^c = 0; \quad I_i^q = 1; \quad I_i^{q,1} = 0; \quad I_i^{q',1} = 1$$

$$c_i = w_i - p - p'; \quad q_i = q; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_{nc}^r (1 - \pi_1) \pi_2$$

$$c_i = w_i - p - p'; \quad q_i = \beta q; \quad q'_i = (1 - \beta)q' \quad \text{with prob.} \quad \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2)$$

$$\text{If } I_i^c = 0; \quad I_i^q = 1; \quad I_i^{q,1} = 0; \quad I_i^{q',1} = 0$$

$$c_i = w_i - p; \quad q_i = q; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_{nc}^r (1 - \pi_1) \pi_2$$

$$c_i = w_i - p; \quad q_i = \beta q; \quad q'_i = 0 \quad \text{with prob.} \quad \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2)$$

$$\text{If } I_i^c = 0; \quad I_i^q = 0; \quad I_i^{q,2} = 1; \quad I_i^{q',2} = 0$$

$$c_i = w_i - p; \quad q_i = (1 - \beta)q; \quad q'_i = 0 \quad \text{with prob.} \quad 1$$

$$\text{If } I_i^c = 0; \quad I_i^q = 0; \quad I_i^{q,2} = 0; \quad I_i^{q',2} = 1$$

$$c_i = w_i - p'; \quad q_i = 0; \quad q'_i = 0 \quad \text{with prob.} \quad \pi_2$$

$$c_i = w_i - p'; \quad q_i = 0; \quad q'_i = (1 - \beta)q' \quad \text{with prob.} \quad (1 - \pi_2)$$

$$\text{If } I_i^c = 0; \quad I_i^q = 0; \quad I_i^{q,2} = 0; \quad I_i^{q',2} = 0$$

$$c_i = w_i; \quad q_i = 0; \quad q'_i = 0 \quad \text{with prob.} \quad 1$$

where $X_i = \{c_i, I_i^c, I_i^k, I_i^q, I_i^{q,1}, I_i^{q,2}, I_i^{q',1}, I_i^{q',2}\}$. As can be seen in the previous problem, this model is a sequential game in which each individual i has five information sets in three rounds of decisions for an individual who becomes a non-criminal or two rounds of decisions for an individual who becomes a criminal. In the first round, each individual i has an occupational choice. In the second, non-criminals make a decision on whether to buy a new durable good or not and criminals are faced by a random match probability that determines whether they rob or not. And in the last round, some non-criminals will make a further decisions whether to buy a durable good, new or stolen, or not, whereas criminals decide whether to keep the stolen property or not. In the next section, I introduce the solution concept I use to solve the problem laid out in equation (2.2).

2.3 Characterization of the Equilibrium

In this section, I derive the Sub-game Perfect Nash Equilibria of this game. I first determine the optimal response of each non-criminal and criminal in each of their information sets at the last stage. Sequentially, I move one step backwards to obtain the optimal response of each non-criminal at their second round of decisions, and finally, I find who becomes a criminal and who does not. All these decisions will depend on the variables under the government's control.

2.3.1 Last Round of Decisions

At this stage, each individual i has perfect knowledge of her types (i.e., each i knows the values of α_i and w_i), as well as whether they have become a criminal or not. Additionally, each criminal i who makes a decision on this stage has stolen a durable good successfully, and is making a decision whether to sell it or not. Using problem (2.2), each criminal i 's preference relation can be expressed in the following

way:

$$\begin{aligned}
\text{sells} \succ \text{keeps} & \quad \text{if } \alpha_i < \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \\
\text{sells} \sim \text{keeps} & \quad \text{if } \alpha_i = \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \\
\text{sells} \prec \text{keeps} & \quad \text{if } \alpha_i > \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'}
\end{aligned} \tag{2.3}$$

From a criminal's perspective at this stage, the values of p' and π_2 are taken as given, and q' is an exogenous parameter of the model. Consequently, the cutoff of the right-hand side of equation (2.3) is exogenous from her perspective. This implies that a criminal i 's supply of a stolen durable good is given by:

$$q_i^{'s} = \begin{cases} 1(\text{sells})(\sigma_i^{\text{sells}} = 1, \sigma_i^{\text{keeps}} = 0) & \text{if } \alpha_i < \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \\ 1(\text{sells}) \sigma_i^{\text{sells}} + 0(\text{sells}) \sigma_i^{\text{keeps}} & \text{if } \alpha_i = \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \\ 0(\text{keeps})(\sigma_i^{\text{sells}} = 0, \sigma_i^{\text{keeps}} = 1) & \text{if } \alpha_i > \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \end{cases}$$

where σ_i^{sells} and σ_i^{keeps} are the mixed strategy probabilities for criminal i of selling and keeping her stolen property respectively. Disregarding the mixed strategy probabilities, and assuming that when α_i is equal to the cutoff on the right-hand side of equation (2.3) the good is sold, the supply of a stolen durable good is:¹⁶

$$q_i^{'s} = \begin{cases} 1(\text{sells})(\sigma_i^{\text{sells}} = 1, \sigma_i^{\text{keeps}} = 0) & \text{if } \alpha_i \leq \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \\ 0(\text{keeps})(\sigma_i^{\text{sells}} = 0, \sigma_i^{\text{keeps}} = 1) & \text{if } \alpha_i > \frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \end{cases} \tag{2.4}$$

In turn, each non-criminal i who makes a decision at this stage is in any of the following two situations: either she bought a new durable good in the second round of decisions and her property was stolen by criminals; or she did not buy a durable good in the second round of decisions. In any of these cases, a non-criminal i has to make a decision whether to buy again a new durable good, a stolen durable good or not buy a durable good at all. The following proposition provides a useful result:

Proposition 1 *Risk-neutral non-criminals, with a utility function as in equation (2.1), will have the following preference relation with respect to buying a new durable good (q), a stolen durable good (q'), and not buying a good at all (0), at the last round of decisions, regardless of whether they have bought a new durable good or not in their*

¹⁶From now on, I will disregard mixed strategies.

second round:

$$\begin{aligned}
 q \succ q' & \text{ if } \alpha_i > \frac{p-p'}{(1-\beta)[q-(1-\pi_2)q']} & q \succ 0 & \text{ if } \alpha_i > \frac{p}{(1-\beta)q} & q' \succ 0 & \text{ if } \alpha_i > \frac{p'}{(1-\beta)(1-\pi_2)q'} \\
 q \sim q' & \text{ if } \alpha_i = \frac{p-p'}{(1-\beta)[q-(1-\pi_2)q']} & q \sim 0 & \text{ if } \alpha_i = \frac{p}{(1-\beta)q} & q' \sim 0 & \text{ if } \alpha_i = \frac{p'}{(1-\beta)(1-\pi_2)q'} \\
 q \prec q' & \text{ if } \alpha_i < \frac{p-p'}{(1-\beta)[q-(1-\pi_2)q']} & q \prec 0 & \text{ if } \alpha_i < \frac{p}{(1-\beta)q} & q' \prec 0 & \text{ if } \alpha_i < \frac{p'}{(1-\beta)(1-\pi_2)q'}
 \end{aligned} \tag{2.5}$$

The threshold values in equation (2.5) help determine whether a non-criminal, with an α_i , buys a durable good again or not; and when she buys it, these threshold values also help determine the legal status of the bought good. Again, from a non-criminal's perspective, the values of p , p' and π_2 are taken as given, and q , q' and β are all exogenous parameters of the model. As a result, all three cutoffs of equation (2.5) are exogenous from the non-criminals' perspective. We can rank all these three cutoffs depending on the values of (p/p') . Using this ranking, the following proposition is obtained.

Proposition 2 *A non-criminal i 's optimal demand schedule at the last round of decisions, regardless of whether she bought a durable good or not in the second round of decisions, is:*

$$\begin{aligned}
 \frac{p}{p'} \geq \frac{q}{(1-\pi_2)q'} = \frac{1}{(1-\pi_2)\gamma} & \Rightarrow q_i^{d_2} = \begin{cases} 0 & \text{if } \alpha_i < \frac{p'}{(1-\beta)(1-\pi_2)q'} \\ q' & \text{if } \alpha_i \in \left[\frac{p'}{(1-\beta)(1-\pi_2)q'}, \frac{p-p'}{(1-\beta)[q-(1-\pi_2)q']} \right) \\ q & \text{if } \alpha_i \geq \frac{p-p'}{(1-\beta)[q-(1-\pi_2)q']} \end{cases} \\
 \frac{p}{p'} < \frac{q}{(1-\pi_2)q'} & \Rightarrow q_i^{d_2} = \begin{cases} 0 & \text{if } \alpha_i < \frac{p}{(1-\beta)q} \\ q & \text{if } \alpha_i \geq \frac{p}{(1-\beta)q} \end{cases}
 \end{aligned} \tag{2.6}$$

This last proposition indicates that when the relative price of a new durable good with respect to a stolen durable good is “too” large, there are dynamic incentives for non-criminals to buy a stolen durable good when the illegal market opens, regardless of whether they have bought a new durable good in the second round of decisions and is stolen or have bought none. This proposition also says who has this dynamic incentive: if we interpret α_i as the marginal rate of substitution between quality of the durable good and the numeraire, non-criminals who buy a stolen durable good are those with an intermediate marginal rate of substitution.

Equations (2.4) and (2.6) determine which individuals supply and demand the stolen durable good in the secondary market. However, I cannot determine yet neither

the aggregate supply nor the aggregate demand of the good because both depend on the number of individuals who decide to become criminals or non-criminals and on the number of non-criminals who decide to buy a new durable good in their first round. As the occupational choice precedes what a non-criminal decides to do in her first round of decisions as a non-criminal, I study in the next section the optimal decision of a non-criminal, and in section (2.3.3) I will consider the occupational choice decision.

2.3.2 Third Round of Decisions

As explained earlier, only non-criminals make decisions at this round. They must choose whether to buy a new durable good or not. They know that if they buy a new durable good they might get their property stolen in the street, whereas if they buy merchandise after criminal activities have taken place they would avoid such a situation and be able to acquire a cheaper durable good. This decision comes at a utility cost: a non-criminal who awaits until criminal activities have taken place has not enjoyed $\alpha_i \beta q$ units of quality, expressed in levels of utility, β part of her life.

At this stage, a non-criminal i with α_i decides whether to buy a new durable good ($q_i = q$) and not buy at all ($q_i = 0$) as follows:

$$\begin{aligned}
 q \succ 0 \quad \text{if} \quad \alpha_i &> \frac{\left[1 - (1 - \lambda_{nc}^r(1 - \pi_1))\sigma^q\right] p - (1 - \lambda_{nc}^r(1 - \pi_1))\sigma^{q'} p'}{\left[1 - (1 - \beta)\lambda_{nc}^r(1 - \pi_1)(1 - \pi_2) - (1 - \beta)\left(1 - \lambda_{nc}^r(1 - \pi_1)\sigma^q\right)\right] q - (1 - \beta)(1 - \pi_2)\left(1 - \lambda_{nc}^r(1 - \pi_1)\right)\sigma^{q'} q'} \\
 q \sim 0 \quad \text{if} \quad \alpha_i &= \frac{\left[1 - (1 - \lambda_{nc}^r(1 - \pi_1))\sigma^q\right] p - (1 - \lambda_{nc}^r(1 - \pi_1))\sigma^{q'} p'}{\left[1 - (1 - \beta)\lambda_{nc}^r(1 - \pi_1)(1 - \pi_2) - (1 - \beta)\left(1 - \lambda_{nc}^r(1 - \pi_1)\sigma^q\right)\right] q - (1 - \beta)(1 - \pi_2)\left(1 - \lambda_{nc}^r(1 - \pi_1)\right)\sigma^{q'} q'} \\
 q \prec 0 \quad \text{if} \quad \alpha_i &< \frac{\left[1 - (1 - \lambda_{nc}^r(1 - \pi_1))\sigma^q\right] p - (1 - \lambda_{nc}^r(1 - \pi_1))\sigma^{q'} p'}{\left[1 - (1 - \beta)\lambda_{nc}^r(1 - \pi_1)(1 - \pi_2) - (1 - \beta)\left(1 - \lambda_{nc}^r(1 - \pi_1)\sigma^q\right)\right] q - (1 - \beta)(1 - \pi_2)\left(1 - \lambda_{nc}^r(1 - \pi_1)\right)\sigma^{q'} q'}
 \end{aligned} \tag{2.7}$$

where σ^q and $\sigma^{q'}$ are the behaviorally mixed strategy probability that a non-criminal i assigns to her decisions on her last round of decisions. In our case, these probabilities will only take the values of 1 and 0 because I am disregarding those mixed strategy probabilities that lie within the interval $(0, 1)$ to focus on pure strategy decisions. Hence, in equation (2.7) all the values that conform the cutoff which determine

optimal behavior are exogenous from a non-criminal i 's perspective except for these mixed strategy probabilities.

Combining conditions (2.6) and (2.7), we can determine the following individual demand of a new durable good by a non-criminal i with an α_i at this third round of decisions given λ_{nc}^r and p' :

If $\lambda_{nc}^r < \frac{\beta}{(1-\beta)(1-\pi_1)(1-\pi_2)}$, then:

$$p' < \frac{(1-\beta)(1-\pi_2)\gamma p}{1-(1-\beta)\lambda_{nc}^r(1-\pi_1)(1-\pi_2)} \Rightarrow$$

$$q_i^{d_1} = \begin{cases} 0 & \text{if } \alpha_i < \frac{p-(1-\lambda_{nc}^r(1-\pi_1))p'}{(1-(1-\beta)(1-\pi_2)\gamma-(1-\beta)(1-\gamma)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))q} \\ q & \text{if } \alpha_i \geq \frac{p-(1-\lambda_{nc}^r(1-\pi_1))p'}{(1-(1-\beta)(1-\pi_2)\gamma-(1-\beta)(1-\gamma)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))q} \end{cases} \quad (2.8)$$

$$p' \geq \frac{(1-\beta)(1-\pi_2)\gamma p}{1-(1-\beta)\lambda_{nc}^r(1-\pi_1)(1-\pi_2)} \Rightarrow$$

$$q_i^{d_1} = \begin{cases} 0 & \text{if } \alpha_i < \frac{p}{(1-(1-\beta)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))q} \\ q & \text{if } \alpha_i \geq \frac{p}{(1-(1-\beta)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))q} \end{cases} \quad (2.9)$$

If $\lambda_{nc}^r \geq \frac{\beta}{(1-\beta)(1-\pi_1)(1-\pi_2)}$, then:

$$p' < \frac{(\beta-(1-\beta)(1-\gamma)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))p}{\beta+(1-\beta)\pi_2\lambda_{nc}^r(1-\pi_1)} \Rightarrow$$

$$q_i^{d_1} = \begin{cases} 0 & \text{if } \alpha_i < \frac{p-(1-\lambda_{nc}^r(1-\pi_1))p'}{(1-(1-\beta)(1-\pi_2)\gamma-(1-\beta)(1-\gamma)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))q} \\ q & \text{if } \alpha_i \geq \frac{p-(1-\lambda_{nc}^r(1-\pi_1))p'}{(1-(1-\beta)(1-\pi_2)\gamma-(1-\beta)(1-\gamma)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))q} \end{cases} \quad (2.10)$$

$$p' \geq \frac{(\beta-(1-\beta)(1-\gamma)\lambda_{nc}^r(1-\pi_1)(1-\pi_2))p}{\beta+(1-\beta)\pi_2\lambda_{nc}^r(1-\pi_1)} \Rightarrow$$

$$q_i^{d_1} = \begin{cases} 0 & \text{if } \alpha_i < \frac{\lambda_{nc}^r(1-\pi_1)p}{(\beta+(1-\beta)\pi_2\lambda_{nc}^r(1-\pi_1))q} \\ q & \text{if } \alpha_i \geq \frac{\lambda_{nc}^r(1-\pi_1)p}{(\beta+(1-\beta)\pi_2\lambda_{nc}^r(1-\pi_1))q} \end{cases} \quad (2.11)$$

Figure (A.2) in appendix (A.1) can help us understand this demand function. From a non-criminal's perspective, λ_{nc}^r and p' are exogenous to all non-criminals at this stage. λ_{nc}^r is determined at the second stage, where all individuals make an occupational choice. In equilibrium, λ_{nc}^r will be equal to the number criminals in the

economy. At this stage, it is useful to determine which non-criminal has her property stolen. The value of this variable relative to $\beta/[(1 - \beta)(1 - \pi_1)(1 - \pi_2)]$ determines the non-criminal's response to an increase in the price of a stolen durable good p' .

We can think of $\beta/[(1 - \beta)(1 - \pi_1)(1 - \pi_2)]$ as the ratio of the time that criminals allow non-criminals to enjoy a new durable good when non-criminals buy the good at the third round of decisions and the expected time that the government allows individuals to enjoy the stolen durable good after transactions have taken place in the secondary illegal market. This expected time will be determined by the government's incapability of recovering stolen property at both of its interventions. Hence, if this ratio is "large", we can say that non-criminals have a "safer" environment to enjoy their new durable goods relative to the environment they have to enjoy their demanded stolen property. In contrast, if this ratio is small, we can say that non-criminals has a "riskier" environment to enjoy their new durable goods.

Consequently, we can interpret this ratio as an *index of risk*. Alternatively, we also can interpret this ratio as an *index of the efficiency or inefficiency* of the government's interventions. When this ratio is larger (smaller) than λ_{nc}^r , this condition can be interpreted as implying that the probability of a durable good being stolen is smaller (larger) than the risk posed by government with its interventions. As a result, if the government's interventions increase the equilibrium price of a stolen durable good by posing more risk on participating in this illegal activity, non-criminals will increase (decrease) their demand of new durable goods at this third round of decisions.

As we can see in figure (A.2), the extend to which all these cases apply heavily depend on the number of criminals and non-criminals in the society. Without these numbers, we cannot formally determine the aggregate demand for new durable goods at this round of decisions. Consequently, in the next section, I proceed to determine these values.

2.3.3 Second Round of Decisions: Occupational Choice

The final step to solve this model from an individual's perspective is to find the conditions under which an individual becomes a criminal. At this stage, individuals determine their optimal behavior by solving (2.2). The decision of becoming a criminal will depend on what will happen to an individual when she decides to become a criminal or not, as on how likely a criminal would steal or a non-criminal would get her property stolen, and on her future decisions having decided one occupation or the other. Let ρ^q and ρ^0 be the mixed strategy probabilities associated to a non-criminal i 's optimal decisions of buying a new durable good or not on the third round of decisions. Using equation (2.2) and considering the pure strategies values for ρ^q , ρ^0 , σ^q , $\sigma^{q'}$, σ^{sells} and σ^{keeps} , we obtain the following preference relation between becoming a criminal or not for an individual i with an α_i :¹⁷

$$\begin{aligned} nc \succ c & \text{ if } \alpha_i > a_c \\ nc \sim c & \text{ if } \alpha_i = a_c \\ nc \prec c & \text{ if } \alpha_i < a_c, \end{aligned} \tag{2.12}$$

where

$$\begin{aligned} a_c &= \frac{Ap + Bp' - \lambda_c^r(f_1\pi_1 + (1 - \pi_1)\pi_2f_2\sigma^{sells})}{C + D - E} \\ A &= \left[(1 + \lambda_{nc}^r(1 - \pi_1)\sigma^q)\rho^q + \sigma^q\rho^0 \right] \\ B &= \left[\lambda_{nc}^r(1 - \pi_1)\sigma^{q'}\rho^q + \sigma^{q'}\rho^0 + \lambda_c^r(1 - \pi_1)(1 - \pi_2)\sigma^{sells} \right] \\ &= (f_1\pi_1 + (1 - \pi_1)\pi_2f_2\sigma^{sells}) \\ C &= (1 - (1 - \beta)\lambda_{nc}^r(1 - \pi_1)(1 - \pi_2))\rho^q q \\ D &= (1 - \beta)(\lambda_{nc}^r(1 - \pi_1)\rho^q + \rho^0)(\sigma^q q + (1 - \pi_2)\sigma^{q'} q') \\ E &= (1 - \beta)\lambda_c^r(1 - \pi_1)\sigma^{keeps} q' \end{aligned} \tag{2.13}$$

First, condition (2.13) allows us to identify non-criminals and criminals in the space $\alpha_i \in [0, 1]$. The following proposition summarizes this result.

¹⁷This preference relation is reversed for the case $\sigma^q = 0$, $\sigma^{q'} = 0$, $\rho^q = 0$, $\rho^0 = 1$, $\sigma^{sells} = 0$, and $\sigma^{keeps} = 1$. This case refers to those individuals who would not buy a durable in neither the last nor the third round of decisions when non-criminals, and would keep a stolen durable good for their own consumption when criminals.

Proposition 3 *In an economy inhabited by risk-neutral individuals with the utility function described in equation (2.1) where the parameter α is distributed as a uniform random variable in the interval $[0, 1]$, individuals might be organized along the domain of α according to their occupational choice: low-type individuals will likely become criminals and high-type individuals will likely become non-criminals for all $p' \geq 0$.*

Proposition (3) provides an important result because it tells us the location of the suppliers of stolen property: those *thieves* that steal for a revenue. These individuals have a value of α between zero and $[(1 - \pi_2)p' - \pi_2 f_2]/[(1 - \beta)q']$, which is the cutoff that defines which criminals supply stolen property in equation (2.5).

Equation (2.13) also allows us to characterize the behavior of those criminals who decide to sell the stolen durable goods. Specifically, criminals would be willing to sell their stolen property if

$$p' \geq \frac{\pi_1 f_1}{(1 - \pi_1)(1 - \pi_2)} + \frac{\pi_2 f_2}{(1 - \pi_2)} \quad (2.14)$$

The right-hand side of equation (2.14) represents an expected cost of engaging in property crime and in handling stolen property jointly for each potential criminal who reaches the secondary market.

Now, we can determine the aggregate supply of stolen durable goods in the last round of decisions. But, before entering in this task, a final result must be stated. We do not know yet if there is an α' that divides perfectly criminals and non-criminals in the domain of α . The following proposition provides us with the tranquility that there is at least one value of α that performs the task:

Proposition 4 *In an economy inhabited by risk-neutral individuals with a utility function as in equation (2.2) where the parameter α is distributed as a uniform random variable in the interval $[0, 1]$, there is at least one α_c for which criminals and non-criminals are perfectly divided along the interval $[0, 1]$. Additionally, such α_c is defined such that in equilibrium there is always at least one type of criminal: thieves that steal durable goods for their own consumption.*

Figure (A.3) in appendix (A.1) helps us understand the implications of propositions (3) and (4) and equation (2.14). There are a multiplicity of equilibria in this model. The fact that the economy lies in one equilibrium or another depends on the value that p' assumes and on its projection onto the α space. It is clear on the graph that potential suppliers of stolen property are subject to an economic constraint in order to operate. If this economic restriction is not at least satisfied, potential criminals for profit become well-behave citizens. However, in equilibrium it seems that there are always criminals activities: there will always be individuals who steal for their own consumption.

Figure (A.3) also indicates that the equilibrium under which non-criminals will tend to coexist will depend on the equilibrium value of the probability of having their property stolen in the third round of decisions (λ_{nc}^r) relative to the *index of inefficiency* (defined in section (2.3.2)) and on p' . As a result, many different cases may arise in equilibrium depending on the values of α_c . I will study some specific cases in section (2.4.1). In this section, it remains to say that proposition (4) guarantees the existence of α_c .

2.4 Government Policy Variables

The equilibria examined earlier clearly depend on the policy pursued by the government to allocate its law enforcement activities, given by π_1 and π_2 in the model, and the penalties associated with the apprehension of criminals, f_1 and f_2 . In this section, I examine the possible scenarios that may arise for different values of these variables. The equilibrium at this stage is formally defined as follows:

Definition 1 *Given a set of values for the exogenous parameters $\{\beta, q, q', p\} \in \mathbb{R}_+^4$ and for the government's controls $\{\pi_1, \pi_2, f_1, f_2\} \in \mathbb{R}_+^4$, a Subgame Perfect Nash Equilibrium for equation (2.2) at the second round of decisions consists of a $p^*(\pi_1, \pi_2, f_1, f_2 | \beta, q, q', p) \geq 0$ such that the following equations are all jointly satisfied at p^* :*

$$n_c^{sell} = n_{nc}^{q'} \quad (2.15)$$

$$\lambda_{nc}^r = N_c = F(\alpha_c(p'^*)) \quad (2.16)$$

$$\lambda_c^r = n_{nc}^{q,1} = 1 - F(\alpha_{nc}^{q,1}(p'^*)) \quad (2.17)$$

where n_c^{sell} is the aggregate supply of stolen durable goods, $n_{nc}^{q'}$ is the aggregate demand of stolen durable goods, N_c is the number of criminals in the economy, $n_{nc}^{q,1}$ is the aggregate demand of new durable goods at third round, and $F(\cdot)$ is the marginal cumulative distribution function of α which was assumed to be the Uniform Distribution in the interval $[0,1]$.

Several observations are worth pointing out. First, a non-criminal i 's probability of having her property stolen, (λ_{nc}^r) , and a criminal j 's probability of stealing, λ_c^r , are both endogenous and equal to the proportion of population who engage in criminal activities and buy a new durable good in the third round of decisions, respectively. Consequently, both functional forms of these probabilities are model-specific and do not respond to an ad hoc specification. Second, the aggregate demand of stolen durable goods will have a variety of functional forms that I will study below. Here, it is sufficient to note that these functional forms will depend heavily on the value that λ_{nc}^r assumes in equilibrium relative to the value of the *Index of Inefficiency* as well as on the value of p'^* . Finally, due to proposition (3) and equation (2.14), it is possible to derive the following aggregate supply of stolen durable goods:

$$n_c^{sell} = \begin{cases} \lambda_c^r(1 - \pi_1) \left[\frac{(1-\pi_2)p' - \pi_2 f_2}{(1-\beta)q'} \right] & \text{if } p' \geq \frac{\pi_1 f_1}{(1-\pi_1)(1-\pi_2)} + \frac{\pi_2 f_2}{(1-\pi_2)} \\ 0 & \text{if } p' < \frac{\pi_1 f_1}{(1-\pi_1)(1-\pi_2)} + \frac{\pi_2 f_2}{(1-\pi_2)} \end{cases} \quad (2.18)$$

Figure (A.4) depicts graphically this latter equation. Equation (2.18) depends on three important features: first, the more new durable goods are available in the economy, the larger the potential supply of stolen durable goods. It is clear that without new durable goods in the economy, there is not availability of stolen durable goods in the secondary market. Second, the degree of inefficiency of the government

in controlling criminal activities help determine their profitability. This effect affects the slope of the aggregate supply correspondence in figure (A.4). Third, the degree of inefficiency of the government in controlling criminals activities also help determine participation in the secondary market. This last effect is observed in the size of the discontinuity of the aggregate supply correspondence in figure (A.4).

2.4.1 Subgame Perfect Nash Equilibria

The first set of equilibria presented contains a situation in which all individuals who decide to become non-criminals will also buy a new durable good in the third round of decisions. The following equation presents the aggregate demand for stolen durable goods, $n_{nc}^{q'}$, for these cases:

$$n_{nc}^{q'} = \begin{cases} \lambda_{nc}^r(1 - \pi_1) \left[1 - \frac{p'}{(1-\beta)(1-\pi_2)q'} \right] & \text{if } p' \leq p - (1 - \beta)[q - (1 - \pi_2)q'] \\ \lambda_{nc}^r(1 - \pi_1) \left[\frac{(1-\pi_2)q'p - qp'}{(1-\beta)(1-\pi_2)q' [q - (1-\pi_2)q']} \right] & \text{if } p' > p - (1 - \beta)[q - (1 - \pi_2)q'] \end{cases} \quad (2.19)$$

This demand function also depends on three important factors. First, non-criminals would not demand stolen durable goods if they had not had their property stolen in the first place, ($\lambda_{nc}^r \neq 0$). Second, non-criminals would not demand stolen durable goods if they had not had their property *effectively stolen* in the first place ($\lambda_{nc}^r(1 - \pi_1) \neq 0$). Finally, when the price of a stolen durable good is larger than $p - (1 - \beta)[q - (1 - \pi_2)q']$, those non-criminals with the larger marginal rate of substitution for quality α_i will consume again a new durable good in the last round of decisions. This reduction in the demand of stolen durable goods changes the slope of its aggregate demand function as can be seen in figure (A.5) in appendix (A.1).

Using equations (2.18) and (2.19) to determine an equilibrium, there are potentially four crossing points which generate four different equilibria. Point A in figure (A.5) depicts an equilibrium in which part of the non-criminals who get their property stolen will buy again a new durable good. Point B in figure (A.5) shows an equilibrium in which there is not a single non-criminal who buys again a new durable good in the last round of decisions, but there will be still non-criminals who abstain from buying again

a durable good (not seen on the graph). Point C shows two potential equilibria: on the one hand, the upper segment of the aggregate demand might intersect the aggregate supply at zero. On the other hand, the lower segment of the aggregate demand might intersect the aggregate supply at the same point.

All these cases generate different equilibrium prices for a stolen durable good, p' . There is also a set of values for the aggregate supply and demand of stolen durable goods for which the equilibrium is not defined. Using equation (2.13) to determine α_c for all these cases, the following set of equations defines an equilibrium for points like A or B in figure (A.5):

$$\begin{aligned} \lambda_c^r(1 - \pi_1) \left[\frac{(1 - \pi_2)p' - \pi_2 f_2}{(1 - \beta)q'} \right] = \\ \begin{cases} \lambda_{nc}^r(1 - \pi_1) \left[1 - \frac{p'}{(1 - \beta)(1 - \pi_2)q'} \right] & \text{if } p' \leq p - (1 - \beta)[q - (1 - \pi_2)q'] \\ \lambda_{nc}^r(1 - \pi_1) \left[\frac{(1 - \pi_2)q'p - qp'}{(1 - \beta)(1 - \pi_2)q' [q - (1 - \pi_2)q']} \right] & \text{if } p' > p - (1 - \beta)[q - (1 - \pi_2)q'] \end{cases} \\ \lambda_{nc}^r = \frac{p - \pi_1 \lambda_c^r f_1}{\left[1 - (1 - \beta) \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2) \right] q - (1 - \beta) \lambda_c^r (1 - \pi_1) q'} \\ \lambda_c^r = 1 - \frac{p - \pi_1 \lambda_c^r f_1}{\left[1 - (1 - \beta) \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2) \right] q - (1 - \beta) \lambda_c^r (1 - \pi_1) q'} \end{aligned} \quad (2.20)$$

Solving, we obtain our first set of equilibria for given values of $\{\pi_1, \pi_2, f_1, f_2\}$ and $\{\beta, q, q', p\}$:

$$(\lambda_{nc}^r)^* = \frac{F}{G} \pm \frac{\sqrt{F^2 - G * H}}{G} \quad (2.21)$$

$$(\lambda_c^r)^* = 1 - (\lambda_{nc}^r)^* \quad (2.22)$$

$$(p')^* = \begin{cases} \frac{(1 - \beta)(\lambda_{nc}^r)^*(1 - \pi_2)q' + (1 - \pi_2)\pi_2 f_2(1 - (\lambda_{nc}^r)^*)}{(\lambda_{nc}^r)^* + (1 - \pi_2)^2(1 - (\lambda_{nc}^r)^*)} & \text{if } (p')^* \leq \text{cond}(p') \\ \frac{(\lambda_{nc}^r)^*(1 - \pi_2)(q')^2 p + (1 - \pi_2)q' \pi_2 f_2 [q - (1 - \pi_2)q'] (1 - (\lambda_{nc}^r)^*)}{qq'(\lambda_{nc}^r)^* + (1 - \pi_2)^2 q' [q - (1 - \pi_2)q'] (1 - (\lambda_{nc}^r)^*)} & \text{if } (p')^* > \text{cond}(p') \end{cases} \quad (2.23)$$

where,

$$\begin{aligned} F &= [q - (1 - \beta)(1 - \pi_1)q' - \pi_1 f_1] \\ G &= 2(1 - \beta)(1 - \pi_1)[(1 - \pi_2)q - q'] \\ H &= 2[p - \pi_1 f_1] \\ \text{cond}(p') &= p - (1 - \beta)[q - (1 - \pi_2)q'] \end{aligned}$$

The following equations define an equilibrium for a point like C in figure (A.5):

$$0 = \begin{cases} \lambda_{nc}^r(1 - \pi_1) \left[1 - \frac{p'}{(1-\beta)(1-\pi_2)q'} \right] & \text{if } p' \leq p - (1 - \beta)[q - (1 - \pi_2)q'] \\ \lambda_{nc}^r(1 - \pi_1) \left[\frac{(1-\pi_2)q'p - qp'}{(1-\beta)(1-\pi_2)q'[q - (1-\pi_2)q']} \right] & \text{if } p' > p - (1 - \beta)[q - (1 - \pi_2)q'] \end{cases} \quad (2.24)$$

$$\lambda_{nc}^r = \frac{p - \pi_1 \lambda_c^r f_1}{\left[1 - (1 - \beta) \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2) \right] q - (1 - \beta) \lambda_c^r (1 - \pi_1) q'} \quad (2.25)$$

$$\lambda_c^r = 1 - \frac{p - \pi_1 \lambda_c^r f_1}{\left[1 - (1 - \beta) \lambda_{nc}^r (1 - \pi_1) (1 - \pi_2) \right] q - (1 - \beta) \lambda_c^r (1 - \pi_1) q'} - \frac{\pi_1 f_1}{(1 - \beta)(1 - \pi_1)q'} \quad (2.26)$$

Solving, we obtain

$$(\lambda_{nc}^r)^* = \frac{I}{G} \pm \frac{\sqrt{I^2 - G * J}}{G} \quad (2.27)$$

$$(\lambda_c^r)^* = 1 - (\lambda_{nc}^r)^* - \frac{\pi_1 f_1}{(1 - \beta)(1 - \pi_1)q'} \quad (2.28)$$

$$(p')^* = \begin{cases} (1 - \beta)(1 - \pi_2)q' & \text{if } (p')^* \leq \text{cond}(p') \\ (1 - \pi_2)\gamma p & \text{if } (p')^* > \text{cond}(p') \end{cases} \quad (2.29)$$

where,

$$\begin{aligned} I &= \left[q - (1 - \beta)(1 - \pi_1)q' - \left(1 - \frac{(1 - \pi_2)q}{q'} \right) \pi_1 f_1 \right] \\ J &= 2 \left[p - \frac{q \pi_1 f_1}{(1 - \beta)(1 - \pi_1)q'} \right] \end{aligned}$$

This equilibrium is achieved when the price defined in (2.29) does not satisfy the condition expressed in equation (2.14) above. In other words, the equilibrium price in this second set of equilibria must induce criminals not to participate in the illegal secondary market. If this later condition is not satisfied, the equilibrium would lie on the discontinuous portion of the aggregate supply in which case an equilibrium does not exist.

Note that equations (2.23) and (2.29) are subject to the same conditions. The following proposition states the conditions under which each equilibrium is observed.

Proposition 5 *The conditions for (2.23) or (2.29) to hold in equilibrium are*

$$\begin{aligned} (p')^* &\leq p - (1 - \beta)[q - (1 - \pi_2)q'] & \text{if } p &\leq (1 - \beta)q \\ (p')^* &> p - (1 - \beta)[q - (1 - \pi_2)q'] & \text{if } p &> (1 - \beta)q \end{aligned} \quad (2.30)$$

Figure (A.6) is helpful to understand this last proposition. Suppose that a non-criminal has her property stolen. Then, if the price of a new durable good p is larger than the remaining utility of a new durable good when the good is bought after criminal activities have taken place $(1 - \beta)q$, then she will not buy again a new durable good in the last round. Instead, she will buy a stolen durable good. When p is smaller, there are non-criminals who will buy again a new durable good.

Before entering into the analysis of the government's optimal actions, it is worth noting that the negative roots of equations (2.21) and (2.27) are not defined when $(1 - \pi_2)q = q'$. $(1 - \pi_2)q$ represents the quality enjoyed by a non-criminal i who gets her property stolen in the third round of decisions and decides to buy a new durable good in the last round of decisions. When this quality is equal to the quality that the same non-criminal would enjoy if she consumed a stolen durable good instead, q' , she is indifferent between q and q' in the last round of decisions. This indifference creates another discontinuity in the negative roots of the equilibrium crime rates of equations (2.21) and (2.27).

2.4.2 Investigating the Scenarios Under which the Government Operates

The final step in our investigation is to analyze the scenarios under which the government operates. Let us suppose that the government is only interested in minimizing the percentage of thieves in the economy¹⁸. Thus, equation (2.14) provides the condition under which the government faces either the equilibrium crime rates found in equation (2.21) or in equation (2.27). If the equilibrium price of stolen durable goods is larger than the fixed cost on the right-hand side of equation (2.14), the secondary market for stolen durable goods exists. In this equilibria, the government faces two types of thieves: those who steal to re-sell the stolen property and those who steal to consume it. If the equilibrium price of stolen durable goods is smaller

¹⁸It is clear that the government might have other objectives such as the maximization of a social welfare function. As I am only interested in determining the environments under which the government operates when it is interested in reducing the amount of criminals in the economy, I assume that the government only cares about the crime rate and not about any measure of welfare.

than the fixed cost on the right-hand side of equation (2.14), the secondary market for stolen durable goods does not exist. In this equilibria, the government only faces one type of thief: those who steal to consume the stolen goods.

We can exploit these results to obtain the scenarios under which the government operates. An interesting relationship to determine is the government's tradeoff between π_1 and π_2 for a given crime rate, λ_{nc}^r . If the condition for the existence of the secondary market for stolen durable goods is satisfied, both enforcement technologies π_1 and π_2 are defined, and help determine the equilibrium of the economy. When the condition for the existence of secondary markets for stolen durable goods is not satisfied, π_2 is not defined. As a result, the tradeoff between π_1 and π_2 is only defined when the secondary market for stolen durable goods exists.

Assuming that the conditions for the existence of the secondary market for stolen durable goods are satisfied, the following equation is determined, which shows the tradeoff faced by the government between π_2 and π_1 for a given value of the crime rate, λ_{nc}^r :

$$\pi_2 = \begin{cases} \frac{(1-\beta)(1-\pi_1)(q-q')(\lambda_{nc}^r)^2 - [q - (1-\beta)(1-\pi_1)q' - \pi_1 f_1]\lambda_{nc}^r + (p - \pi_1 f_1)}{(1-\beta)(1-\pi_1)q(\lambda_{nc}^r)^2} & \text{if } p' \geq \frac{\pi_1 f_1}{(1-\pi_1)(1-\pi_2)} + \frac{\pi_2 f_2}{(1-\pi_2)} \end{cases} \quad (2.31)$$

Equation (2.31) shows the government's available technology to obtain a crime rate of λ_{nc}^r , given the equilibrium price for a stolen durable good, p' , which also depends on the value of λ_{nc}^r in equation (2.23). The sign of the relationship between π_2 and π_1 in equation (2.31) is easily determined, and is provided in the following proposition:

Proposition 6 *Given the government's technology found in equation (2.31), the following two conditions are satisfied:*

i . The derivative of π_2 with respect to π_1 is given by the following equation:

$$\frac{\partial \pi_2}{\partial \pi_1} = \frac{(p-f_1)-(q-f_1)\lambda_{nc}^r}{(1-\beta)(1-\pi_1)^2 q (\lambda_{nc}^r)^2} \quad \text{if } p' \geq \frac{\pi_1 f_1}{(1-\pi_1)(1-\pi_2)} + \frac{\pi_2 f_2}{(1-\pi_2)} \quad (2.32)$$

ii . The sign of the derivative of π_2 with respect to π_1 is given by the following equations:

$$\frac{\partial \pi_2}{\partial \pi_1} \geq 0 \quad \text{if} \quad (p - f_1) \geq (q - f_1)\lambda_{nc}^r \quad \text{and} \quad p' \geq \frac{\pi_1 f_1}{(1-\pi_1)(1-\pi_2)} + \frac{\pi_2 f_2}{(1-\pi_2)} \quad (2.33)$$

$$\frac{\partial \pi_2}{\partial \pi_1} < 0 \quad \text{if} \quad (p - f_1) < (q - f_1)\lambda_{nc}^r \quad \text{and} \quad p' \geq \frac{\pi_1 f_1}{(1-\pi_1)(1-\pi_2)} + \frac{\pi_2 f_2}{(1-\pi_2)} \quad (2.34)$$

Proposition (6) states that when the economic conditions for the existence of secondary markets for stolen durable goods are satisfied, the sign of the relationship between π_2 and π_1 depends on a simple linear relationship between the difference of p and f_1 and the difference of q and f_1 , given a value of $\lambda_{nc}^r \in [0, 1]$. If $p > q$, the relationship between π_2 and π_1 is always positive $\forall \lambda_{nc}^r \in [0, 1]$. Hence, if a new durable good has a price larger than its quality, the government has to increase both π_1 and π_2 to keep λ_{nc}^r constant. This only occurs when the price of a stolen durable good is large enough to create the secondary markets for these goods. As a result, the government only faces this scenario when the price of a new durable good is large, and there is a large demand of the good when stolen or a very lax enforcement of criminal activities.

When the price of a stolen durable good is not large enough to create the secondary markets for these goods, the relationship between π_2 and π_1 is not defined. At this range of prices, π_2 does not have any bearing on the equilibrium values of the economy because the market for secondary markets does not exist, and the only type of thief that exists is those individuals who steal to consume the stolen good. This occurs when the fixed costs of supplying a stolen durable good induced by enforcement are large enough to destroy the secondary market for stolen durable goods, or the demand of these goods is very low. In any case, the only enforcement technology that has an influence on the crime rates is π_1 at this range of values for p' .

Two more results can be noted from proposition (6). On the one hand, the effect of f_2 on the relationship between π_2 and π_1 is indirect. From equations (2.21) and (2.27), we can see that f_2 does not affect the equilibrium values of λ_{nc}^r directly. The effect of f_2

is through the equilibrium price for stolen durable goods, p' , and the condition for the existence of secondary markets. From equation (2.23), we can see that an increase in f_2 increases the equilibrium price for stolen durable goods. From equation (2.14), we can see that an increase in f_2 generates a larger fixed costs of supplying stolen durable goods. In equilibrium, the effect of f_2 is ambiguous. A larger f_2 generates a larger p' , which increases the likelihood that the government faces the crimes rates obtained when the secondary markets are functioning. However, an increase in f_2 increases the fixed costs of supplying stolen durable goods, which increases the likelihood that the government faces the crimes rates obtained when the secondary markets for stolen durable goods do not exist. On the other hand, if the conditions for the existence of secondary markets for stolen durable goods are satisfied, $f_1 > \frac{p-q\lambda_{nc}^r}{(1-\lambda_{nc}^r)}$ generates that the relationship between π_2 and π_1 is always negative $\forall \lambda_{nc}^r \in [0, 1)$. As a result, the government is able to manipulate the slope of the relationship between π_2 and π_1 by choosing the value of f_1 to belong to the interval that benefits its interests the most.

2.4.3 An example: Changing π_1 and π_2

Proposition (6) provides the conditions under which a tradeoff between π_1 and π_2 for the government exists. Outside of the ranges defined by proposition (6), either π_2 , π_1 or λ_{nc}^r are defined. To this point, the conditions provided do not secure that an equilibrium actually exists. I conclude our analysis presenting a numerical exercise where I show that there exists a set of values for the exogenous parameters for which an equilibrium exists. This example serves us to present the effect of changes in the values of π_1 and π_2 on the equilibrium values of p' and λ_{nc}^r , as well as on the equilibrium values of the percentage of thieves who steal a durable good either to sell or consume it. Before doing that, some conclusions are noted in order to understand the numerical example presented below.

First, the equilibrium crime rates found in equations (2.21) and (2.27) depends directly on the values of π_1 , π_2 , f_1 , q , q' , p and $(1 - \beta)$. The sign of the relationship between these variables and the crime rates is not clear cut to determine. Additionally,

despite that the model constructed in this paper contains risk-neutral individuals with linear utility functions, the relationship between the crimes rates and its determinants is not linear.

Second, f_2 does not affect directly any of the crimes rates found in equations (2.21) and (2.27). The effect of f_2 on the crime rate is indirect. It affects the equilibrium price for stolen durable goods, p' , in equation (2.23) and the fixed cost of participation in the illegal market for stolen durable goods in equation (2.14). As a result, the effect of f_2 on λ_{nc}^r is ambiguous and only helps determine which crime rate takes place in equilibrium and weather the secondary market for stolen durable goods exists or not.

Finally, equations (2.21) and (2.27) define four possible equilibrium crime rates depending on the value of p' relative to the fixed cost in equation (2.14). It can be shown that the positive roots found in equations (2.21) and (2.27) for the crime rate are both unstable. These set of equilibria will exhibit swings of the crime rate that go from zero to one with small changes in π_1 or π_2 . In contrast, the negative roots in equations (2.21) and (2.27) both exhibit crime rates in the $[0, 1]$ interval for all π_1 and π_2 in their respective domains. As a consequence, I only present numerical results for these second set of equilibrium crime rates.

Figure (A.8) presents an example for the equilibrium values of the total percentage of criminals in the economy, $\lambda_{nc}^r = nc$, the equilibrium price of a stolen durable goods, p' , and the composition of the crime rate in terms of the percentage of thieves who sells and keeps the stolen property. This example assumes that $p = 0.10$, $f_1 = 0$, $f_2 = 0$, $q = 1$, $q' = 0.8$, and $\beta = 0.4$. Additionally, figures (A.8a) and (A.8b) presents the equilibrium values of λ_{nc}^r and p' for two values of p , ($p \in \{0.10, 0.12\}$). The choice of these values have the following consequences. First, at $f_1 = 0$ and $f_2 = 0$, any $p' > 0$ generates the secondary market for stolen durable goods. Second, $q = 1$ and $q' = 0.8$ imply that a stolen durable good has a 20% less quality than a new durable good. Third, $\beta = 0.4$ implies that criminal activities take place at a 40% of the lifetime of the durable goods and individuals. As a result, there is another 60% of the lifetime of both the durable goods and individuals to enjoy a durable good, weather new or stolen. Finally, the discontinuity found in section (2.4.1) for the negative roots

of λ_{nc}^r in equations (2.21) and (2.27) is given at $\pi_2 = \frac{q-q'}{q} = 0.2$.

Several results are worth noting from this numerical example. First, there exists at least one equilibrium crime rate $\lambda_{nc}^r \in [0, 1]$ and an equilibrium price of the stolen durable goods $p' \in [0, p = 0.10)$ for every value of π_1 and π_2 , given the values of the exogenous parameters assumed for the example. Figure (A.8a) shows that an increase in p increases the equilibrium value of $\lambda_{nc}^r \forall \pi_1 \in [0, 1]$ and $\pi_2 \in [0, 1)$. Figure (A.8b) shows that an increase in p increases the equilibrium value of $p' \forall \pi_1 \in [0, 1]$ and $\pi_2 \in [0, 1)$. Additionally, when $f_1 = 0$ and $f_2 = 0$, p becomes a lower bound for the equilibrium crime rate. This lower bound is approached when π_1 gets close to 1, $\forall \pi_2 \in [0, 1)$. In other words, when the government approaches a situation in which almost all thieves are captured, there is a potential $p\%$ of thieves who are willing to steal a durable good either to supplement their income or satiate their demand for the stolen durable good. This strong result is obtained because the financial penalty of engaging in criminal activities is zero. For values of f_1 or f_2 larger than zero, this result does not hold any longer.

Second, the maximum values of the crime rate and the price for stolen durable goods are both reached at $\pi_1 = 0$ and $\pi_2 = 0$. However, their minimum values are reached at different combination of values of the enforcement technologies. λ_{nc}^r reaches its minimum value at $\pi_1 = 1, \forall \pi_2 \in [0, 1)$, and p' reaches its minimum value at $\pi_2 = 1, \forall \pi_1 \in [0, 1]$. Consequently, π_1 is more effective to control individuals from engaging in theft of durable goods, and π_2 is more effective to reduce the equilibrium price of stolen durable goods.

Third, increments in π_1 and π_2 generate a reduction in λ_{nc}^r . This is not true for its components. On the one hand, an increase in π_2 generates an increase in the percentage of thieves who engage in criminal activities to consume the good, and a reduction in the percentage of those who wants to sell it. On the other hand, an increase in π_1 generates a reduction in both the percentage of thieves who engage in criminal activities to consume and sell the good. As a result, an increase in π_1 generates a reduction in both components of the total crime rate, whereas an increase in π_2 generates an increase in percentage of thieves who wants to consume the stolen

durable good. In fact, our numerical example shows that the percentage of thieves who wants to consume the good is maximized at $\pi_1 = 0$ and $\pi_2 = 1$ and minimized at $\pi_1 = 1$ and $\pi_2 = 0$. In turn, the percentage of thieves who wants to sell the good is maximized at $\pi_1 = 0$ and $\pi_2 = 0$ and minimized at $\pi_2 = 1$, $\forall \pi_1 \in [0, 1]$.

In other words, our numerical example shows that π_2 has ambiguous effects on the equilibrium crime rates. On the one hand, an increase in π_2 reduces the economic incentives of thieves to engage in criminal activities for a profit. On the other hand, an increase in π_2 generates that more thieves find profitable engaging in criminal activities to satiate their consumption. Our numerical example shows that the net outcome is to reduce marginally the total percentage of thieves in the economy. However, increments in π_2 substantially increases the equilibrium percentage of thieves who seek to consume the stolen durable.

Taken all these numerical results together, a conclusion is obtained: the most effective policy to reduce the percentage of thieves who engage in theft of durable goods for a profit is π_2 , and the most effective policy to reduce the percentage of thieves who engage in theft to consume the durable good is π_1 . In other words, if the government wants to minimize the percentage of thieves in the economy who want to sell the stolen property, it has to focus on controlling the existence of the secondary market for stolen durable goods. If the government wants to minimize the percentage of thieves who want to consume the stolen durable good, it has to focus on capturing thieves *in flagranti*. However, both policies have to be used together. The reason is that a large π_2 generates a large percentage of thieves who engage in theft to consume the good. The perfect combination of π_1 and π_2 is determined when equation (2.32) is in equilibrium, which will depend on the assumptions about the government's budget constraints and the technology that associates every dollar collected in tax revenue with the government's enforcement activities.

Before concluding this analysis, figure (A.7) in appendix (A.1) presents the same numerical example for the government's technology found in proposition (6). The figure presents an example where $f_1 = 0$, $f_2 = 0$, $p = 0.10$, and $q = 1$. These values imply that for the range of values of λ_{nc}^r presented in the figure, ($\lambda_{nc}^r \in$

$[0.10; 0.11; 0.12; 0.13; 0.14; 0.15; 0.16]$, the relationship between π_2 and π_1 is always negative. The figure also shows that this relationship is not always defined for the entire domain of π_1 for a given value of the crime rate, λ_{nc}^r . Additionally, the graph shows that when $\lambda_{nc}^r \leq 0.10$, the relationship between π_2 and π_1 is not defined either. In other words, given the values for the exogenous parameters assumed for this example, there is not a combination of π_2 and π_1 that allows the government to reach a crime rate lower than $\lambda_{nc}^r = 0.10$. This result was expected because 0.10 is equal to the price of a new durable good assumed for this example, which was encountered to be a lower bound for the crime rate in figure (A.8) for the same numerical values of the exogenous parameters used to compute figure (A.7).

2.5 Conclusions

In this paper, I extend a model of property crime by incorporating a market for illegal goods. The secondary market is formed by individuals who rationally decide to become criminals, to steal durable goods, and to sell them in this market, and by non-criminals who demand stolen goods. The model develops a few additional elements. First, criminal activities take place because individuals target durable goods either for re-selling or for consumption. Second, criminals activities take place because there is a potential demand for stolen property. This demand is composed of individuals buying stolen property willingly. Finally, I assume that the government performs two crime control activities: it captures thieves *in flagranti* and controls the illegal transactions that take place in the secondary markets for stolen durable goods.

In this simplified framework, the following results are obtained. First, under certain conditions individuals with low preferences for the durable good may have incentives to engage in criminal activities: they would steal goods and sell them in the secondary market. Second, depending on the combination of law enforcement activities put in place by the government, individuals with a “low-middle” preference for the durable good would become criminals, steal goods, and keep them for their own consumption. Finally, some non-criminals that are subject to crime and lose their property may have

incentives to replace the stolen good by purchasing it in the secondary illegal market. This last conclusion is consistent with the fact that even though individuals openly complain about property crime, if the price of stolen goods is low enough, they may have incentives to purchase illegal goods, indirectly supporting and encouraging illegal activities and more crime.

A noteworthy result of this simplified model is that non-criminals who do not purchase a new durable good only exist in equilibrium when there are not criminals who are willing to engage in criminal activities for a profit. This occurs in equilibrium due to a combination of three assumptions: on the one hand, non-criminals are assumed to be able to buy stolen property only when the secondary market for stolen durable goods are functioning. On the other hand, those non-criminals who decide to buy durable goods in the last round of decisions face a utility cost in terms of the consumption of durable goods. As the economy is assumed to be uniquely inhabited by risk neutral individuals, the combination of these three assumptions make non-criminals maximize their utility when they only buy new durable goods in the second round of decisions. In order for non-criminals who do not buy a new durable good to exist when there are criminals in equilibrium, a more general model must incorporate a richer dynamic setup where non-criminals also have the secondary markets for stolen durable goods functioning at the beginning of their lives. It also must include individuals with a different risk aversion, which implies that income effects also must be incorporated into the analysis.

From a policy perspective, the model presented in this paper contains several important insights. First, the government can manipulate the costs associated to crime to destroy the incentives for the secondary markets to exist. These costs make part of a participation cost that criminals internalize in their decisions, which might lead them not to participate in the illegal secondary markets for stolen durable goods. Second, when the costs of participation in the illegal secondary market for stolen durable goods are low enough to allow criminals to create markets for stolen property, the most effective policy that the government has to reduce the total crime rate is to capture criminals *in flagranti*. Third, if the government is unable to maintain a

high rate of *in flagranti* captures, the most effective policy to reduce the incentives for secondary markets for stolen durable goods to exist is to focus public resources on capturing criminals when they are selling stolen property in the secondary markets for stolen durable goods. However, this policy has to be combined with *in flagranti* captures because when the government only focus on controlling illegal transaction in the secondary market for durable goods, this policy might incentive the criminals to engage in theft to satiate their own demand for durable goods.

As a whole, this model confirms some of the ideas behind why criminals engage in theft of durable goods contained in the criminology studies of property crime. The model presented in this paper underlines three factors as the most important to determine what makes a good “hot” for criminals: Valuable, Enjoyable and Disposable. When a *durable good* has a *large* price relative to its price as stolen, criminals might engage in theft of this good to either supply it or consume it.

Chapter 3

Optimal Drug Supply Control: The Relationship between Drug Addiction and Property Crime

3.1 Introduction

There are many reasons why drug supply control policies are common in many Western societies. One reason is that statistical, historical and anecdotal evidence show a positive correlation between drug addiction and property crime. Narcotics are special commodities with a minimum consumption requirement that might induce drug consumers to property crime when unsatisfied. A model of endogenous occupational choice is used to determine the optimal percentage of drugs that the government has to seize in order to minimize the number of thieves in the economy.

Minimum drug consumption requirements affect the way individuals value their income. According to Cozzi, 2006, a drug user might feel “unhappy” if her income is not *sufficiently “high”* to cover her minimum drug consumption requirement. This unhappiness might lead the user to become a risk-lover who is willing to accept a low expected income from criminal activities to engage in property crime to supplement her minimum drug consumption requirement. In this environment, optimal drug control policies that reduce the availability of narcotics in the economy might generate

two effects: On the one hand, the government might generate more thieves because a more expensive minimum drug consumption bundle might induce more addicts to engage in property crime. On the other hand, an increase in the price of drugs might decrease an addict's marginal valuation of an extra dollar for drug consumption. If this effect predominates over the minimum drug consumption cost effect, addicts might be induced to reduce their property crime rates. The final effect will depend on the income and addiction distributions of the economy.

Given the complexity of the relationship among addiction, income distribution and crime, the model used in this paper is based on four assumptions: first, there is a parameter that captures the preference for the unique (composite) drug commodity in the economy, which has an exogenous discrete distribution composed of three categories: zero, light, and heavy preferences¹. This distribution helps determine the number of people in each category and their optimal drugs consumption level per income level. Second, there is also a parameter that captures the minimum drug consumption requirement that corresponds to the individuals' *addiction* levels. For simplicity, it is assumed that the addiction parameter distribution is indirectly determined by the drug preference parameter distribution, which implies that the addiction distribution is also composed of three categories: zero, light, and heavy addiction levels. In this economy, I also assume that individuals live one period to focus the attention on the government's incentives to optimally control the supply of drugs in the presence of *structural* drug consumption and addiction that might lead to property crime. As a result, the addiction distribution generates levels of addiction that the model would otherwise fail to obtain endogenously by a lack of a dynamic setting.

Third, there is an income distribution captured by a *positive skewed Kumaraswamy distribution function*, which is assumed to be independently distributed from the

¹Note that there is a fundamental distinction between the definitions of weak and strong preferences in microeconomics and the definitions of light and heavy preferences used in the text. Weak and strong preferences refer to a topological preference relationship that determines whether a *single* individual weakly or strongly prefers a consumption bundle to another with different quantities for the same goods. Light and heavy preferences refer to the intensity of attraction of *two* individuals for the same consumption bundle.

distribution of the drug preference parameter. This implies that there are all levels of income at every drug preference category. Finally, individuals can optimally decide whether to supplement their income with property crime or not. These last two assumptions permit to optimally determine the number of individuals who engage in property crime, given the income, drug preference, and addiction distributions.

In this economy, the government can decide what percentage of the drug commodity to seize in order to minimize the percentage of thieves². This decision is performed in two scenarios: in the first scenario, the government decides the amount of drugs to seize without any budget constraint. In the other scenario, the government's decision is subject to a budget constraint and a balanced budget requirement. Additionally, it is assumed that the government can use the income from the fines paid by captured thieves to finance its enforcement activities. In this sense, jail costs are not considered, and the government's optimal decision is not affected by these extra costs of enforcement. Hence, the model is only able to capture the deterrence effects and not the incapacitating effects of enforcement.

The results indicate that when the government is not subject to a budget constraint and its objective is to minimize the percentage of thieves in the economy, the government must allocate all the resources on controlling thieves and *zero* on controlling the supply of drugs. The reason is simple: drug supply controls increase the price of drugs, which in turn increases the individuals' incentives to commit property crime. Hence, when the government is not subject to a budget restriction, the best government's strategy is to capture as many thieves as possible without inducing addicts to property crime through increases in the price of drugs. When there is a

²This assumption might not be the best one to capture the real world dynamics of some drug markets. In many countries such as the U.S., the government also spends on capturing drug consumers. However, there are many other countries, such as Portugal or Colombia, where the consumption of drugs is a legal activity but the production of drugs is an illegal one prosecuted by the government. The model constructed in this paper abstracts from the expenditure made by the government to capture drug users. As a result, it is aimed to capture the dynamics of the drug markets of countries such as Portugal or Colombia. To capture the U.S. reality more appropriately, the model needs to be slightly adjusted to incorporate the expenditure made by the government to capture drug users. However, given the fact that the estimated percentage of drug users captured by the U.S. government is only 0.5% (See Caulson et al., 2011), the model presented in the text might also be a good approximation for the U.S. reality assuming that the expenditure to control drug users is highly inefficient to have a bearing on drug users' criminal decisions.

budget constraint and a minimum expenditure requirement for the government, the government must spend resources on both controlling thieves and the supply drugs. This result is due to a balanced budget and minimum expenditure requirements: as the technology to capture thieves is expensive, it is optimal for the government to supplement its budget with the fines from captured addicts who get induced to crime by the optimal drug supply control policies. With sufficient revenue to spend on controlling thieves, it is optimal for the government to subsidize the consumption of drugs.

The novelty of this model revolves around at least three aspects: first, despite the intense debate on drug control policies, there is not a formal model that studies the government's optimal decision to control drugs, when this policy might induce addicts to commit property crime. To my knowledge, this model is a first approach to a formal analysis of that decision using game theory. Second, the existing models of crime do not consider a minimum consumption requirement to model the incentives that individuals have to commit property crime. The model presented in this paper can be easily extended to incorporate other types of commodities with a minimum level requirement, which might induce people to crime when unsatisfied. Third, the Kumaraswamy distribution that captures the income distribution is a novelty in the economics of crime. This function is very versatile and permits to parameterize the skewness in the income distribution. This parametrization was used to perform comparative static analysis on income bias distribution improvements. In this regard, this model introduces a versatile distribution function that might help study other phenomena of crime, where the income distribution skewness needs to be manipulated parametrically.

Using this model, two comparative static analysis exercises are performed. In the first exercise, the technology of drug seizure is improved. This generates that the government destroys the drug more easily. This improvement generates two changes: one the one hand, the government increases the amount of resources devoted to seizing drugs relative to the amount of resources devoted to controlling thieves. That happens until the government becomes more efficient at seizing drugs. On the other hand,

the government reduces the amount of resources spent on controlling thieves, generating a larger total percentage of thieves in equilibrium. A second exercise involves increasing the parameter that captures the income distribution skewness, generating a more centered income distribution. This exercise presents a very insightful and counterfactual result: when there is sufficient revenue to optimally control thieves, the government *subsidizes* the consumption of drugs in order to reduce the incentives of addicts to engage in property crime.

This paper is organized as follows: section (3.1) is the introduction. Section (3.2) presents a short literature review on the relationship between drug addiction and property crime. Section (3.3) presents the model without a budget constraint for the government, and the respective results. Section (3.4) introduces a budget constraint and enforcement technologies for the government. It also presents the results associated to these new restrictions. Section (3.5) contains the comparative analysis exercises. Section (3.6) concludes the paper and section (A.2) contains the appendix.

3.2 Literature Review

Drug supply control policies seem to be based on the *criminal career paradigm* that results from criminology studies on criminal careers. This paradigm is well summarized by Blumstein et al., 1986 and Blumstein et al., 2003. According to this view, drug consumption generates an incentive for consumers to engage in criminal behaviors when they cannot *afford* the minimum consumption requirement that drugs seem to have.

Despite the intense debate about the influence that drugs have on triggering a criminal career in criminology studies, few work has been done using the new tools of economics. Cozzi, 2006, for example, builds a model populated by infinitely-lived individuals who can supplement their income with property crime and drug dealing. He aims to indirectly estimate the percentage of the U.S. property crime that can be explained by hard drug consumers, who prey on society to satiate their drug con-

sumption minimum requirement. His results show that predatory crime to finance addiction explains 26% of U.S. property crime in 1996.

Similarly, Entorf and Winker, 2008 test whether the consumption of drugs is statistically significant to explain property crime in the German States. They find that the proxies for drug consumption are all statistically significant for all major property crimes considered. Dobkin and Nicosia, 2009 exploit a unique data set in methamphetamine hospital admissions during a major supply disruption in California in 1995 to test whether a drug supply disruption reduces the costs associated with drug consumption. The authors find that the intervention accomplished many of the expected outcomes of drug supply control policies. It increased methamphetamine prices from 30 to 100 dollars per gram, decreased supplied purity from 85% to 25%, reduced methamphetamine-related drug treatment center admissions in 35%, declined the share of arrestees testing positive for methamphetamine in 55% and felony arrests for methamphetamine possession and sale fell in 50%. However, the intervention increased robberies in 17.9% and consumption was not totally interrupted because heavy consumers temporarily substituted methamphetamine with other drugs or consumed the low-quality product available in the market. Also, pre-intervention values were reached again 4 months after the intervention.

All these studies indicate a positive correlation between drug consumption and property crime. Regardless the bulk of policy advices from these studies requesting policy intervention to reduce availability of narcotics, there is not, to my knowledge, a formal model that investigates the optimal amount of drugs that the government must seize to minimize the amount of thieves in the economy. Instead, the analysis of drugs in economics has been mainly circumscribed to testing the rational addiction hypothesis proposed by Becker and Murphy, 1988. They define a good as addictive when it generates reinforcement –the more you consume an addictive good, the more you want to keep consuming it–, and tolerance –the more that you consume the good, the lower your future utility given the amount of future consumption. In the view

of Becker and Murphy, 1988, individuals are rationally addicted. This implies that in the presence of addictive goods, individuals recognize the addictive nature of the goods they consume. However, individuals still consume those goods considering their full price. In other words, individuals take into account the current and future costs of addiction to consume additive goods.

Since its publication, the model of Becker and Murphy, 1988 became the standard approach to modeling addictive processes. Some attempts have been made to study optimal drug supply control policies in the context of this model. Caulkins et al., 2001 study the optimal choice of enforcement vs treatment in an environment with a single type of drug consumer and a predetermined addiction process for the representative consumer. Their results indicate that the combination of both expenditures depends on at which phase of the addiction process the society is: if the epidemic is initiating and control begins early, it is optimal to use large amounts of enforcement and treatment to cut short the epidemic. When the epidemic is mature, it is optimal to spend more resources on treatment than on enforcement, even though both programs receive positive amounts of resources. In this paper, the government's objective is to minimize the consumption level of drugs, which is assumed to represent a fraction of the total social costs induced by drug consumption.

Even though drug addiction models do not explicitly consider the incentives of addicts to commit property crime, several lessons can be learned from these models. These lessons will be used in the next sections to incorporate the crime decisions of addicts in a model of crime. The first lesson is that the drug consumption distribution appears to be stable from cohort to cohort, at least in the U.S. and the main European Countries of which information is available³. In other words, the percentage of individuals who consume drugs tends to be constant over time in most countries where data use exists for long periods of time, such as the U.S.. Cozzi, 2006 shows that the

³See UNITED NATIONS OFFICE ON DRUGS AND CRIME, 2012b for historical data on drug use in the world.

distribution of drug initiation and drug prevalence in the U.S. for a series of years seems to overlap one on top of the others. This implies that human beings seem to replicate the same behavior with respect to drugs from cohort to cohort. Musto, 1991 argues that drug consumption is not a late 20th century phenomenon but that has been a common practice since the invention of the most consumed “illegal narcotics” of the modern times. He argues that today’s consumption and prevalence rates resemble those of the 1920’s in the U.S.. As a result, drug consumption simply follows a cyclic process where at times there are more consumers and at other times less, but the long-run proportion of drug consumers in the population tends to be stationary.

Second, the consumption of drugs seems to have three groups clearly differentiated: zero, light and heavy drug consumers. Behrens et al., 1997 study a model in which they investigate the optimal amount of prevention of light users vs treatment of heavy users during the course of a drug epidemic. In this model, the authors show the different drug consumption paths followed by consumers when they have different degrees of addiction. They emphasize the importance of controlling for this feature of addiction because heavy users are the individuals with larger propensity to engage in deviant behaviors derived from their drug consumption, which might involve property crime.

Third, low income might induce drug addicts to property crime. Blumstein et al., 2003 show how criminal careers are usually triggered by a combination of low income and heavy addiction to drugs. Leshner, 1997 shows that heavily addicted low-income users usually spend a fraction of their income to cover the subsistence level of legal goods and the remaining on narcotics. In that sense, drug consumption might force consumers to behave sub-optimally when their income does not cover their minimum drug consumption requirement. As a result, these consumers have the largest likelihood to engage in criminal activities.

Finally, all addiction models assume that initiation into drugs is exogenously given.

There are usually two alternatives used to model initiation. The first alternative is used by Becker and Murphy, 1988, who assume that consumers start a path of consumption due to a negative shock, like being laid off or losing a relative, that triggers an initial stock of consumption that affects future drug consumption decisions through a sort of “addiction function”. The other alternative is used by Behrens et al., 1997 and Caulkins et al., 2001 based on the historical paper written by Musto, 1991. They assume that drug consumption can be thought of as an epidemic, which implies that initiation might be modeled using an exogenous function that takes the number of initial *contaminated* individuals as given.

3.3 Model without a Budget Restriction for the Government

3.3.1 Preliminaries

In order to understand the problem faced by the government, a simple graphical example might help us lead the discussion, which is based on the literature summarized in section (3.2). Figure (3.1) presents four cases where increases in the drug prices generate both an increase and a decrease in property crime. Each graph presents the indirect utility function of an individual –on the y-axis–, as a function of her level of income –on the x-axis. Consequently, each point on any of the lines drawn in figure (3.1) represents the subjective optimal valuation that the individual gives to each of her feasible levels of income. Additionally, each graph presents the decision of an individual of becoming a criminal or not. In the graph, w_0 represents the income of an individual who has not yet decided to become a criminal. w_h and w_l represent the income the individual would obtain if he became a criminal or not, respectively. w_b is the expected income of engaging in criminal activities.

From this graph, several features are worth mentioning. First, w_h and w_l depend on several factors, among which the income distribution is one of their main determi-

nants. As a result, w_h can either be larger or smaller than w_l . The most relevant case for crime is the one in which w_h is larger than w_l . In this case, individuals might find it profitable to engage in criminal activities when their income is low enough to induce them to commit crime. Second, the indirect utility functions can be either positive or negative. Following the argument laid out by Cozzi, 2006, a positive indirect utility is interpreted as indicating that the individual is “happy” with the consumption level induced by her income. A negative indirect utility indicates that the individual is “unhappy” with her income level. According to the argument of Cozzi, 2006, addicts feel unhappy when they cannot afford the minimum level of drug consumption that they have accumulated throughout their lifetime. In the paper written by Cozzi, 2006, when individuals are in the negative part of their indirect utility functions, they can either engage in criminal activities or stop consuming drugs, depending on an exogenous distribution of age that determines whether an individual makes one decision or the other. In the argument of Cozzi, 2006, older individuals seem to opt out of drug consumption, whereas younger individuals tend to engage in criminal activities. However, at any point in time, the government always faces an exogenously determined proportion of individuals willing to engage in criminal activities when they have an income that makes them feel “unhappy”.

Third, the individual has a minimum income level that makes her feel “happy”. In the presence of addiction, this minimum income level is determined by the cost of the individual’s minimum drug consumption requirement bundle, which is valued at the equilibrium drug market price. Fourth, minimum drug consumption requirements usually generate that addicts value an extra dollar of income differently when this extra income falls within the happiness region than when it falls within the unhappiness region. In other words, addiction generates kinked indirect utility functions, with different slopes at the unhappiness and happiness regions. The kink point is located at the minimum income level induced by addiction. Additionally, the value of the slopes depends on the drug price and the parameters that capture the preferences for consuming drugs in the economy. It is expected that highly-addicted individuals are more subjectively affected with increases in drug prices. As a result, their minimum

income level and indirect utility slopes are more reactive to changes in the drug prices.

Fifth, if indirect utility functions are kinked and linear, individuals might either be risk-lovers, risk-neutrals or risk-averse. The type of agent the government has to handle with depends on the slope of the indirect utility function at the happiness and unhappiness regions. If the slope of the indirect utility function is larger at the happiness region, individuals become risk-lovers when their income falls within the unhappiness region. If the slope of the indirect utility function is smaller at the happiness region, individuals are risk-averse. If the slopes are the same in both regions, individuals are risk-neutrals in the entire domain of the individual's feasible income.

Finally, if indirect utility functions are kinked and linear, drug control policies that increase the equilibrium drug price have three diverging effects: it might increase, reduce, or not affect the equilibrium percentage of thieves in the economy. Figure (3.1a) presents an example where an increase in the drug price generates an increase in the crime rates. In this figure, the individual has an initial income, w_0 that is larger than the expected income obtained from criminal activities, w_b . Before intervention⁴, the individual does not engage in criminal activities because she does not find profitable doing it, ($w_0 < w_b$). After intervention, w_l falls within the unhappiness region of income. As this individual is a risk-lover at this region, an increase in the drug price makes w_b an acceptable bet for the individual. This occurs because the individual starts accepting an expected income from criminal activities larger than or equal to w_B . At this income, the individual obtains the same expected utility from engaging in criminal activities than at the sure outcome. As $w_b > w_B$, the individual becomes a criminal with increases in the drug price.

⁴Before the government increases the drug price from p_d^1 to p_d^2 in the graph.

(a) Optimal Drug Control that Increase Property Crime, $p_d^1 < p_d^2$

(b) Optimal Drug Control that do not Affect Property Crime, $p_d^1 < p_d^2$

(c) Optimal Drug Control that Reduce Property Crime, $p_d^1 < p_d^2$

(d) Optimal Drug Control that Reduce Property Crime, $p_d^1 < p_d^2$

Figure 3.1: Relationship between Property Crime, Drug Addiction, and Optimal Drug Control Policies

Figure (3.1b) presents an example where an increase in the drug price does not generate an increase in the crime rates. If agents do not find it profitable to engage in criminal activities, they will simply not engage in criminal activities. For these individuals, the economic incentives are the most important determinants of their criminal decisions. The most interesting cases are shown in figures (3.1c) and (3.1d). Figure (3.1c) presents an example where optimal drug policies result in a risk-loving individual becoming a non-criminal when she is a criminal in the first place. If the minimum income level induced by addiction changes less than the slope of the indirect utility function in the happiness region, drug control policies combined with the appropriate economic incentives for criminals reduce the crime rates of the economy. Figure (3.1d) presents an example where risk-neutral thieves becomes risk-averse non-criminals. Notice that drug control policies generate a reduction in crime when they

make individuals more risk-neutral or risk-averse. In other words, the minimum income level induced by addiction must react less to changes in the drug price than the slope of indirect utility function in the happiness region of income.

The final effect of drug control policies depend on the distribution of addiction and income in the economy. In the section (3.3.2), a model of crime is presented where individuals can endogenously decide to become criminals or not. In that economy, the government is able to reduce the availability of narcotics in the market. Given the income, drug attraction, and addiction distributions, the model studies the optimal behavior of the government to control drugs when this policy might incentivize individuals to commit crime. This subsection is concluded underlining that the answer is not a priori an easy one for at least two reasons. On the one hand, there is not a priori a reason to assume that the slope of the indirect utility function in the unhappiness region of income is larger than, equal to, or smaller than the slope of the indirect utility function in the happiness region. The model presented below shows that when individuals have lexicographic preferences for the consumption of drugs, and the same parameter captures their attraction for drugs and their addiction, individuals always have an indirect utility function with a larger slope in the happiness region than in the unhappiness region. Figure (3.1c) shows that even in this case the government can generate an increase in the drug price that reduces the crime rates of the economy. This occurs when the equilibrium drug price is large enough to make individuals become nearly risk-neutral in their entire domain of their feasible income. On the other hand, the effect of the interrelation between income, drug attraction, and addiction levels on the crime rates is not a simple one to determine. Some assumptions on this relationship are necessary in order to give a definitive answer on the effect of drug control policies on property crime.

3.3.2 The Model

Drug Demand

The literature reviewed in section (3.2) and the discussion in section (3.3.1) offer several insights to model the relationship between drug addiction and property crime. One alternative is used by Cozzi, 2006 to study how much property crime is explained by hard drug addiction in the U.S.. The model developed in this paper shares a series of methodological assumptions with the model developed by Cozzi, 2006, but it differs in the focus of the analysis. The main features of the framework used in this paper are briefly explained below.

The economy is populated by N individuals, where N is normalized to 1 for simplicity. Each individual lives one period of life. In models of drug addiction, individuals usually live for several years. As the focus of those models is on the dynamic decisions of the *same* addicts throughout their life time, it is compulsory to consider several years in the analysis. Here, the main interest is to study the optimal response of the government to a possible *structural* feature of consumption. Despite that drug addicts might make diverging decisions with respect to becoming a criminal or not throughout their life time, drug addicts' experiences seem to repeat from one cohort to the others. So, at any point in time, there is a potential similar distribution of addicts, with similar addiction levels, that can be incentivized to property crime in the same way. Should the government pursue drug supply policies that reduce the availability of drugs in the market in the presence of a stationary or structural addiction distribution in the economy?

The first attempt to answer the latter question assumes that individuals make a one-time decision. This assumption is equivalent to performing the analysis in the last period of life of a cohort who already knows their drug consumption and addiction distributions. Hence, this assumption is innocuous as far as individuals base their criminal decisions on today's optimal utility function, disregarding future arrays of utility that derives from criminal decisions. In that sense, this modeling strategy extends the model constructed by Imrohoroglu et al., 2000 by incorporating

a minimum drug consumption requirement that places consumers on an “unhappy” or “dissatisfactory” path of utility when income is below the necessary level to cover the minimum drug consumption requirement.

The model proposed in this paper is based on figure (A.9) in appendix (A.2). In this economy, individuals are heterogenous along two dimensions. Every individual i receives from nature a parameter ϵ_i that captures her preference for drugs. Following Behrens et al., 1997, there are three types of individuals in the economy: individuals with zero ($\epsilon_i = 0$), light ($\epsilon_i = \underline{\epsilon}$), and heavy ($\epsilon_i = \bar{\epsilon}$) preferences for the single (composite) drug commodity available in the market. The marginal probability density function of ϵ_i is:

$$f_{\epsilon}(\epsilon_i) = \begin{cases} n_{\epsilon_i=0} & \text{if } \epsilon_i = 0 \\ n_{\epsilon_i=\underline{\epsilon}} & \text{if } \epsilon_i = \underline{\epsilon} \\ n_{\epsilon_i=\bar{\epsilon}} = 1 - n_{\epsilon_i=\underline{\epsilon}} - n_{\epsilon_i=0} & \text{if } \epsilon_i = \bar{\epsilon} \end{cases} \quad (3.1)$$

where $n_{\epsilon_i=\bar{\epsilon}}$, $n_{\epsilon_i=\underline{\epsilon}}$, and $n_{\epsilon_i=0}$ represent the percentage of people in the economy who have heavy, light, and zero preferences for the consumption of drugs. Since this probability density function is independent of income, there are all levels of income at every preference category. This is assumed because a priori there is no evidence that support that income is a good explanatory variable for initiation into drug consumption (see Ritter and Chalmers, 2011)⁵. A more comprehensive analysis would include different specifications for the correlation between income and drug consumption. This analysis is beyond the scope of the present paper. Consequently, it is left as future research.

Every individual i also receives from nature a parameter w_i that determines her income. Income is assumed to follow a Kumaraswamy distribution, where the pdf of

⁵In the argument laid out by Becker and Murphy, 1988, income might help explain drug addiction in the economy. However, this occurs due to a inter-temporal income effect. Once individuals initiate into the consumption of drugs (which occurs due to exogenous factors such as when individuals get laid off or divorced) and are “hooked” to consuming them, income might trigger a larger addiction in the future due to the fact that rich people might spend more resources on illegal narcotics today, depending on whether these commodities are normal or inferior goods from the individuals’ perspective. However, initiation into drugs is not *per se* necessarily positively correlated with income.

this distribution is expressed as:

$$f_w(w_i) = \begin{cases} 0 & \text{if } w_i < 0 \\ \alpha_{1,w} \alpha_{2,w} \frac{w_i^{(\alpha_{1,w}-1)}}{w_{max}^{\alpha_{1,w}}} \left(1 - \left(\frac{w_i}{w_{max}}\right)^{\alpha_{1,w}}\right)^{(\alpha_{2,w}-1)} & \text{if } 0 \leq w_i \leq w_{max} \\ 0 & \text{if } w_i > w_{max} \end{cases} \quad (3.2)$$

where $\alpha_{1,w}$ and $\alpha_{2,w}$ are two parameters that help determine the skewness and kurtosis of the Kumaraswamy distribution respectively and w_{max} is the maximum income available in the economy. A good feature of using the Kumaraswamy distribution to proxy the income distribution of the economy is that there is a range of values for $\alpha_{1,w}$ and $\alpha_{2,w}$ that generate a Kumaraswamy distribution function that resembles the income distribution of real economies. The Kumaraswamy distribution function also allows to manipulate the income distribution skewness and kurtosis parametrically. These features are exploited in section (3.5) to perform numerical comparative static analysis. In appendix (A.2), figure (A.10) shows an example in which the distribution of the population is organized by income and three levels of drug addiction.

In turn, individuals can also engage in theft to supplement their final income. Following Imrohoroglu et al., 2000 and Cozzi, 2006, it is supposed that a successful thief steals from her victim a fraction of the mean income, $\eta\bar{w}$, as a customary rule, where $0 < \eta < 1$. Also, a thief finds a victim with a probability λ_r and the government captures her with a probability π_T . As a result, a thief steals $\eta\bar{w}$ with a probability $\lambda_r(1-\pi_T)$ and steals nothing with a probability $1-\lambda_r(1-\pi_T)$. In turn, a non-thief who has her income successfully stolen losses the same fraction $\eta\bar{w}$. She gets her income stolen when she encounters a thief, which occurs with a probability λ_{gr} . Consequently, a non-thief has her income successfully stolen with probability $\lambda_{gr}(1-\pi_T)$ and does not have her income successfully stolen with a probability $1-\lambda_{gr}(1-\pi_T)$ ⁶.

Given ϵ_i and w_i , each individual i solves the following problem:

⁶Thieves' actions are assumed to be non-violent. As a result, thieves perform their actions in a way that only affects non-thieves economically, without infringing on them any psychological cost by violence.

$$\begin{aligned}
\max_{c_i, d_i, Th_i} \quad & U_i = \begin{cases} \left((1 - \epsilon_i)c_i^\theta + \epsilon_i(d_i - a_\epsilon \epsilon_i)^\theta \right)^{\frac{1}{\theta}} & \text{if } I_i^j \geq p_d a_\epsilon \epsilon_i \\ \epsilon_i^{\frac{1}{\theta}} (d_i - a_\epsilon \epsilon_i) & \text{if } 0 \leq I_i^j < p_d a_\epsilon \epsilon_i \end{cases} \quad (3.3) \\
\text{s.t.} \quad & \left. \begin{aligned} I_i^0 &= w_i(1 - \tau) = c_i + p_d d_i && \text{with prob. } (1 - \lambda_r) \\ I_i^1 &= w_i(1 - \tau)(1 - f) = c_i + p_d d_i && \text{with prob. } \lambda_r \pi_T \\ I_i^2 &= w_i(1 - \tau) + \eta \bar{w} = c_i + p_d d_i && \text{with prob. } \lambda_r(1 - \pi_T) \end{aligned} \right\} && \text{if } Th_i = 1 \\
\text{s.t.} \quad & \left. \begin{aligned} I_i^0 &= w_i(1 - \tau) = c_i + p_d d_i && \text{with prob. } 1 - \lambda_{gr}(1 - \pi_T) \\ I_i^3 &= c_i + p_d d_i && \text{with prob. } \lambda_{gr}(1 - \pi_T) \end{aligned} \right\} && \text{if } Th_i = 0 \\
\text{with} \quad & I_i^3 = \begin{cases} w_i(1 - \tau) - \eta \bar{w} & \text{if } p(w_i \geq \frac{\eta \bar{w}}{(1 - \tau)}) \\ 0 & \text{if } p(w_i < \frac{\eta \bar{w}}{(1 - \tau)}) \end{cases}
\end{aligned}$$

where c_i represents the demand of individual i of the numerarie good. For simplicity, the price of the numerarie is set equal to $p_c = 1$. d_i is the drug demand of individual i . p_d is the drug price. I_i^j represents any of the *net* income levels I_i^0, I_i^1, I_i^2 and I_i^3 . τ is the income tax rate and f is the fine paid by thieves when captured, which is supposed to be a fraction of the thief's income. $a_\epsilon \epsilon_i$ represents individual i 's minimum drug consumption requirement or addiction level. a_ϵ is assumed to be equal for every individual i in the economy. As a result, the addiction level of individual i depends on her preference for the drug, ϵ_i . Th_i represents individual i 's decision of becoming a thief. If $Th_i = 1$, individual i is a thief, and her expected budget constraint is represented by the set of equations with the label $Th_i = 1$ in equation (3.3). If $Th_i = 0$, individual i is not a thief, and her expected budget constraint is represented by the set of equations with the label $Th_i = 0$ in equation (3.3). $\theta \in (0, 1)$ is the parameter of the CES function that captures the elasticity of substitution between c_i and d_i .

Notice that U_i depends on I_i^j . When I_i^j is larger than $p_d a_\epsilon \epsilon_i$, individual i 's utility is captured by a CES utility function. At this range of values for I_i^j , individual i maximizes her utility subject to any of the two sets of budget constraints of equation (3.3). Consequently, the indirect utility function of the CES function represents the happiness region of net income in figure (3.1). However, when I_i^j is below $p_d a_\epsilon \epsilon_i$, the

CES function is not defined. In this range of values for I_i^j , addicts can still consume if $I_i^j \geq 0$. However, they set their legal consumption to their subsistence level, which is 0 for the numerarie, and their remaining income is spent on drugs. As a result, a linear function that depends uniquely on the value that d_i assumes captures the unhappiness region of income. In this sense, U_i captures the argument laid out by Leshner, 1997 regarding the way low-income drug users set their drug consumption habits to their income availability. This assumption implies that individual i exhibits lexicographic preferences with respect to her net income⁷.

In turn, the valuation of individual i when she is in the unhappiness region of income depends directly on $\epsilon_i^{\frac{1}{\theta}}$. A larger ϵ_i implies a negative valuation, which occurs to those individuals with a large attraction for drugs. As a result, drug control policies might affect more to these type of individuals. Also notice that individual i 's net income is never negative. This is assumed because there is not a feasible outcome at a negative net income. Hence, if an individual has an income below $\eta\bar{w}$ and is a non-thief who gets her income stolen, she will lose her disposable income and consume at her minimum feasible consumption point, $(c_i = 0, d_i = 0)$.

Drug Supply

Equation (3.3) determines the drug demand for individual i . This equation will be used below to determine the aggregate drug demand of the economy. That task will be performed later on. Until now, nothing has been said about the drug supply side, and the income generated in this sector. As the main interest of the paper is on property crime in the presence of drug addiction, it is assumed that the economy has the following exogenous drug supply function:

$$S_T(p_d, \pi_c) = (1 - \pi_c)A_s p_d^{\sigma_s} \quad (3.4)$$

⁷It can be proven that with the lexicographic preferences assumed for the individuals of this economy, the price-elasticity of drugs demand is 1% on both the happiness and unhappiness regions of income. As a result, all the numerical results presented below are not based on the assumption that individuals exhibit a price-inelastic drugs demand –common assumption made in this literature to support strong claims about the consequences of drug policy.

where $S_T(p_d, \pi_c)$ represents the drug supply at the price p_d and the percentage of drug seized by the government's drug control policies, π_c . A_s is a productivity parameter, and σ_s is the price-elasticity of the drug supply function. It is assumed that A_s and σ_s are both exogenous parameters. The profits obtained in this industry are also assumed to belong to individuals outside of the economy. Consequently, drug supply policies affect the incentives of addicts to engage in criminal activities through the effect of π_c on the equilibrium price. That policy will be analyzed in sections (3.3.5) and (3.4.3).

3.3.3 The Solution

Before analyzing the optimal behavior of the government, it is necessary to find the solution for each individual. Equation (3.3) is the individual i 's problem. This problem applies for every individual i with an income w_i and a preference parameter ϵ_i . The preference parameter also determines the minimum level of drug consumption that the individual wants to consume, $a_\epsilon \epsilon_i$. When $\epsilon_i > 0$, individual i 's utility function is kinked at the value $a_\epsilon \epsilon_i$. As a result, individual i 's problem must be solved according to her economic capacity to reach that minimum drug consumption level. If her net income I_i^j is larger than $p_d a_\epsilon \epsilon_i$, she will be able to maximize her utility without considering the discontinuity on her utility function. Otherwise, individual i 's optimal decision involves a corner solution where $c_i = 0$, and $d_i = \frac{I_i^j}{p_d}$ for $0 \leq I_i^j \leq p_d a_\epsilon \epsilon_i$.

Then, let's initially find out the equilibrium values of c_i and d_i when $I_i^j > p_d a_\epsilon \epsilon_i$. To do that, let's take First Order Conditions (FOC) to equation (3.3) with respect to c_i and d_i , assuming a value of $I_i^j > p_d a_\epsilon \epsilon_i$. This results in the following equilibrium equations:

$$c_i(p_d; \{\epsilon_i, I_i^j\}) = \frac{((1 - \epsilon_i)p_d)^{\frac{1}{1-\theta}} [I_i^j - p_d a_\epsilon \epsilon_i]}{((1 - \epsilon_i)p_d)^{\frac{1}{1-\theta}} + \epsilon_i^{\frac{1}{1-\theta}} p_d} \quad (3.5)$$

$$d_i(p_d; \{\epsilon_i, I_i^j\}), = \frac{\epsilon_i^{\frac{1}{1-\theta}} I_i^j + ((1 - \epsilon_i)p_d)^{\frac{1}{1-\theta}} a_\epsilon \epsilon_i}{((1 - \epsilon_i)p_d)^{\frac{1}{1-\theta}} + \epsilon_i^{\frac{1}{1-\theta}} p_d} \quad (3.6)$$

Equations (3.5) and (3.6) can be used to determine the indirect utility function of each individual i given $I_i^j > p_d a_\epsilon \epsilon_i$. Performing that operation, and combining the results for the indirect utility functions encountered when $I_i^j \leq p_d a_\epsilon \epsilon_i$, the following kinked indirect utility function is obtained:

$$V_i(I_i^j, \epsilon_i) = \begin{cases} (I_i^j - p_d a_\epsilon \epsilon_i) A_0(p_d; \epsilon_i) & \text{if } I_i^j \geq p_d a_\epsilon \epsilon_i \\ (I_i^j - p_d a_\epsilon \epsilon_i) A_1(p_d; \epsilon_i) & \text{if } 0 \leq I_i^j < p_d a_\epsilon \epsilon_i \end{cases} \quad (3.7)$$

where $A_0(p_d; \epsilon_i)$ and $A_1(p_d; \epsilon_i)$ are two variables defined in equations (A.1) and (A.2) in appendix (A.2). Equation (3.7) defines an expected indirect utility function for each I_i^j , which uses the income distribution to determine the probabilities that individual i is on any of the two indirect utility functions in equation (3.7). Using the income distribution defined in equation (3.2), and the fact that I_i^j assumes the values I_i^0 , I_i^1 , I_i^2 , and I_i^3 in equation (3.3), it is possible to determine the following expected indirect utility functions, which are the expected payoffs represented at the end of the extensive-form representation tree in figure (A.9):

$$\left. \begin{array}{l} U_{1,i}^e(w_i, \epsilon_i; p_d, \tau, f) \\ U_{2,i}^e(w_i, \epsilon_i; p_d, \tau, \eta \bar{w}) \\ U_{3,i}^e(w_i, \epsilon_i; p_d, \tau) \end{array} \right\} \text{When } Th_i = 1 \quad (3.8)$$

$$\left. \begin{array}{l} U_{4,i}^e(w_i, \epsilon_i; p_d, \tau) \\ U_{5,i}^e(w_i, \epsilon_i; p_d, \tau, \eta \bar{w}) \\ U_{6,i}^e(w_i, \epsilon_i; p_d, \tau) \end{array} \right\} \text{When } Th_i = 0 \quad (3.9)$$

where each of these expected indirect utility functions are defined in equations (A.4), (A.5), (A.6), (A.7), (A.8), and (A.9) in appendix (A.2). It is clear that each $U_{j,i}^e$ depends on w_i , ϵ_i , p_d and τ , but some payoffs change according to the occupational choice of individual i . We can use these payoffs to compute the expected utilities of individual i in the two occupations to determine for which values of w_i and ϵ_i , individual i becomes a thief.

Using the matching and enforcement probabilities defined in the section (3.3.2), we can compute the following expected payoffs for individual i in each occupational choice:

$$E(Th_i = 1|w_i, \epsilon_i) = \lambda_r \left[\pi_T U_{1,i}^e + (1 - \pi_T) U_{2,i}^e \right] + (1 - \lambda_r) U_{3,i}^e \quad (3.10)$$

$$E(Th_i = 0|w_i, \epsilon_i) = \lambda_{gr} \left[\pi_T U_{4,i}^e + (1 - \pi_T) U_{5,i}^e \right] + (1 - \lambda_{gr}) U_{6,i}^e \quad (3.11)$$

As a result, individual i becomes a thief when the following condition is satisfied:

$$E(Th_i = 1|w_i, \epsilon_i) - E(Th_i = 0|w_i, \epsilon_i) > 0 \quad (3.12)$$

We can rearrange equation (3.12) in terms of w_i . To do that, we can use the fact that in equilibrium $\lambda_r + \lambda_{gr} = 1$, a condition that will be explained below in section (3.3.4). Here, we can exploit this condition to determine the percentage of thieves in the economy in terms of w_i . By doing that, equation (3.12) can be rearranged in the following way:

$$\begin{aligned} w_i &> \frac{B_1 p_d a \epsilon_i - B_2}{B_0 (1 - \tau)} = g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f) \quad \text{if } B_0 > 0 \\ w_i &\leq \frac{B_1 p_d a \epsilon_i - B_2}{B_0 (1 - \tau)} = g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f) \quad \text{if } B_0 \leq 0 \end{aligned} \quad (3.13)$$

where B_0 , B_1 and B_2 are defined in equations (A.10), (A.11), and (A.12) in appendix (A.2). Equation (3.13) defines the ranges of values of w_i for which individual i finds profitable to become a criminal, given the value of ϵ_i . This equation determines points such as point B in figures (3.1a) and (3.1c), or point J in figure (3.1c). In other words, equation (3.13) determines incomes such as w_B and $w_{B'}$ in figures (3.1a) and (3.1c) for which the individuals find profitable engaging in criminal activities. Notice that equation (3.13) defines a range of values for w_i for which individuals find profitable to engage in criminal activities depending on the sign of B_0 . If B_0 is negative, equation (3.13) determines that the poorest individuals in the economy will engage in criminal activities. If B_0 is positive, the richest individuals will engage in criminal activities. Despite that this second result is unusual, it cannot be ruled out a priori from the final equilibrium. As a result, this possibility will be considered in the analysis, regardless of the fact that in equilibrium, B_0 might never be positive.

Equation (3.13) also helps determine the equilibrium demand of drugs, which will depend on the equilibrium percentage of thieves in the economy. Before analyzing the concept of equilibrium used, it is necessary to determine individual i 's drug demand, d_i . This demand helps determine the equilibrium drug price, p_d , which affects the function $g(\epsilon_i; \dots)$ in equation (3.13). Individual i 's drug demand is also a kinked function. It will depend on the values that I_i^j assumes, which, in turn, depends on w_i and the occupational choice of the individual. Then the analysis is split to determine all segments of each individual i 's kinked drug demands. Let's start the analysis computing the expected demand of each individual i at every occupational choice, given the values of I_i^j . To attain that, we must differentiate between individual i 's consumption when I_i^j is larger than $a_\epsilon p_d \epsilon_i$ and when it is smaller. Let us call $\bar{d}_i(I_i^j)$ and $\underline{d}_i(I_i^j)$ to individual i 's drug demands when net income is larger and smaller than $a_\epsilon p_d \epsilon_i$, respectively. $\bar{d}_i(I_i^j)$ is the same as in equation (3.6), given a value for I_i^j . $\underline{d}_i(I_i^j) = \frac{I_i^j}{p_d}$. Hence, using the income distribution in equation (3.2), and the net incomes in equation (3.3), we get the following expected demand functions for each value that the net income I_i^j assumes:

$$d_i^e(I_i^0) = \bar{d}_i(I_i^0) + (\underline{d}_i(I_i^0) - \bar{d}_i(I_i^0))p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)}) \quad (3.14)$$

$$d_i^e(I_i^1) = \bar{d}_i(I_i^1) + (\underline{d}_i(I_i^1) - \bar{d}_i(I_i^1))p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)(1-f)}) \quad (3.15)$$

$$d_i^e(I_i^2) = \bar{d}_i(I_i^2) + (\underline{d}_i(I_i^2) - \bar{d}_i(I_i^2))p(w_i \leq \frac{p_d a_\epsilon \epsilon_i - \eta \bar{w}}{(1-\tau)}) \quad (3.16)$$

$$d_i^e(I_i^3) = [\bar{d}_i(I_i^3) + (\underline{d}_i(I_i^3) - \bar{d}_i(I_i^3))p(w_i \leq \frac{p_d a_\epsilon \epsilon_i + \eta \bar{w}}{(1-\tau)})]p(w_i > \frac{\eta \bar{w}}{(1-\tau)}) \quad (3.17)$$

These four expected demands apply to both occupational choices of individual i . She will be on any of these four expected demands depending on her occupational choice, the matching probabilities, and the government's intervention to stop or help her. Taking into account the latter factors, we can determine the expected drug demand of individual i according to her occupational choice in the following way:

$$D_i^e = \begin{cases} (1 - \lambda_{gr})[\pi_T d_i^e(I_i^1) + (1 - \pi_T) d_i^e(I_i^2)] + \lambda_{gr} d_i^e(I_i^0) & \text{if } Th_i = 1 \\ (1 - \lambda_{gr}(1 - \pi_T)) d_i^e(I_i^0) + \lambda_{gr}(1 - \pi_T) d_i^e(I_i^3) & \text{if } Th_i = 0 \end{cases} \quad (3.18)$$

Equation (3.18) concludes the analysis from the individual i 's perspective. Equations (3.13) and (3.18) determine the behavior of every individual i in the economy in terms of crime and drug demand. Both sets of equations, when aggregated, help determine simultaneously the equilibrium amount of thieves and drug demanded in the economy. In the next section, the equilibrium concept used to determine those values is explained.

3.3.4 Definition of Equilibrium

Figure (A.9) shows that each individual i has two decisions: an occupational choice and a consumption decision. These choices vary from individual to individual according to the values that w_i and ϵ_i assume. In aggregate, there is a pair of values for these two variables that determine the equilibrium percentage of thieves and drug demand in the economy. These equilibrium values also depend on the values that the government's control variables assume. Definition (1) clearly establishes the equilibrium conditions for this economy. To understand and construct that definition, some more structure is needed.

Equations (3.13) and (3.18) depend on the values of w_i and ϵ_i . However, ϵ_i assumes discrete values. As a result, we can compute functions that help determine the equilibrium percentage of thieves and the drug demand for each category of ϵ_i , which depend only on the income distribution. To determine these functions, we must note that equation (3.13) depends on the sign of the variable B_0 , which is defined in equation (A.10) in appendix (A.2). B_0 does not depend on w_i , but depends on ϵ_i and the government's controls, which might affect its sign. Taking the latter into account, we can construct non-linear functions for the equilibrium conditions of the percentage of thieves and drug demand that depends on the income distribution, the values of ϵ_i , and the value of B_0 in the following way:

$$N_T^{\epsilon_i} = \begin{cases} n_{\epsilon_i} \int_{g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f)}^{w_{max}} f_w(w_i) dw_i & \text{if } B_0 > 0 \\ n_{\epsilon_i} \int_0^{g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f)} f_w(w_i) dw_i & \text{if } B_0 \leq 0 \end{cases} \quad (3.19)$$

$$D_{\epsilon_i}^e = \begin{cases} n_{\epsilon_i} \left[\int_{g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f)}^{w_{max}} D_i^e(\epsilon_i | Th_i = 1) f_w(w_i) dw_i + \int_0^{g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f)} D_i^e(\epsilon_i | Th_i = 0) f_w(w_i) dw_i \right] & \text{if } B_0 > 0 \\ n_{\epsilon_i} \left[\int_0^{g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f)} D_i^e(\epsilon_i | Th_i = 1) f_w(w_i) dw_i + \int_{g(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f)}^{w_{max}} D_i^e(\epsilon_i | Th_i = 0) f_w(w_i) dw_i \right] & \text{if } B_0 \leq 0 \end{cases} \quad (3.20)$$

$\forall \epsilon_i = \{0, \underline{\epsilon}, \bar{\epsilon}\}$, and $n_{\epsilon_i} = \{n_{\epsilon_i=0}, n_{\epsilon_i=\underline{\epsilon}}, n_{\epsilon_i=\bar{\epsilon}}\}$. Equation (3.19) indicates the percentage of individuals with a preference parameter ϵ_i that finds profitable engaging in theft. Equation (3.20) shows the drug aggregate demand for all individuals who have a preference parameter ϵ_i , regardless of their occupational choice. These two equations will help determine the equilibrium values below. We can now formally state the equilibrium conditions for the economy:

Definition 1 *Given a set of values for the exogenous parameters $\{\theta, a_\epsilon, A_s, \sigma_s, \eta\}^8 \in \mathfrak{R}_+^5$ and for the government's controls $\{\pi_c, \pi_T, f, \tau\} \in [0, 1]$, a Nash Equilibrium for equation (3.3) consists of a drug price, $p_d(\pi_c, \pi_T, f, \tau | \rho, a_\epsilon, A_s, \sigma_s, \eta) \geq 0$, and a percentage of thieves, $N_T(\pi_c, \pi_T, f, \tau | \rho, a_\epsilon, A_s, \sigma_s, \eta)$, that solve the following equations simultaneously:*

$$N_T(p_d, \pi_T, \tau, \eta \bar{w}, f) = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} N_T^{\epsilon_i}(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f) \quad (3.21)$$

$$D_T(p_d, \pi_T, \tau, \eta \bar{w}, f) = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} D_{\epsilon_i}^e(\epsilon_i; \lambda_{gr}, p_d, \pi_T, \tau, \eta \bar{w}, f) = S_T(p_d, \pi_c) \quad (3.22)$$

$$\lambda_{gr} = \frac{N_T}{N} \quad (3.23)$$

$$\lambda_r = \frac{N_{NT}}{N} \quad (3.24)$$

$$\frac{N_{NT}}{N} + \frac{N_T}{N} = N = 1 = \lambda_r + \lambda_{gr} \quad (3.25)$$

⁸I could include among the exogenous parameters those for the distribution functions in equations (3.1) and (3.2). For the sake of exposition, they are taken as part of the distributions. As a result, those parameters are implied when the distributions are used in the computation of the equilibrium.

where $N_T^{\epsilon_i}$ and $D_{\epsilon_i}^e$ are defined in equations (3.19) and (3.20) respectively, and $S_T(p_d, \pi_c)$ is the drug supply function defined in equation (3.4).

Two points are worth noting in Definition (1). First, equations (3.23) and (3.24) define the equilibrium conditions for the matching technologies. Equations (3.23) indicates that, in equilibrium, a non-thief i 's probability of having her property stolen must be equal to the percentage of thieves in the economy. Equations (3.23) says that a thief i 's probability of stealing must be equal to the percentage of non-thieves in the economy. Taken together, the latter functional forms are model-specific and do not respond to an ad hoc specification. In turn, equation (3.25) imposes the condition that the percentage of thieves plus the percentage of non-thieves must be equal to one, which implies that the matching probabilities must also sum up 1 in equilibrium, $\lambda_{gr} + \lambda_r = 1$. This condition was used in section (3.3.3) to determine equation (3.13). This latter equation gives rise to equations (3.19) and (3.20), which are used to determine the equilibrium percentage of thieves, N_T , in equation (3.21). As a result, the equilibrium conditions of N_T and p_d can be determined using only equations (3.21) and (3.22), subject to $\lambda_{gr} = N_T$ and given the values for the exogenous parameters and the government's control variables. N_T and p_d can be used to determine D_T and S_T , and the values for $N_T^{\epsilon_i}$ and $D_{\epsilon_i}^e$, $\forall \epsilon_i = \{0, \underline{\epsilon}, \bar{\epsilon}\}$.

Second, as the model has either time or a dynamic sequence of movements, the equilibrium solution is a simple Nash Equilibrium. This equilibrium concept determines that we must find a pair of values for N_T and p_d , contingent on every possible value of the government's control variables, $\{\pi_T, \pi_c, \tau, f\}$, and the exogenous variables of the model, $\{\theta, a_\epsilon, A_s, \sigma_s, \eta\}$. See Fudenberg and Tirole, 1991 for a thorough analysis of this equilibrium concept. The results are presented in the next section. As the set of equations defined by equations (3.21) and (3.22) are highly non-linear, numerical methods are used to determine the solution. For the sake of exposition, the analysis of the results will extensively make use of figures to understand the equilibria, without formal proofs of the results presented.

3.3.5 Results

Definition (1) determines the conditions under which an equilibrium for N_T and p_d is reached. This definition does not impose any restriction for the government. Hence, there is a pair of equilibrium values, (N_T, p_d) , per each value of $\{\pi_T, \pi_c, \tau, f\}$ in their respective domains. To determine the final output, we must analyze each of its components. Section (3.3.5) analyzes the equilibrium condition in equation (3.21), and section (3.3.5) does it for the equilibrium condition in equation (3.22). As these equations define a system of non-linear equations, numerical methods were needed to reach the solution. To compute the equilibria, values for the exogenous parameters were assumed, which are presented in table (A.1) in appendix (A.2). From now on, any numerical result will be based on these values, unless otherwise indicated.

Before entering into the numerical analysis, two important results are presented. These results are based on the discussion presented in section (3.3.1), and will help understand the numerical results obtained in the following sections. The first result is associated to the slopes of the indirect utility function in the happiness and unhappiness regions found in section (3.3.1). Equation (3.7) presents the indirect utility function for each individual in the economy. In this equation, the happiness and unhappiness regions are determined by the net income. When I_i^j is larger than the value of the minimum drug consumption requirement, $p_d a_{\epsilon i}$, individuals feel happy with their income level. When I_i^j is smaller, individuals feel unhappy. If an individual i is not attracted to drugs so that $\epsilon_i = 0$, she will never be unhappy, and always be risk-neutral. Based on equation (3.7), the following proposition is obtained:

Proposition 1 *If individuals in the economy have the utility function defined by the lexicographic preferences in equation (3.3), the indirect utility function found in equation (3.7) for the unhappiness region will always have a smaller slope than the indirect utility function found in equation (3.7) for the happiness region.*

Proposition (1) provides with a very useful result. It states that when individuals exhibit lexicographic preferences of the type defined in equation (3.3), the government

will always face risk-lover individuals with an unhappiness region increasing with the equilibrium drug price. Proposition (1) can be proved very easily comparing the value of $A_0(p_d; \epsilon_i)$ with the value of $A_1(p_d; \epsilon_i)$, which are the slopes of the indirect utility functions found in equation (3.7). These two variables are defined in equations (A.1) and (A.2) in appendix (A.2). Performing basic algebra, it is seen that $A_0(p_d; \epsilon_i) > A_1(p_d; \epsilon_i) \forall \epsilon_i < 1$ and $p_d > 0$. Another important result associated to the slopes of the indirect utility functions is the following:

Proposition 2 *If individuals have the indirect utility function defined by equation (3.7), the following result holds $\forall \epsilon_i \in [0, 1)$ and $p_d > 0$:*

$$\frac{\delta A_0(p_d; \epsilon_i)}{\delta p_d} < \frac{\delta A_1(p_d; \epsilon_i)}{\delta p_d} \quad (3.26)$$

Proposition (2) states that when individual exhibits the utility function defined in equation (3.3), the slope of the indirect function defined in the unhappiness region will change faster with changes in p_d than the slope of the indirect function defined in the happiness region. As a result, drug control policies will never be able to incentivize individuals to become either risk-neutral or risk-averse individuals when they have the preferences defined in equation (3.3).

Proposition (2) presents an important result because it says that the numerical results found in the following sections are based on the decision of risk-lovers. Given the preferences defined in equation (3.3), should the government optimally control the availability of narcotics in the markets? The following sections present numerical examples where the answer is no. In the next section, it is analyzed numerically the existence of an equilibrium crime rate given a fixed value for the drug price, p_d . In the next one, it is analyzed numerically the existence of an equilibrium drug price, given a fixed value for the crime rate, N_T .

Multiple Equilibria

Equation (3.21) defines the equilibrium condition for N_T . This equation depends on both endogenous variables, p_d and $N_T = \lambda_{gr}$. As a result, the solution to this

equation involves a fixed-point for N_T , for every value of p_d and the government's control variables. See Stokey and Lucas, 1989 for a formal analysis of fixed-point problems and their solutions. Given that equation (3.21) satisfies the conditions for having at least a fixed-point solution for N_T , the following result is stated:

Result 1 *Given a set of values for the exogenous parameters $\{\theta, a_\epsilon, A_s, \sigma_s, \eta\} \in \mathbb{R}_+^5$ and for the government's controls $\{\pi_c, \pi_T, f, \tau\} \in [0, 1]$, there are two equilibrium values $N_T^1(p_d, \pi_c, \pi_T, f, \tau)$ and $N_T^2(p_d, \pi_c, \pi_T, f, \tau)$ for the total percentage of thieves that make equation (3.21) be in equilibrium, per value of the drug price, p_d . Additionally, these two values satisfy the following conditions:*

$$1. N_T^1(p_d, \pi_c, \pi_T, f, \tau) < N_T^2(p_d, \pi_c, \pi_T, f, \tau) \quad \forall \{\pi_c, \pi_T, f, \tau\} \in [0, 1] \quad \text{and } p_d \in \mathbb{R}_+.$$

$$2. \frac{\delta N_T^1(p_d, \pi_c, \pi_T, f, \tau)}{\delta p_d} > 0 \quad \text{and} \quad \frac{\delta N_T^2(p_d, \pi_c, \pi_T, f, \tau)}{\delta p_d} < 0.$$

$$3. \frac{\delta N_T^1(p_d, \pi_c, \pi_T, f, \tau)}{\delta \pi_c} = \frac{\delta N_T^1(p_d, \pi_c, \pi_T, f, \tau)}{\delta p_d} \frac{\delta p_d}{\delta \pi_c} \quad \text{and} \quad \frac{\delta N_T^2(p_d, \pi_c, \pi_T, f, \tau)}{\delta \pi_c} = \frac{\delta N_T^2(p_d, \pi_c, \pi_T, f, \tau)}{\delta p_d} \frac{\delta p_d}{\delta \pi_c}.$$

$$4. \exists \underline{\pi}_T(p_d, f, \tau) \in [0, 1] \mid \forall \pi_T \in [0, \underline{\pi}_T(p_d, f, \tau)]:$$

$$N_T^1(p_d, \pi_c, \pi_T, f, \tau) = \overline{N}_T^1(p_d, \pi_c, \underline{\pi}_T(p_d, f, \tau), f, \tau) \quad \text{and},$$

$$N_T^2(p_d, \pi_c, \pi_T, f, \tau) = \underline{N}_T^2(p_d, \pi_c, \underline{\pi}_T(p_d, f, \tau), f, \tau).$$

Instead of providing a formal proof of Result (1), a graphical exposition is used to exemplify its results. Figure (A.11) depicts equation (3.21) along the π_T and N_T dimensions, for $p_d \in \{1, 3\}$. Figure (A.11) also depicts the values of N_T for which equation (3.21) is in equilibrium, which occurs when both sides of the equation are equal. If we redefine equation (3.21) as a non-linear equation in two unknowns, the redefined non-linear function is in equilibrium when it crosses the zero plane at the $\{N_T, \pi_T\}$ space. The equilibria stated in Result (1) is represented by points a and b in figure (A.11). At these two points, there are two values of N_T that make both

sides of equation (3.21) equal, given the specific values of π_T , τ , and f . Figure (A.11) also shows that there is a pair of values for N_T that makes equation (3.21) be in equilibrium, for every value of π_T and p_d .

The values represented by points a and b in figure (A.11) also show the result in Numeral 1 in Result (1). In other words, if point a represents N_T^1 and b represents N_T^2 in Result (1), it is clear that $N_T^2 > N_T^1$. This is also true for every value that connects a and b along the zero plane on the $\{N_T, \pi_T\}$ space for different values of π_T . Figure (A.12) in appendix (A.2) replicates selected layers of figure (A.11) for different values of π_T and p_d . In this graph, the result of Numeral 1 in Result (1) is more evident. There are two values of N_T that makes equation (3.21) be in equilibrium. These two numbers are always apart, being the solutions at the right-hand side of point b in figure (A.12) always larger than the solutions at the left-hand side of point a in the same figure. Consequently, Numeral 1 in Result (1) enables us to define N_T^1 as the low-(value) equilibrium and N_T^2 as the high-(value) equilibrium for the total percentage of thieves or total criminal rates.

The results of Numeral 2 and 4 in Result (1) are also evident in figure (A.12). Numeral 2 states that when p_d increases, the low equilibrium increases and the high equilibrium decreases. As a result, a variation in the drug price generates divergent effects on the criminals rates at these two equilibria. Numeral 4 states that there is a *lower* bound for π_T that generates an *upper* bound for the low equilibrium criminal rate, $\overline{N}_T^1$, and a *lower* bound for the high equilibrium criminal rate, $\underline{N}_T^2$. The lower bound $\underline{\pi}_T(p_d, f, \tau)$ depends on the values of $\{f, \tau\}$ and the drug price, p_d . Hence, there will be one $\underline{\pi}_T$ for every equilibrium drug price and values of $\{f, \tau\}$. These two results are shown in figure (A.12). The graph shows 6 layers that are scattered in pairs. Each pair represents the redefined non-linear function of equation (3.21) for a value of π_T and two values for the drug price, $p_d \in \{1, 3\}$. In this graph, it is clear that an increase in price from 1 to 3 generates a marginal increase in N_T^1 and an almost negligible decrease in N_T^2 . The graph also shows the upper and lower bounds to which N_T^1 and N_T^2 tend with increases in π_T and p_d .

Notice that equation (3.21) does not directly depend on the value of π_c . Hence, the effect of π_c will be captured through its effect on the drug price, which increases the cost of the drug consumption bundle for the consumers. Hence, another important result that can be derived from equation (3.21) is stated in Numeral 3 in Result (1). The effect of drug control policies on crime rates depends on the effect of these policies on the equilibrium price. Given Numeral 2 in Result (1), if $\frac{\delta p_d}{\delta \pi_c} > 0$, $\frac{\delta N_T^1(p_d, \pi_c, \pi_T, f, \tau)}{\delta \pi_c} > 0$ and $\frac{\delta N_T^2(p_d, \pi_c, \pi_T, f, \tau)}{\delta \pi_c} < 0$, and the opposite otherwise. This result is important because it will help explain the effects of π_c studied in section (3.4).

Equilibrium Drug Demands and Prices

To determine the full equilibrium of p_d and N_T , the optimal behavior of equation (3.22) needs to be considered. Equation (3.22) determines a common clearing market condition for the drug market. In this equation, the most interesting function to analyze is the drug demand function, because the drug supply is exogenously given by equation (3.4). The following result arises from equation (3.22):

Result 2 *Given a set of values for the exogenous parameters $\{\theta, a_\epsilon, A_s, \sigma_s, \eta\} \in \mathbb{R}_+^5$ and for the government's controls $\{\pi_c, \pi_T, f, \tau\} \in [0, 1]$, there is at least a drug price, p_d^* , that makes equation (3.22) be in equilibrium per value of the crime rate, N_T .*

Result (2) helps assure that there is at least an equilibrium price for the system of equations defined by equations (3.21) and (3.22), per value of N_T . Yet, the result does not say anything about p_d^* being the price that determines both criminal rates found in Result (1), $\{N_T^1, N_T^2\}$. Then, the equilibrium values to determine are those that satisfy both Results.

Figure (A.13) in appendix (A.2) shows an aggregate drug demand along the dimensions of π_T and N_T . The graph shows that there is one value for the aggregate drug demand per value π_T and N_T . As a result, as the drug supply is not affected by either π_T , f or τ , there will be a drug supply that crosses at a single point the demand for drugs at every value of N_T . This is true for any combination of π_T and N_T . Our

task is now to find those values that clear equations (3.21) and (3.22) simultaneously. This is performed in the next section.

Unrestricted Optimal Drug Supply Control

Taking into account the results of sections (3.3.5) and (3.3.5), the final equilibria for p_d and N_T can be computed. Using the Results (1) and (2), the following result is obtained:

Result 3 *Given a set of values for the exogenous parameters $\{\theta, a_\epsilon, A_s, \sigma_s, \eta\} \in \mathfrak{R}_+^5$ and for the government's controls $\{\pi_c, \pi_T, f, \tau\} \in [0, 1]$, there is a equilibrium drug price, p_d^* , and a pair of crime rates $\{N_T^1, N_T^2\}$ such that the following two conditions are simultaneously satisfy:*

$$N_T^1(p_d^*, \pi_T, \tau, f) \equiv \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} N_T^{\epsilon_i}(\epsilon_i; N_T^1, p_d^*, \pi_T, \tau, f) \quad (3.27)$$

$$N_T^2(p_d^*, \pi_T, \tau, f) \equiv \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} N_T^{\epsilon_i}(\epsilon_i; N_T^2, p_d^*, \pi_T, \tau, f) \quad (3.28)$$

$$D_T(p_d^*, \pi_T, \tau, f) = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} D_{\epsilon_i}^e(\epsilon_i; N_T^1, p_d^*, \pi_T, \tau, f) \equiv S_T(p_d^*, \pi_c) \quad (3.29)$$

$$D_T(p_d^*, \pi_T, \tau, f) = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} D_{\epsilon_i}^e(\epsilon_i; N_T^2, p_d^*, \pi_T, \tau, f) \equiv S_T(p_d^*, \pi_c) \quad (3.30)$$

Result (3) indicates that there is an equilibrium price, p_d^* , for every pair of equilibrium values for the crime rates, N_T^1 and N_T^2 , that clears equation (3.21). Additionally, it also indicates that either crime rate, N_T^1 or N_T^2 , can be used to determine the equilibrium price, p_d^* , that clears equation (3.22). Notice that Result (3) does not say anything about the properties of these equilibrium values, especially for the case of π_c . The reason is that it is not always clear-cut how to sign the derivatives of these equilibrium equations with respect to their arguments without having an explicit function for computing the derivatives.

However, the effects of π_c can be studied numerically. Figure (A.14) presents an example for the equilibrium values for N_T , (N_T^1, N_T^2) , for all values of π_c and π_T in

the $[0, 1]$ interval, given fixed values for the other control variables of the government, $\{\tau = 0.07, f = 0.20\}$. The graph shows that the low crime rate, N_T^1 , decreases with larger values of π_T , and the high crime rate, N_T^2 , increases with π_T . In the figure, it is also shown the upper and lower bounds for the values of N_T found in Result (1). It is clear that N_T^2 is *not a common outcome* of real life economies. It is unclear under which conditions an equilibrium of this type arises. However, N_T^1 appears to be the type of equilibrium of real economies. From now on, the results will be analyzed only for the low crime rate, N_T^1 .

In turn, the effect of π_c on N_T^1 is unclear in figure (A.14). There are two factors for this result: on the one hand, it seems as the graph does not show a change in the crime rate with increases in π_c . This is due to the scale of the changes. As the effect of π_c on the crime rates is through the drug price, changes in p_d generate small changes in N_T . When these changes are depicted in a single graph, their effects almost disappear. On the other hand, the increase in π_c does not always generate an increase in the percentage of thieves in the economy. A priori, an increase in π_c might have diverging effects on the crime rates due to its effects on the equilibrium drug price as was discussed in section (3.3.1). Figure (A.15) shows another instance in which drug control policies might reduce the crime rates of the economy. The discussion laid out in section (3.3.1) might help understand this result. In this economy, when individuals are on the happiness or unhappiness regions of their linear indirect utility function, they compare the expected incomes of becoming a criminal or not disregarding their addiction levels. The only factor that matters is the probability that both *lottery* outcomes are within the same region. In this case, the expected income of becoming a criminal is larger than the expected income from becoming a non-criminal for the individuals who have the following income:

$$w_i < \frac{\eta\bar{w}(1 - \pi_T)(\lambda_r - \lambda_{gr})}{(1 - \tau)\lambda_r\pi_T f} \quad (3.31)$$

This value increases with $\eta\bar{w}$, τ , and the number of non-criminals, λ_r , and decreases with the other factors. If λ_r is low, this bound might also be low, depending on the

values of f , π_T and τ . This bound does not directly depend on the value of p_d . Hence, drug control policies do not affect directly the decisions of individuals in this case. When the outcomes of becoming a criminal or not do not fall within the same income regions in figure (3.1), equation (3.31) does not apply any more. I computed an equivalent bound for an income level w_i given a value of ϵ_i in equation (3.13). The sign of the change of this equation with respect to their arguments cannot be determined as easily as for the case of equation (3.31). However, equation (3.13) shows two very interesting results. On the one hand, this equation depends on the value that p_d assumes. That was not the case for equation (3.31). As a result, drug control policies affect directly the economic incentives of criminal activities in the total equilibrium. On the other hand, it can be proven from equation (3.13) that the effect of changes in the drug price might have diverging effects on the economic incentives of addicts to engage in criminal activities. The sign of the derivative of the right-hand side of equation (3.13) will depend on how much this function react to changes in $a_\epsilon \epsilon_i p_d^9$. If this change is large when p_d changes, individuals will be incentivized to crime even though the economic revenue from criminal activities is not very large. This is especially true for highly-addicted individuals.

Figure (A.15) plots N_T^1 in terms of π_c , divided by groups of addiction. The graph shows that increases in the drug control rate, π_c , lead all three categories to increase their crime rates. However, there is a sufficiently high value of π_c that leads *lightly-addicted* individuals to reduce their criminal rates, while highly addicted individuals increase their rates to their highest, per value of f and τ . The total outcome is a compounded rate composed of the reactions of all three categories.

From figure (A.15), three comments are in order: first, despite that there are some values of π_c for which lightly-addicted individuals might decrease their crime rates,

⁹In fact, the derivative of the right-hand side of equation (3.13) with respect to p_d is positive if the following condition is satisfied:

$$p_d a_\epsilon \epsilon_i > \frac{B_0(\frac{\delta B_2}{\delta p_d}) - B_2(\frac{\delta B_0}{\delta p_d}) - B_0 B_1 a_\epsilon \epsilon_i}{B_0(\frac{\delta B_1}{\delta p_d}) - B_1(\frac{\delta B_0}{\delta p_d})}$$

the case depicted in figure (A.15b) is just a special case for the effect of π_c on N_T . In general, all types of addicts tend to increase their crime rates with increases in π_c . At least, that is true for the numerical example presented in this paper. Second, individuals with zero addiction also increase their crime rates with increases in π_c . A priori, these individuals are not directly affected by the drug supply control policy. However, this policy directly affects the other two categories, especially the heavily-addicted individuals. The reaction of individuals with zero addiction to increases in the percentage of thieves in the other two categories of addiction is also to increase their crime rates. This is a feature of the crime model laid out in equation (3.3). The crime rate presents inertia because individuals find profitable engaging in criminal activities when many other individuals are also performing these activities. Finally, it is notorious in figures (A.14) and (A.15) that a $\pi_c > 0$ always increases the crime rates relative to $\pi_c = 0$. In other words, the government *always* increases the crime rates with a marginal increase in π_c , from $\pi_c = 0$ to $\pi_c > 0$. This is true even for the case $\pi_c = 1$. The latter gives rise to the following result:

Results 4 *Let $N_T^1(\pi_c, \pi_T, \tau, f)$ and $p_d^*(\pi_c, \pi_T, \tau, f)$ represent the equilibrium values that solve equations (3.21) and (3.22), respectively. If the objective of the government is to reduce the total percentage of thieves in the economy, $N_T^1(\pi_c, \pi_T, \tau, f)$, not subject to a budget constraint, there is a $\bar{\pi}_T(\pi_c, \tau, f) \in [0, 1]$ such that, $\forall \pi_T \geq \bar{\pi}_T$, and $\forall \{\tau, f\} \in [0, 1]$, N_T^1 reaches a minimum value of zero at $\pi_c = 0$.*

Result (4) determines the government's optimal behavior in terms of the drug supply control policy, π_c . It states that, if the government aims to reduce the percentage of thieves in the economy, the best strategy is to spend all its resources on capturing thieves and not on controlling drugs. The reason can be extracted from Result (4) and figure (A.15). If the government's actions increase the economic incentives of addicts to engage in criminal activities, the best strategy for the government is to maintain those incentives at their minimum levels. That occurs when $\pi_c = 0$.

The latter intuition is numerically confirmed in figure (A.16). The graph depicts a set of layers for the optimal low crime rate, N_T^1 , along the dimensions of π_T and π_c , for several values of f and τ . The graph shows several features already commented: first, there is a $\bar{\pi}_T(\pi_c, \tau, f)$ for each of these layers such that the minimum value for N_T^1 is reached at $\pi_c = 0$. Those minimum points are shown by *Min Point* in figure (A.16). Second, the special cases depicted in figure (A.15) are represented by the Area A in figure (A.16). It is clear that there are some values of f and τ for which a high value of π_c generates a decrease in the percentage of lightly-addicted thieves. However, the graph also shows that those points are special cases. In fact, there is a maximum point for N_T^1 at the points $\pi_c = 1$ and $\pi_T = 0$, $\forall \{f, \tau\} \in (0, 1]$. In order words, the maximum percentage of thieves is reached, for all values of f and τ in the $(0, 1]$ interval, when the government spends all its resources in controlling the supply of narcotics, and nothing on capturing thieves. At these points, all categories of addiction have the largest possible crime rates.

The latter occurs because the equilibrium price is not large enough to induce individuals to become non-criminals with drug control policies¹⁰. A final result for this section is shown in figure (A.17). This graph shows the drug equilibrium prices, p_d , along the π_T and π_c dimensions, for the same values of f and τ as in figure (A.16). It also shows the equilibrium prices when the high crime rate, N_T^2 , is considered for the same values of the government's control variables. The graph shows that these two sets of equilibrium price values are very similar for both equilibrium crime rates. This was expected from Result (2). As there is a single value of p_d for every pair of equilibrium crime rates, (N_T^1, N_T^2) , the equilibrium prices for both crime rates are the same. The graph also shows that π_c affects more the equilibrium price than π_T . That was also expected because π_c affects directly the availability of drugs in the market, whereas π_T only imposes the costs to criminal activities, without directly

¹⁰This result might be partially to the assumption that individuals in this economy follow a CES utility function, which implies that the price-elasticity of drug demand is 1%. The exploration of a more general utility function that captures a more general price-elasticity of drug demand is needed to determine the extend to which this result depends on the CES utility function. That task is left for future research.

influencing the results in the drug market. Notice that the largest equilibrium price value depicted in figure (A.17) is around 2.7. This value is small relative to the needed price to induce addicts to become more risk-neutral, as was argued in section (3.3.1). The needed price value for the numerical values of the exogenous parameters assumed in this paper is larger than 3.5.

3.4 Model with a Budget Restriction for the Government

Result (4) secures an equilibrium outcome for the government in terms of π_T and π_c , for every value of f and τ . However, governments are usually not free to spend all what they want, on what they want as they have budgets constraints. That is why it is introduced the government's budget in this section to determine its optimal drug policy in the presence of a budget.

3.4.1 The Model: The Budget Constraint of the Government

In order to determine the optimal behavior of the government subject to a budget constraint, some more structure is needed. Several assumptions are made for this purpose. First, it is assumed that the government has the following functional forms for the enforcement variables:

$$\pi_T = \frac{a_T r_T}{1 + a_T r_T} \quad (3.32)$$

$$\pi_c = \frac{a_c r_c}{1 + a_c r_c} \quad (3.33)$$

where equations (3.32) and (3.33) are known as predatory functions or functional responses in Ecology. These functions are also used in the economics of crime to model the predation activities of the government. For an example in the use of these functions, see Mejia, 2008 who uses an alternative functional form to determine the interdiction policies of the Colombian government in its war against narcotics. r_T

and r_c are the amount of resources spent by the government on capturing thieves and drugs respectively. a_T and a_c capture the productivity of these predatory functions. Larger values of a_T and a_c imply that the government is more effective at capturing thieves and drugs, respectively, for the same levels of expenditure, r_T and r_c . In this setup, π_c can be interpreted as a tax if positive and a subsidy if negative. The reason is that π_c acts as an indirect tax that captures a percentage of drugs in the market. A $\pi_c > 0$ indicates that the government must *seize* a percentage of drugs. A $\pi_c < 0$ indicates that the government must *increase* the availability of drugs in π_c %.

I also assume that thieves or drug consumers face fines but no jail time. When the government captures a thief, it charges a fine f to her, which is a percentage of the thief's income. I also assume that the government uses the income of the fines, apart from the income raised from income taxes, to finance its expenditure on r_T and r_c . Given these assumptions, the government's budget constraint can be expressed in the following way:

$$r_T + r_c = \tau \bar{w} + (1 - \tau)f(1 - \lambda_{gr}) \left[\sum_{\epsilon_i = \{0, \underline{\epsilon}, \bar{\epsilon}\}} n_{\epsilon_i} \bar{w}_T(\epsilon_i) \right] \quad (3.34)$$

where,

$$\begin{aligned} \bar{w}_T(\epsilon_i) &= \int_{g(\epsilon_i; \dots)}^{w_{max}} w_i f_w(w_i) \quad \text{if } B_0 > 0 \\ \bar{w}_T(\epsilon_i) &= \int_{g(\epsilon_i; \dots)}^{w_{max}} w_i f_w(w_i) \quad \text{if } B_0 \leq 0 \end{aligned} \quad (3.35)$$

Equation (3.35) represents the mean income of thieves with a drug preference parameter of ϵ_i . This function also depends on the value of B_0 , as the set of indirect utility functions in equation (3.7). Equation (3.34) implies that the government's budget constrain depend on an income tax, $\tau \bar{w}$, charged to all individuals in the economy, regardless of their occupational choice. Equation (3.34) also depends on the expected income obtained by the government from fines charged on thieves when captured. This expected income depends on the thieves' income, net of what the government charges for income tax.

Taking into account this budget constraint, the government's minimization problem can be expressed in the following way¹¹:

$$\min_{\{\pi_c, \pi_T, f, \tau\}} \quad \alpha_T N_T^*(\pi_c, \pi_T, f, \tau) + (1 - \alpha_T)[r_T + r_c] \quad (3.36)$$

$$\text{s.t} \quad r_T + r_c = \tau \bar{w} + (1 - \tau)f(1 - \lambda_{gr}) \left[\sum_{\epsilon_i = \{0, \underline{\epsilon}, \bar{\epsilon}\}} n_{\epsilon_i} \bar{w}_T(\epsilon_i) \right] \quad (3.37)$$

Equation (3.36) represents the government's objective function. This function is composed of the optimal total percentage of thieves, given the values of the government's control variables, and the amount of resources spent on enforcement activities. α_T is an exogenous parameter in the $[0, 1]$ interval. This parameter captures the ponderation that the government gives to controlling thieves. Figures (A.18) and (A.19) show examples of equations (3.36) and (3.37). Three points are worth noting here: first, the government is able to obtain more relaxed budget constraints with increases f and τ . This implies that the government is able to reach larger values of both π_c and π_T with increments in f and τ . Second, the budget constraint is defined for all possible values of N_T , among which the equilibrium values are also counted. Figure (A.18) shows the budget constraints using the low crime rate found in Result (1), N_T^1 . The graph shows that the projections of the budget constraint onto the N_T^1 space decrease with increments in f . Thus, the government accomplishes two objectives increasing f : the government is able to reach larger values for both enforcement technologies, and the equilibrium crime rates are smaller.

Finally, figure (A.19) shows the government's maximization problem for three budget constraints, and for a ponderation $\alpha_T = 0.5$ in its objective function. On the graph, it is clear that there is a region generated by large values of π_T and small values of π_c for which this function appears to have a minimum. However, that minimum seems not be the point found in Result (4). Before analyzing the equilibrium values obtained, the following section introduces the definition of equilibrium when the government is subject to a budget constraint.

¹¹An alternative government's objective function might involve maximizing a social welfare function. No attempt is made to perform such an exercise.

3.4.2 Definition of Equilibrium

When the budget constraint for the government is introduced, Definition (1) does not apply any longer. Using the budget constraint defined in equation (3.34) and the objective function defined in equation (3.36), the new definition of the equilibrium is:

Definition 2 *Given a set of values for the exogenous parameters $\{\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T\} \in \mathbb{R}_+^8$, a Nash Equilibrium for equations (3.3) and (3.36) consists of a drug price, $p_d^*(\pi_c^*, \pi_T^*, f^*, \tau^*) \geq 0$, a percentage of thieves, $N_T^*(\pi_c^*, \pi_T^*, f^*, \tau^*)$, and the government's optimal controls, $\{\pi_c^*, \pi_T^*, f^*, \tau^*\}$, that solve the following equations simultaneously:*

$$N_T(p_d^*, \pi_T^*, \tau^*, f^*) = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} N_T^{\epsilon_i}(\epsilon_i; \lambda_{gr}, p_d^*, \pi_T^*, \tau^*, f^*) \quad (3.38)$$

$$D_T(p_d^*, \pi_T^*, \tau^*, f^*) = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} D_{\epsilon_i}^e(\epsilon_i; \lambda_{gr}, p_d^*, \pi_T^*, \tau^*, f^*) = S_T(p_d^*, \pi_c^*) \quad (3.39)$$

$$\lambda_{gr} = \frac{N_T}{N} \quad (3.40)$$

$$\lambda_r = \frac{N_{NT}}{N} \quad (3.41)$$

$$\frac{N_{NT}}{N} + \frac{N_T}{N} = N = 1 = \lambda_r + \lambda_{gr} \quad (3.42)$$

$$r_T(\pi_T^*) + r_c(\pi_c^*) = \tau \bar{w} + (1 - \tau^*) f^* (1 - \lambda_{gr}) \left[\sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} n_{\epsilon_i} \bar{w}_T(\epsilon_i; \pi_c^*, \pi_T^*, f^*, \tau^*) \right] \quad (3.43)$$

$$\{\pi_c^*, \pi_T^*, f^*, \tau^*\} \in \operatorname{argmin} \{ \alpha_T N_T^*(\pi_c^*, \pi_T^*, \tau^*, f^*) + (1 - \alpha_T) [r_T(\pi_T^*) + r_c(\pi_c^*)] \} \quad (3.44)$$

where $N_T^{\epsilon_i}$ and $D_{\epsilon_i}^e$ are defined in equations (3.19) and (3.20) respectively, and $S_T(p_d, \pi_c)$ is the drug supply function defined equation (3.4). $r_T(\pi_T^*; a_T)$ and $r_c(\pi_c^*; a_c)$ are two functions derived from equations (3.32) and (3.33), respectively.

Equations (3.38) to (3.42) in Definition (2) are equivalent to those encountered in Definition (1). The additional restrictions are those related to the government's values. It is now required that the government's control variables are in equilibrium. That equilibrium is defined by a set of values for π_c , π_T , f , and τ that minimizes the government's objective function defined in equation (3.36), subject to the balanced budget constraint in equation (3.43). In the next section, the equilibrium for this economy is encountered and exemplified for a set of values of the exogenous parameters. With that equilibrium at hand, two comparative static analysis were performed

in section (3.5). In the first exercise, the value of a_c , the productivity parameter of the drug enforcement technology π_c defined in equation (3.33), is increased. In the second, $\alpha_{1,w}$ is increased. $\alpha_{1,w}$ is the parameter that captures the skewness of the income distribution. Increasing $\alpha_{1,w}$ improves the income distribution in the economy. Then, section (3.5) also studies the effect of income distribution improvements on the crime rates, and the government's optimal decisions.

3.4.3 Results: Restricted Optimal Drug Supply Control

Definition (2) determines the conditions for an equilibrium to exist. Notice that the set of equations in the definition are defined for all the equilibrium values of N_T . In Result (1), two values for N_T were found to be equilibrium values per value of p_d , and the government's control variables. In the sequel, the results for the low crime rate, N_T^1 , are only presented. Based on Definition (2), the following result arises:

Result 5 *Let $N_T^1(\pi_c, \pi_T, \tau, f)$ and $p_d^*(\pi_c, \pi_T, \tau, f)$ represent the equilibrium values that solve equations (3.38) and (3.39). If the objective of the government is to minimize equation (3.36), using $N_T^1(\pi_c, \pi_T, \tau, f)$ as the crime rate objective, subject to the budget constraint in equation (3.37), the following two conditions are satisfied:*

i. $\exists \Theta^1 \subset \mathbb{R}_{++}^8$ such that $\forall \{\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T\} \in \Theta^1$:

$$\begin{aligned} & \pi_c^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \\ & \pi_T^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \\ & \tau^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \\ & f^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \end{aligned} \in \begin{cases} (0, 1] \\ \operatorname{argmin}\{\text{Equation (3.36)}\} \end{cases} \quad (3.45)$$

ii. $\exists \Theta^2 \subset \mathbb{R}_{++}^8$ such that $\forall \{\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T\} \in \Theta^2$:

$$\begin{aligned}
& \pi_T^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \\
& \tau^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \\
& f^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \\
& \pi_c^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \in \begin{cases} (0, 1] \\ \operatorname{argmin}\{Equation (3.36)\} \end{cases} \quad (3.46) \\
& \pi_c^*(\theta, a_\epsilon, A_s, \sigma_s, \eta, a_T, a_c, \alpha_T) \in \begin{cases} (-1, 0] \\ \operatorname{argmin}\{Equation (3.36)\} \end{cases}
\end{aligned}$$

Result (5) provides the solution for the government's problem in equations (3.36) and (3.37). It states that there is at least two types of solutions: one type is composed of strictly positive values of the government's control variables. The other is composed of strictly positive values of the government's control variables, except for π_c^* . Here, π_c^* is negative. If π_c is understood as a proxy for a tax rate on the drug composite commodity, a positive π_c^* is a *tax* and a negative π_c^* is a *subsidy*. Hence, Numeral *i* in Result (5) indicates that π_c^* is a tax in equilibrium, and Numeral *ii* indicates that π_c^* is a subsidy¹².

Figures (A.20) and (A.21) show an example for Numeral *i* in Result (5), which solve the system of equations in Definition (2). The equilibrium is shown from two perspectives. Figure (A.20) shows the solution from above the objective function, and figure (A.21) does it from below. Point A on both graphs indicate the equilibrium point. At this point, all the control variables are strictly positive.

Using the parameters in table (A.1) to perform the numerical analysis, it is encountered that the drug policy variable is positive, but small. The equilibrium value for $\pi_c^* = 0.0159$. This value is computed for a series of changes in certain parameter values in the next section. Before entering into that analysis, it is noted here that the graphs show that π_c^* is strictly positive due to the government's budget requirements. When the government also aims to minimize the amount of resources spent on enforcement activities, the chosen equilibrium points will represent those expenditure

¹²These results were found using numerical approximations. The method used to obtain these results is a build-in function in MATLAB called `fgoalattain`, which uses a sequential quadratic programming (SQP) method with non-linear constraints to attain the solution. Using this method, the restriction $\pi_c = 0$ was imposed to obtain the solution. The solver never converged to this lower bound when its optimal solution was $\pi_c^* < 0$.

concerns. The point shown in the graph considers a budget ponderation of $\alpha_T = 0.5$. As the point that minimizes N_T^1 requires to set a high value of π_T , as was found in Result (4), budget considerations force the government to control the availability of drugs in the market. The reason is that more thieves provide more resources to spend when captured. As π_c increases the equilibrium drug price, as was seen in figure (A.17), a larger p_d^* induces more individuals to crime, increasing the government's resource availability for a given value of π_T^* . This is especially true for low values of π_c . At those points, marginal increments in this variable always generate positive changes in the crime rates of all categories.

3.5 Comparative Statics Analysis

Result (5) provides a useful solution that can be exploited in several manners. In this section, two exercises of comparative static analysis are performed. The first exercise changes the value of a_c and is presented in section (3.5.1). The second exercise consists of changing $\alpha_{1,w}$, the parameter that captures the income distribution skewness. This second exercise is presented in section (3.5.2).

3.5.1 Technological Improvement in π_c

Table (3.1) presents the equilibrium values of N_T , p_d , and the government's control variables for changes in a_c . It also presents the equilibrium values of the percentage of thieves, the aggregate drug demand and the government's income sources per category of addiction. Except for the drug demand, supply, and price values, all results are expressed in percentage points. The results in table (3.1) are computed using the numerical values of the exogenous parameters of table (A.1), allowing a_c to change from 1 to 3.04. This implies that it is easier for the government to seize drugs in the market with each increment in a_c . At the initial equilibrium, the government is more effective at capturing thieves than seizing drugs ($a_c = 1 < a_T = 2$). Once $a_c > 2$, the government becomes more effective at seizing drugs. The results in table (3.1) are also presented for three values of $\alpha_T \in \{0.2, 0.5, 0.8\}$. A low value of α_T implies that

the government ponderates the number of thieves less than its expenditure level in its objective function. A high value implies the opposite.

The results in table (3.1) show that the exercise performed in this subsection belongs to the type of equilibrium found in Numeral i in Result (5); regardless the value of α_T , π_c^* is always positive and increases with larger values of a_c . The intuition behind these two results is simple: On the one hand, Result (4) stated that the government's best strategy to minimize the percentage of thieves in the economy is to spend a large amount of resources on π_T . However, when the government faces a budget constraint, that maximum value of π_T is not always an attainable point. As a result, the government is forced to seek other sources of income to finance its enforcement activities. A positive π_c^* induces addicts to crime through its effect on p_d^* . As a percentage π_T^* of thieves is captured and the government uses the fines charged on them to finance its enforcement activities, it is optimal for the government to induce addicts to crime to supplement its income.

The latter intuition is confirmed when the equilibrium values of π_c^* for the different values of α_T are compared. A larger value of α_T reduces the value of π_c^* . This implies that when the government ponderates the equilibrium value of the crime rate more than the expenditure levels, π_c^* tends to be smaller, inducing less addicts to crime. The latter generates a smaller total amount of thieves because non-addicts are also incentivized to reduce their crime rates.

On the other hand, table (3.1) also shows that increments in a_c lead the government to change the percentage of resources dedicated to seizing drugs, which increases π_c^* . That variation depends on the value that a_c assumes relative to that of a_T . When $a_c < a_T$, an increment in a_c induces the government to increase the percentage of resources spent on r_c relative to r_T . Once the government becomes more effective at seizing drugs than at capturing thieves, the percentage of resources dedicated to seizing drugs are reduced and the percentage spent on controlling thieves increased. However, the drug control policy keeps receiving an important proportion of the budget when $a_c > a_T$.

When the government has a minimum expenditure requirement along with a min-

imum crime rate concern, the best strategy is to find the cheapest combination of enforcement expenditure that minimizes the government's objective. When a_c increases, π_c becomes a relatively cheaper alternative, which also helps raise revenue indirectly through the fines on captured thieves who are induced to commit property crime by a larger drug price, p_d . As an increase in p_d moderately increases the crime rate, the government is able to redistribute resources from the thief-controlling activity, π_T , to drug-seizing activity, π_c , without increasing the value of its objective function. However, that redistribution reaches a maximum point. When the government becomes more effective at seizing drugs than at capturing thieves, the best strategy is to increase the resources spent on controlling thieves again. The reason is that every dollar spent on r_c generates more thieves than it increases the efficiency of the budget redistribution. As a result, more resources are needed on the thief-controlling activity in equilibrium.

In sum, minimum expenditure requirements incentivize the government to control narcotics in the market. In this model, that optimally occurs because the government can use the fines obtained from captured thieves to finance its enforcement activities when it is subject to a budget constraint. When the government is less efficient at seizing drugs, the government spends more resources on capturing thieves than on controlling drug availability. Once the government starts becoming more efficient at seizing drugs, the percentage of resources spent on seizing drugs starts to increase. When the government becomes more efficient at seizing drugs than at capturing thieves, the percentage of resources spent on seizing drugs decreases, and on controlling thieves increases. However, the percentage of resources spent on the drug control policy is always larger with increments in a_c .

	$\alpha_T = 0.5$					$\alpha_T = 0.8$					$\alpha_T = 0.2$				
	1.00	1.51	2.02	2.533	3.04	1.00	1.51	2.02	2.53	3.04	1.00	1.51	2.02	2.53	3.04
a_c	1.00	1.51	2.02	2.533	3.04	1.00	1.51	2.02	2.53	3.04	1.00	1.51	2.02	2.53	3.04
N_T^*	18.55	20.26	20.77	20.78	20.53	18.62	20.23	20.64	20.64	20.5	19.36	20.94	21.25	21.18	20.99
$N_T^{\overline{c}}$	1.81	1.97	2.02	2.02	1.99	1.81	1.96	2.00	2.00	1.99	1.88	2.03	2.06	2.05	2.04
$N_T^{\underline{c}}$	3.96	4.34	4.46	4.47	4.41	3.97	4.34	4.43	4.43	4.40	4.14	4.50	4.57	4.56	4.52
N_T^0	12.79	13.95	14.30	14.29	14.13	12.84	13.93	14.20	14.20	14.10	13.34	14.41	14.62	14.57	14.44
p_d	0.549	0.563	0.572	0.579	0.584	0.549	0.562	0.571	0.578	0.583	0.551	0.564	0.573	0.580	0.5843
$D_{\epsilon_i=\overline{c}}$	1.266	1.232	1.210	1.195	1.185	1.266	1.234	1.212	1.197	1.187	1.260	1.228	1.207	1.193	1.184
$D_{\epsilon_i=\underline{c}}$	0.557	0.538	0.525	0.517	0.511	0.557	0.539	0.526	0.518	0.512	0.554	0.536	0.524	0.516	0.511
$D_{\epsilon_i=0}$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$D_T = \sum_{\epsilon_i \in \{0, \underline{c}, \overline{c}\}} D_{\epsilon_i}$	1.827	1.774	1.739	1.716	1.700	1.827	1.777	1.743	1.719	1.703	1.818	1.767	1.735	1.713	1.698
S_T	1.827	1.774	1.739	1.716	1.700	1.827	1.777	1.743	1.719	1.703	1.818	1.767	1.735	1.713	1.698
S_T^c	0.030	0.119	0.180	0.221	0.251	0.029	0.115	0.174	0.216	0.246	0.045	0.130	0.187	0.226	0.254
$S_T^p = S_T^c + S_T$	1.857	1.893	1.919	1.937	1.951	1.857	1.891	1.917	1.935	1.949	1.863	1.897	1.922	1.939	1.952
π_T^*	25.30	24.02	23.85	23.88	23.87	25.40	24.20	23.89	23.87	23.97	25.25	24.31	24.15	24.21	24.34
π_c^*	1.59	6.30	9.37	11.42	12.87	1.58	6.06	9.09	11.16	12.60	2.41	6.86	9.73	11.65	13.00
τ^*	2.36	2.57	2.63	2.63	2.60	2.36	2.57	2.62	2.62	2.60	2.46	2.66	2.69	2.69	2.66
f^*	19.21	19.76	19.73	19.69	19.81	19.07	19.58	19.75	19.76	19.72	18.88	19.17	19.22	19.18	19.13
$\overline{w}$	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36	7.36
$I_G^{T\tau} = \tau^* \overline{w}$	93.51	93.37	93.34	93.34	93.35	93.49	93.39	93.36	93.36	93.36	93.49	93.40	93.36	93.39	93.38
$I_G^{\epsilon_i=0}$	4.42	4.50	4.52	4.52	4.52	4.43	4.49	4.51	4.50	4.50	4.43	4.48	4.50	4.48	4.49
$I_G^{\epsilon_i=\underline{c}}$	1.45	1.50	1.51	1.51	1.51	1.46	1.49	1.50	1.50	1.50	1.46	1.50	1.51	1.50	1.50
$I_G^{\epsilon_i=\overline{c}}$	0.62	0.63	0.63	0.63	0.63	0.62	0.63	0.63	0.63	0.63	0.62	0.62	0.63	0.63	0.63
$I_G^{Tf} = \sum_{\epsilon_i \in \{0, \underline{c}, \overline{c}\}} I_G^{\epsilon_i}$	6.49	6.63	6.66	6.66	6.65	6.51	6.61	6.64	6.64	6.64	6.51	6.60	6.64	6.61	6.62
$I_G^T = I_G^{T\tau} + I_G^{Tf}$	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
r_c	8.71	21.97	24.61	24.50	23.63	8.62	21.10	23.96	24.03	23.10	12.76	23.28	25.08	24.58	23.38
r_T	91.29	78.03	75.39	75.50	76.37	91.38	78.90	76.04	75.97	76.90	87.24	76.72	74.92	75.42	76.62
$E_T^T = r_c + r_T$	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Table 3.1: Equilibrium Values of the Economy for Changes in a_c

3.5.2 Income Distribution Improvement

In contrast to the results presented in the previous subsection, the exercise presented here belongs to the type of equilibrium found in Numeral *ii* in Result (5). Table (3.2) presents the results for the second comparative static exercise performed. In this case, the value of $\alpha_{1,w}$ is changed from 1.4 to 2.2. Figure (A.22) depicts the income distributions of all the values of $\alpha_{1,w}$ presented in table (3.2) organized by addiction category. The graph shows that all income distributions becomes more centered with larger values of $\alpha_{1,w}$. That is, each increment in $\alpha_{1,w}$ induces to improvements in the income distribution of the economy.

Table (3.2) presents three results worth noting: first, improvements in the income distribution of all categories of drug addiction reduce the crime rate in general. This occurs despite the fact that the potential amount of resources to steal increases with $\bar{w}$. Second, income distribution improvements generates that the government obtains larger amount of resources from captured thieves in equilibrium, which leads the government to reduce the equilibrium values of f^* and τ^* .

Finally, when $\alpha_{1,w}$ is sufficiently large, π_c^* becomes a subsidy. This occurs because income improvements increase the equilibrium drug price, p_d^* . When the government has enough revenue to spend on the thief-controlling activity, it becomes optimal for the government to try to incentivize addicts not to engage in criminal activities by subsidizing the availability of drugs in the market, which helps reduce the equilibrium drug price. To accomplish that goal, the government dedicates part of its budget to increase the supply of drugs in the market. That budget is appropriated to the amount of resources dedicated to controlling thieves. This result is counterintuitive to any previous analysis on drugs. In previous analysis, the government always controls drugs in equilibrium. In this model, it is optimal for the government to subsidize the consumption of drugs because it reduces the incentives of addicts to engage in criminal activities.

	$\alpha_T = 0.5$					$\alpha_T = 0.8$					$\alpha_T = 0.2$				
	1.56	1.72	1.88	2.04	2.20	1.56	1.72	1.88	2.04	2.20	1.56	1.72	1.88	2.04	2.20
$\alpha_{1,w}$	17.45	16.26	15.20	14.23	13.34	17.48	16.33	15.27	14.33	13.45	18.36	17.37	16.36	15.46	14.64
N_T^*	1.71	1.61	1.51	1.42	1.32	1.72	1.61	1.52	1.43	1.34	1.80	1.72	1.62	1.54	1.46
$N_T^{\bar{c}}$	3.68	3.39	3.13	2.91	2.68	3.69	3.41	3.15	2.93	2.73	3.89	3.63	3.38	3.16	2.98
$N_T^{\underline{c}}$	12.05	11.26	10.56	9.90	9.23	12.07	11.31	10.61	9.97	9.38	12.68	12.02	11.36	10.76	10.21
N_T^0	0.575	0.597	0.616	0.634	0.650	0.5743	0.597	0.616	0.634	0.650	0.577	0.599	0.619	0.637	0.652
p_d	1.348	1.420	1.484	1.540	1.597	1.348	1.420	1.484	1.540	1.591	1.341	1.413	1.476	1.532	1.582
$D_{\epsilon_i} = \bar{\epsilon}$	0.554	0.554	0.555	0.557	0.560	0.554	0.554	0.555	0.557	0.560	0.551	0.550	0.552	0.553	0.556
$D_{\epsilon_i} = \underline{\epsilon}$	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
$D_{\epsilon_i} = 0$	1.904	1.975	2.040	2.098	2.157	1.905	1.976	2.040	2.098	2.150	1.894	1.964	2.028	2.086	2.138
$D_T = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} D_{\epsilon_i}$	1.904	1.975	2.040	2.098	2.157	1.905	1.976	2.040	2.098	2.150	1.894	1.964	2.028	2.086	2.138
S_T	0.021	0.009	-0.003	-0.014	-0.026	0.020	0.009	-0.003	-0.014	-0.025	0.037	0.027	0.016	0.004	-0.006
S_T^c	1.925	1.985	2.037	2.084	2.130	1.925	1.984	2.037	2.083	2.125	1.931	1.991	2.043	2.090	2.132
$S_T^p = S_T^c + S_T$	24.62	24.01	23.46	22.96	22.50	24.72	24.11	23.57	23.09	22.65	24.69	24.21	23.78	23.38	23.00
π_T^*	1.11	0.46	-0.13	-0.68	-1.20	1.05	0.45	-0.15	-0.69	-1.20	1.94	1.38	0.76	0.21	-0.29
π_c^*	1.97	1.66	1.42	1.23	1.08	1.97	1.67	1.43	1.24	1.09	2.07	1.77	1.53	1.34	1.19
τ^*	18.01	17.28	16.76	16.39	16.12	17.91	17.16	16.62	16.23	15.94	17.57	16.65	16.03	15.58	15.23
f^*	8.19	8.96	9.66	10.32	10.99	8.19	8.96	9.66	10.32	10.99	8.19	8.96	9.66	10.32	10.99
$\bar{w}$	92.45	91.42	90.39	89.38	88.47	92.45	91.44	90.42	89.41	88.54	92.44	91.43	90.44	89.47	88.62
$I_G^{T,\tau} = \tau^* \bar{w}$	5.16	5.91	6.65	7.37	8.03	5.17	5.89	6.62	7.35	7.97	5.17	5.89	6.61	7.31	7.92
$I_G^{\epsilon_i=0}$	1.65	1.84	2.02	2.19	2.35	1.65	1.83	2.01	2.19	2.34	1.66	1.84	2.01	2.18	2.33
$I_G^{\epsilon_i=\underline{\epsilon}}$	0.73	0.84	0.95	1.06	1.15	0.73	0.84	0.95	1.05	1.14	0.73	0.84	0.94	1.05	1.13
$I_G^{\epsilon_i=\bar{\epsilon}}$	7.55	8.58	9.61	10.62	11.53	7.55	8.56	9.58	10.59	11.46	7.56	8.57	9.56	10.53	11.38
$I_G^{T,f} = \sum_{\epsilon_i \in \{0, \underline{\epsilon}, \bar{\epsilon}\}} I_G^{\epsilon_i}$	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
$I_G^T = I_G^{T,\tau} + I_G^{T,f}$	6.43	2.84	-0.85	-4.75	-8.90	6.07	2.77	-0.98	-4.78	-8.81	10.77	8.06	4.68	1.36	-1.97
r_c	93.57	97.16	100.85	104.75	108.90	93.93	97.23	100.98	104.78	108.81	89.23	91.94	95.32	98.64	101.97
r_T	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100
$E_G^T = r_c + r_T$															

Table 3.2: Equilibrium Values of the Economy for Changes in $\alpha_{1,w}$

3.6 Conclusions

Drugs are special commodities. They seem to generate a minimum consumption requirement in their consumers. This minimum requirement might incentivize addicts to engage in property crime. A model of crime is used to determine the optimal amount of resources that the government must spend to control drugs in the market in order to minimize the percentage of thieves in the economy.

The analysis is performed under two scenarios. In the first scenario, the government's objective is to minimize the total percentage of thieves in the economy not subject to a budget constraint. In the second scenario, the government faces a budget constraint and aims to minimize the enforcement expenditure apart from the crime rate.

The numerical results computed in this paper indicate that when the government does not face a budget constraint, the best strategy is to spend only on capturing thieves and not on seizing drugs. The reason is that drug control policies increase the equilibrium drug prices, which increases the addicts' incentives to engage in property crime. By spending nothing on controlling drugs, the government keeps the economic incentives of addicts to engage in criminal activities at its minimum levels. This occurs because the government is not able to induce an equilibrium drug price that makes drug addicts become more risk-neutral with changes in p_d .

In contrast, when the government faces a budget constraint, and there is a minimum expenditure requirement, the best strategy for the government is to control a positive percentage of drugs in the market. The reason is that the government is able to supplement its budget with the income obtained from captured addicts engaged in crime. When the government has sufficient funds to control the optimal percentage of thieves in equilibrium, the best strategy of the government is to subsidize the consumption of drugs. This occurs because income improvements increase the equilibrium price of drugs, but it does not occur to a point in which individuals become risk-neutral, so that the economic incentives of enforcement have a larger influence on individual's criminal decisions. At the equilibrium values encountered for p_d , people

are incentivized to commit crime. Hence, it is optimal for the government to reduce those incentives through increasing the availability of drugs in the market.

The results in this paper are mainly based on numerical exercises. As such, their validity only applies as long as the numerical values chosen resembles real economies. As this exercise was never attempted, the results in this paper serve as an academic curiosity. When individuals are drug addicts which make some of them become risk-lovers, the government is not able to generate an equilibrium drug price that reduces the crime rates of addicts for at least the high range of values that were assumed for the exogenous parameters of this model.

Chapter 4

The Effects of Drug Enforcement on Violence in Colombia 1999–2010

4.1 Introduction

Illegal markets for narcotics are usually correlated positively with violence¹. This correlation has elicited an intense debate because it is still unclear whether violence creates the incentives for the illegal markets for narcotics to exist or viceversa, and who are the main perpetrators of such violence. In this debate, the effects of the government's enforcement activities on the violence generated in these markets have generally been underestimated. I argue that drug enforcement has first- and second-order effects on the violence generated in these markets, especially in source countries².

In those countries, the government engages in prosecuting activities that sometimes involve military expenditure to enforce prohibition. As prohibition applies to commodities supplied by *decentralized markets*, drug dealers are able and willing to use their profits to fight back the government's prosecuting activities. This military power also allows them to solve their potential commercial disputes violently, if needed. This is called the *drug war in source countries*. Thus, the first-order effect

¹Violence is generally measured as the rate of homicides or displacement per 100,000 inhabitants.

²A source country is defined as a country that has historically produced narcotics. For a list of illicit drugs and source countries, see CIA, 2013.

refers to the direct violence that results from the government and drug dealers' military expenditures on the *drug war*. The second-order effect refers to the violence that emerges from the drug dealers' military expenditure on their drug war. This war occurs due to the absence of a legal system where drug dealers can solve their commercial disputes pacifically and drug markets exhibiting contracting environments with high transaction costs induced by enforcement.

To test the latter hypotheses, I use information on violence, drug and drug enforcement variables from Colombia during the period 1999 – 2010. Since 1999, Colombia has formally embarked in a program called “Plan Colombia”, aimed at reducing the amount of cocaine produced and distributed in the country and overseas. This program involves, among others, the use of military tactics to incentivize Colombians not to participate in the cocaine market. As a result, the Colombian central government has declared all citizens who decide to produce narcotics and use force to fight back its drug enforcement activities as military targets.

To test the effects of the government's drug enforcement military activities, it would be ideal to use a set of measures that permits to compare the levels of military expenditures of all participants in the drug war per municipality. However, the Colombian vice-president's office only collects information on drug enforcement and drug war outcomes for every municipality of the country. With that multiplicity of measurement units and, in certain cases, same-purpose variables, three problems arise.

First, some drug enforcement and drug war variables are *almost perfectly spatially correlated*. This correlation generates a multicollinearity problem that results in estimations with erratic and statistically insignificant estimates associated with those variables. Second, even if we are able to orthogonalize those variables, their estimated coefficients might be affected by their measurement units, which makes the estimates' magnitude meaningless and unreliable. If we decide to use single measures that proxy for the drug war military expenditures, it is a priori unclear which variables are more appropriate to proxy for those expenditures. When we find *a way* to categorize and organize them, it is again unclear how to interpret the measurement units of the re-

sulting proxies due to the measurement units diversity of the variables that compose them. Finally, some of the proxies for drug war military expenditure are endogenous to the proxies for violence.

The simplest way to circumvent the first two problems is to construct a set of indices that proxy for the government's and drug dealers' military expenditures. The methodology proposed in this paper to compute these indices permits to categorize municipalities according to the government's military expenditure against drug dealers (Eradication Index), drug dealers' military expenditure against the government (Anti-Eradication Index) and drug dealers' military expenditure against other drug dealers (Drug Dealers' War Index). The methodology employed allows me to compute these indices having similar measurement units, which make their estimated coefficients objectively comparable. Additionally, as these indices are computed such that they are all in the unit interval and the regressands are expressed in logarithms, the indices' estimated coefficients indicate the *average percentage* in which the violence rate increases in the municipalities with the *largest military expenditure* relative to those with *zero military expenditure* on drug war.

To overcome the last problem, I employ a joint strategy: On the one hand, I use the strategy proposed by Mejia and Restrepo, 2011 to disentangle the real effects of drug production on enforcement variables. Due to technological reasons associated with the quality of terrain, climate and locational characteristics of the Colombian territory, cocaine production is more productive at low altitudes. The strategy of Mejia and Restrepo, 2011 consists of running a 2SLS model using the altitude per municipality as an exogenous source of variation in the first stage to determine how much violence is explained by the Colombian drug war. I argue that given the Colombian government's centralized structure in drug enforcement decision making and policy application, two other sources of variation can be used: the distance of a municipality to Bogotá, the country's capital, and to the capital of *departamento*³ in which it is lo-

³A *departemento* is similar to a U.S. state, but differs from an administrative viewpoint. A state has a constitution apart from the national constitution, whereas a *departemento* follows the single set of rules determined by the national constitution and legislature. After the constitution of 1991, Colombia initiated a decentralization process that involved the appropriation by *departamentos* and

cated. A priori, there is no reason why drug enforcement variables are correlated with municipalities' altitude and distances to capitals other than by a technological issue associated with cocaine production. To control for potential omitted variables that also help explain violence in the Colombian municipalities, I run a panel data Spatial Durbin Model, which helps control for fixed, temporal and geographical factors.

On the other hand, using the latter sources of variation and the idea that drug war military expenditures are determined by the municipalities' spatial and geographical characteristics for cocaine production, I am able to reclassify municipalities according to their spatially-determined drug war military expenditures. As this reclassification does not use violence variables to estimate the proxies to recompute the indices, any correlation between the recomputed indices and violence variables can be understood as a causal correlation.

My results suggest that the Colombian violence is explained by both the central government's drug enforcement activities and the actions taken by drug dealers to fight back that enforcement. Furthermore, that violence is also explained by the efforts exerted by those groups to control the territory, where they not only produce narcotics but also extract the rents from other natural resources (such as gold and petroleum). Additionally, I find that the war among drug dealers has also an important effect on the levels of violence in Colombia. Drug dealers use violent methods to resolve their conflicts, affecting both the homicide rate and the displacement rate in the country.

This paper is organized as follows: section (4.1) is this introduction. Section (4.2) presents a short overview of the theoretical relation among drugs, drug enforcement, and violence. Section (4.3) presents the data used to test my hypotheses, with an emphasis on the spatial characteristics of the data used. Section (4.4) explains the empirical strategy pursued to test my hypotheses. Section (4.5) presents the results. Section (4.6) concludes the paper and section (A.3) contains the appendix.

municipalities of their property taxes. However, both the police and the army are financed with national taxes and their prosecuting activities are decided entirely at the national level.

4.2 Theoretical Background

4.2.1 A General Perspective

Illegal markets for narcotics are usually associated with violence. This correlation has triggered an intense debate on who generates such violence and whether violence really leads to the production of narcotics or viceversa. The empirical evidence on this correlation is mixed, and three competing hypotheses have emerged as possible explanations for this regularity. A first hypothesis states that it is violence that generates the production of narcotics. Using a unique data set on Western Casualties in Afghan territory during the war against the Taliban regime after the 9/11, Lind et al., 2012 argue that the rise in Afghan opium production since 2002 can be explained by the deterioration of the social and economic infrastructure that emerged after the war. They argue that the conflict made “illegal opportunities more profitable as they increase the perceived lawlessness and destroy infrastructure crucial to alternative crops” (p. 1).

These authors use as an exogenous measure of conflict the number of western soldiers killed in Afghan territory, who, they argue, had nothing to do with drug eradication activities. They claim that the conflict against the Taliban generated a negative externality that led many Afghan farmers to produce heroin. Díaz and Sanchez, 2004, using information from Colombian municipalities for the period 1994 – 2000 and spatial econometric methods, show that the geographical intensification of conflict in Colombia, measured as the number of attacks perpetrated by irregular groups such as FARC, ELN and AUC ⁴, is the principal cause of the expansion of illegal crops of coca and poppy plants in the country. The authors demonstrate the close geographical correlation between the illegal groups’ presence and the production of cocaine in the municipalities in which they operate.

In both studies similar doubts linger. On the one hand, why are these “rebel”

⁴FARC (Fuerzas Revolucionarias de Colombia) and ELN (Ejército de Liberación Nacional) are both leftist guerilla groups, and AUC (Autodefensas Unidas de Colombia) is a right-wing paramilitary group.

groups also located in geographical areas with coca or poppy crops and the largest homicide rates? Aren't these groups directly involved in the production of narcotics to budget their war, for which they also fight back the government's eradication activities? On the other hand, why do individuals recur to the production of drugs? And why is this production profitable when anything else is not?

In regards to the first doubt, Lind et al., 2012 cannot disregard the possibility that heroin production might have been generated by the need of the Taliban for a quick revenue, which they called drugs-for-arms hypothesis. The same applies to the Colombian guerrillas and paramilitary groups and their involvement in the cocaine traffic⁵. If the drugs-for-arms hypothesis is true, this would imply that the relationship between violence and the production of narcotics is biunivocal: when a group in conflict needs a quick and secured source of revenue, they may recur to the production of narcotics to obtain it, even if unintended in the first place, which in turn generates more violence. Such violence might be associated with the military expenditure of those groups to accomplish their political goals or defend their territory from the government's eradication activities. Thus, the politically-motivated violence is the only one that can be ascribed to the first hypothesis, as the other is triggered by the existence of narcotics in that territory and the intention of the government to eradicate it militarily.

As the first hypothesis does not give a satisfactory answer to the latter questions, a second hypothesis arises in the literature: the production, transportation, distribution, and retailing of drugs generate violence. This hypothesis relies on the fact that illegalization leaves drug dealers without a legal system to resolve their commercial and legal disputes. Caulkins et al., 2006 argue that drug dealers use violence to resolve disputes and secure geographical positions in the retail market for narcotics. They argue that those individuals who have a larger propensity to use violence secure themselves the safest places on the retail market, which is where drug enforcement has the smallest probability to affect them negatively. As for a source country,

⁵see LeoGrande and Sharpe, 2000 and Thoumi, 2002 for a detailed analysis of the evolution of the illegal markets for narcotics in Colombia and its effects on violence.

Angrist and Kugler, 2008, using a similar data set as Díaz and Sanchez, 2004, state that the productivity of soil and the geographical location of Colombia create huge incentives for illegal groups to exploit these resources to produce illegal goods such as cocaine. Hence, municipalities with a significant production of cocaine are more violent. This relation is explained by the competition among rival groups, who compete for a share in the market, and with the government, who plays a predatory game with these groups. In this literature, the production of drugs is an endogenous variable that depends on the amount of enforcement and military capabilities of irregular groups to fight back the prosecuting agencies and their rival competitors (See Mejia and Posada, 2008 and Mejia, 2008 for papers that develop this idea).

In a recent paper, Mejia and Restrepo, 2011 propose an identification strategy to disentangle the causal relationship between the existence of illegal markets and violence. Based on several insights about the technological features of the production of cocaine in Colombia provided by Mejia and Rico, 2010⁶, these authors use the altitude of a municipality to proxy for the productivity of the cultivation of the coca plant. The underlying idea is that the plant produces more cocaine when harvested between 0 and 1700 meters above the sea level. As a result, if the existence of illegal markets has a real causal effect on violence, a 2SLS strategy that uses the altitude of each municipality might help uncover such a relationship. They show, using a panel of Colombian municipalities, that the existence of illegal markets for cocaine has a positive effect on the level of violence in Colombia.

From the paper written by Mejia and Restrepo, 2011 two drawbacks can be pointed out. On the one hand, altitude might also be correlated with drug enforcement activities of the Colombian government, and not only with what drug dealers do to gain a market share in the Colombian cocaine market. Hence, we must also control for enforcement activities of the Colombian government to be able to use the production of cocaine as a proxy for the violence generated by drug dealers in the illegal markets for cocaine. On the other hand, it is unclear why drug dealers have to resolve disputes violently when they can agree not to. In other words, illegality is not a sufficient con-

⁶See Gootenberg, 2008 for a thorough analysis of cocaine production in the Andean Countries.

dition to secure a violent outcome. Mirron, 2001 argues that not all illegal activities generate violence or even an illegal market for them. He argues that there must be something else that induces both the illegal markets and violence to coexist. Using a panel of countries in which gun control data exist, he suggests that “differences in the enforcement of drug prohibition are an important factor in explaining differences in violence rates across countries”(p. 615).

Mirron, 2001 relies on two factors that must be satisfied in order for illegal markets to exist and generate violence. First, a banned activity must generate huge amounts of resources to its suppliers. And second, enforcement activities are high, making transaction costs in the illegal markets sufficiently high as to impede drug dealers use of coasean-type mechanisms to resolve their possible commercial disputes. The Colombian case satisfies both conditions: Colombian regions have a huge comparative advantage in producing goods that the rest of the world is highly interested in demanding at relatively high prices even when illegal. This powerful financial incentive generates that illegal groups try to create a public good —i.e., security for the production of drugs— in the most suitable regions. Additionally, enforcement efforts by the Colombian government have been relatively high, especially since “Plan Colombia” was enacted and put into action in 1999.

The last two hypotheses insinuate that the bulk of violence is explained by what drug dealers do against each other. However, the drug war also implies that the enforcement agencies engage in prosecuting activities and military actions against drug dealers, especially in source countries. For instance, “Plan Colombia” is the archetypal case of enforcement activities by the government that involve the use of military tactics and methods to eradicate the production and manufacture of narcotics (see Acevedo et al., 2008 and GAO, 2008). This program has received good evaluations by its overall effects on the reduction of violence in Colombia, especially in the reduction of homicides of people younger than 29 years old (see Barón, 2009). Nonetheless, is it possible to assure that the government’s drug enforcement actions do not have an effect on violence?

I argue that they do. There are two type of effects that enforcement activities

have on violence: first–and second–order effects. A first–order effect is, for instance, the number of soldiers and police officers as well as the number of drug dealers who die in the drug war. This is an effect of enforcement because this violence occurs usually in the course of the eradication activities performed by the government, in which they use military tactics to reach the areas where production is taking place. As rebel groups obtain sufficient funds from the traffic of a highly demanded illegal commodity, when the government performs eradication activities, its enforcement agencies are threatened by military machinery that eventually reach them mortally too⁷. The second–order effect is the number of drug dealers who get killed in their drug war. This is an effect of enforcement because illegality and high enforcement efforts place wealthy drug dealers in an anarchic contractual environment where the death and displacement of people seem to be the common results.

4.2.2 A Simple Model

To clarify ideas, let us suppose that we have the economy laid out in section (A.3.1). In that economy, we could split municipality j 's rate of violence⁸ in the following way:

$$v_j = \beta_1 M_j^g + \beta_2 M_j^r + \beta_3 M_j^{ir} + \text{rest} \quad (4.1)$$

where $\beta_1 M_j^g$ represents the proportion of violence that is attributed to the government's drug enforcement military expenditure in municipality j , M_j^g . $\beta_2 M_j^r$ represents the proportion of violence that is explained by the drug dealers' anti-enforcement military expenditure in municipality j , M_j^r . $\beta_1 M_j^g + \beta_2 M_j^r$ is called in section (4.2.1) the first–order effect of enforcement. Finally, $\beta_3 M_j^{ir}$ represents the proportion of violence

⁷If violence is measured as the rate of forcefully displaced people, the first–order effect is the number of civilians that are displaced by both the eradication and anti-eradication activities performed by both groups involved in the drug war.

⁸The rate of homicides and displacement per 100,000 inhabitants will be used below as proxies for the rate of violence. In the next section, the composition of both rates are explained. Here, I will use violence as a generic term to refer to those empirical estimates of violence.

explained by drug dealers' military expenditure to control the territory to produce drugs, M_j^{ir} . This is called the second-order effect of enforcement.

If we had perfect and reliable information on M_j^g , M_j^r and M_j^{ir} and each category in which v_j can be divided, including the categories of our interest, we could easily determine the values of β_1 , β_2 and β_3 by solving simple linear equations for each municipality. However, such information is unavailable, at least for Colombia. v_j is only available at aggregated levels, and there is only information on drug enforcement and drug war outcomes. In the next section, I explain the information available. In this one, two consequences of such a lack of *perfect* information on drug war military expenditures and violence variables are emphasized: on the one hand, β_1 , β_2 and β_3 will have to be estimated using regression analysis. The latter implies that these betas will represent average values for the time period considered.

On the other hand, we need to control for three factors to obtain reliable estimates of the betas: first, we must control for v_j 's over-counting. Second, proxies for M_j^g , M_j^r and M_j^{ir} must be constructed allowing for objectively comparable and reliable estimates. They also must represent the fact that Colombian drug military expenditures have a geographical component that must be accounted for. Finally, some of the available proxies for M_j^g , M_j^r and M_j^{ir} are endogenous to the proxies for violence. Consequently, we must find an exogenous source of variation that determines those military expenditures, which is at the same time uncorrelated with the used proxies for violence.

In the next section, I describe my strategy to circumvent the problems associated with the military expenditures measurement. In section (4.4), I explain the empirical strategy to tackle the endogeneity and over-counting problems. There, I also explain the strategy used to obtain the exogenous proxies for military expenditures that take into account their spatial components.

4.3 The Data

4.3.1 Sources and Variables

To test the model laid out in equation (A.24), I use the homicide rate per 100,000 inhabitants as a proxy for violence. These rates are collected by the Colombian vice president's office, and are a compilation of violent homicides that occurred in each of the 1122 municipalities of the country during the period 1999-2010⁹. Each of these rates contains the number of individuals who were assassinated violently. It includes police officers, soldiers and prosecutors as well as any other individual who *dies violently* in each municipality. In this regards, the Colombian vice president's office does not keep separate records of each of the categories that compose the total homicide rate of every municipality. Consequently, as a measure of violence, it includes more homicides than can actually be ascribed to the drug war. In the empirical strategy section, I explain how I handle this problem.

As a robustness check of my results, I also use the number of forcefully displaced people per municipality that the same source collects to compute the rate of displacement per 100,000 inhabitants for each municipality. The source defines an individual as forcefully displaced when the person is *forced* to migrate within the national territory because her life, security, and/or freedom are at stake due to the military actions of any of the groups involved in the conflict (i.e., guerrillas, AUC, drug dealers or the government's forces themselves). Because of the latter definition, I can also test whether the geographically-located drug enforcement activities of the central government are generating displacements or these are only the result of the existence of drugs as Mejia and Restrepo, 2011 claim.

I use information on drug enforcement outcomes collected by the vice-president's office to proxy for the Colombian government's drug enforcement military expenditure on every municipality. This data set contains information on the amount of coca

⁹For an analysis of the sources, its quality, and possible explanations about their discrepancies, see: Restrepo and Aguirre, 2007. For the official definition of the variables used in this paper, see: Vice-Presidencia de Colombia, 2012 (Spanish Version).

crops hectares that Colombia's prosecuting agencies eradicated either manually or by aspersión in the period 1999 – 2010. It also includes the number of performed operations in each intervened municipality to eradicate the number of declared hectares. This data set also contains information on the number of destroyed labs dedicated to the production of narcotics in the same period. Since 1999, the Colombian vice-president's office also started to collect information on the amount of attacks initiated by the government's enforcement agencies, such as the army or the police, against illegal groups. These groups include drug gangs and politically-motivated groups, such as FARC, ELN or AUC, also known to be involved in the production of narcotics.

To my knowledge, the number of attacks initiated by the government has never been used to proxy for drug enforcement activities of the central government in Colombia. Figure (4.1) shows that this omission is not a minor one. The graph depicts the Colombian homicide rate and the logarithm of the coca crops of the municipalities with high¹⁰ and low levels of government attacks. From the graph, it is clear that municipalities with more military attacks by the government have substantially larger homicide rates and coca production than municipalities with fewer of them.

Apart from the endogeneity problem associated with using the previous variable as a proxy for the Colombian government's drug enforcement military expenditure, running all these variables together also results in a multicollinearity problem because some of them are almost perfectly correlated. There are several ways to avoid this issue. One way is to perform a principal component analysis to orthogonalize these variables. Another way is to perform a common factor analysis, which determines the least number of factors that can account for the common variance of the set of enforcement variables (See Comrey, 1973 and Hair et al., 1992 for analysis on these methods). As both methods depend on the variables' measurement units, it is unclear the measurement units of the resulting proxy, which affects the way I interpret the estimated results of drug enforcement variables on violence.

¹⁰To compute figure (4.1), a municipality was defined as a high-government-attacked municipality when it was included in the upper tail of the distribution of the number of attacks initiated by the government against irregular groups (defined by the 70th percentile of the distribution or above).

Another methodology to circumvent the multicollinearity problem is the one used by the Index of Economic Freedom, which summarizes in a single measure 10 variables exhibiting a potential multicollinearity problem if used together¹¹. Caudill et al., 2000 argue that when the variables to compute an index are trying to proxy for a single dimensional variable, indexing and common factor analysis give equivalent results when their estimated proxies are used in regression analysis. However, indexing is simpler and indices can be computed such that they allow for objectively comparable estimates in regression analysis, avoiding the issue of the measurement units presented in the other two methodologies. Besides, Index Theory¹² allows us to assure that an index has the following two properties: first, it is able to capture the distribution of any compact set used to create the index, converting the moments' units of the domain set into the index units. Second, the correspondence that maps the domain set into the index numbers affects the accuracy of the index to capture the domain set distribution.

Bearing that in mind, I construct the following Eradication Index:

$$I_E = \frac{\sum_i^6 I_{E,i}}{18} \quad (4.2)$$

where¹³,

$$I_{E,i} = \begin{cases} 3 & \text{if } Var_i > percentile(a_i, 70) \\ 2 & \text{if } percentile(a_i, 30) < Var_i < percentile(a_i, 70) \\ 1 & \text{if } min(a_i) < Var_i < percentile(a_i, 30) \\ 0 & \text{if } Var_i = 0 \end{cases} \quad (4.3)$$

where a_i is a non-zero vector composed of the elements of Var_i , and Var_i is any of the 6 aforementioned variables used to compute this index.

¹¹Beach and Kane, 2008 presents an analysis of the Index of Economic Freedom

¹²See Hájek, 2009 for a mathematical analysis of the properties of indices.

¹³The choice of the percentile values to construct these indices are based on the distributions of its composing variables. However, my results are not sensitive to small changes in the threshold values for each category.

Figure 4.1: Homicide Rate and Coca Crops divided by Intensity of Government's Attacks

Several features are worth noting about the latter index. First, the index-composing variables are split between those municipalities with zero and strictly positive drug enforcement outcomes. This implies that my initial comparison will be between these two categories. Second, the highest possible score for a municipality is 18^{14} . Thus, $I_E \in [0, 1]$. Third, if I run the model laid out in equation (A.24), using I_E to proxy

¹⁴There are six variables. If a municipality scores 3 in all 6 enforcement variables (i.e., it is located in the 70th percentile or above in the distributions of all the index composing variables), it will score $18=6 \times 3$.

for the government's drug enforcement military expenditure and the regressands in logarithms, $\beta_1 I_E$ would measure the percentage in which a municipality's violence rate changes with an enforcement level of I_E relative to a municipality with zero enforcement. To clarify the latter idea, let us assume that we have a municipality's violence rate v expressed in logarithms. This v assumes different values depending on which level of drug war intensity a municipality has. If the latter possibility is true, let $v_{I_E=1}$ and $v_{I_E=0}$ represent a municipality's violence rate with a drug enforcement index of 1 and 0, respectively. *Ceteris paribus*, β_1 can be expressed as follows:

$$\beta_1 = v_{I_E=1} - v_{I_E=0} = \beta_1(I_E = 1 - I_E = 0)$$

As the v 's are expressed in logarithms, β_1 represents the percentage in which the violence rate changes by going from $I_E = 0$ to $I_E = 1$. As a result, if β_1 is positive, it means that drug enforcement increases in $\beta_1\%$ the Colombian municipalities' violence rate. If β_1 is negative, it means that drug enforcement decreases that rate in the same percentage. Fourth, I_E possesses 18 possible values, permitting to measure exhaustively the different eradication levels produced by the government across the country. If we wanted to determine the change in the violence rate's growth rate explained by moving I_E from one eradication level I_E^i to a higher one I_E^j , we would simply perform the algebraic operation $\beta_1(I_E^j - I_E^i)$.

The vice-president's office also collects information on the number of attacks perpetrated by irregular groups against official buildings, such as police stations or military bases, and official forces, such as the police or army. This variable has traditionally been used to proxy for the geographically-located military activities of irregular groups in Colombia. In fact, this is the main variable that Díaz and Sanchez, 2004 use to test whether violence increases cocaine production. According to paper written by Díaz and Sanchez, 2004, this variable might be endogenous to the existing proxies for violence. Apart from this endogeneity problem, I could also construct an index for this variable to obtain comparable estimates with those of the previous index. As

a result, I construct the following Anti-Eradication Index:

$$I_{AE} = \begin{cases} \frac{3}{3} = 1 & \text{if } irreattacks > percentile(a, 70) \\ \frac{2}{3} & \text{if } percentile(a, 30) < irreattacks < percentile(a, 70) \\ \frac{1}{3} & \text{if } min(a) < irreattacks < percentile(a, 30) \\ \frac{0}{3} = 0 & \text{if } irreattacks = 0 \end{cases} \quad (4.4)$$

where a is again a non-zero vector composed of the elements of *irreattacks*, and *irreattacks* is the number of attacks perpetrated by irregular groups against the government's security forces. This index satisfies similar features to the ones mentioned for the previous index. In this case, β_2 represents the highest possible percentage change in the violence rate that is explained by the irregular groups' highest level of military expenditure against drug enforcement ($I_{AE}=1$). As in the previous case, if I wanted to determine the change in the violence rate' growth rate explained by moving I_{AE} from one eradication level I_{AE}^i to a higher one I_{AE}^j , I would again simply perform the algebraic operation $\beta_2(I_{AE}^j - I_{AE}^i)$.

In turn, Mejia and Restrepo, 2011 use the coca cultivation figures from SIMCI¹⁵ to proxy for the drug dealers' war. The vice-president's office also collects information on two other variables that I argue also capture that war: the number of massacres committed by irregular groups in their regions or areas of influence, and the number of incidents and accidents with mine fields. These two variables are also available from 1999 to 2010, and they are computed taking into account how closely they are related to the conflict among irregular groups in Colombia. In that sense, massacres are defined to be perpetrated by irregular groups in their conflict on their areas of influence¹⁶, and mine fields appear to be used by irregular groups to protect their coca, marihuana and poppy fields¹⁷.

Running these variables together also results in a multicollinearity problem as in the eradication index case. Following the same logic laid out for that index, I construct

¹⁵Sistema Integrado de Monitoreo de Cultivos Ilícitos– A United States Office for Drugs and Crime in Colombia. See its web-site: UNITED NATIONS OFFICE ON DRUGS AND CRIME, 2012a.

¹⁶See Human Right Watch, 2010 for a thorough analysis of the possible causes, main perpetrators, and main modus operandi in which massacres are committed in Colombia.

¹⁷see Human Right Watch, 2007 for a thorough analysis of guerrilla use of landmines in Colombia, and its consequences on the civil population.

the following Drug Dealers War Index:

$$I_{DW} = \frac{\sum_i^3 I_{DW,i}}{9} \quad (4.5)$$

where,

$$I_{DW,i} = \begin{cases} 3 & \text{if } Var_i > percentile(a_i, 70) \\ 2 & \text{if } percentile(a_i, 30) < Var_i < percentile(a_i, 70) \\ 1 & \text{if } min(a_i) < Var_i < percentile(a_i, 30) \\ 0 & \text{if } Var_i = 0 \end{cases} \quad (4.6)$$

where a_i is again a non-zero vector composed of the elements of Var_i , and Var_i is any of the 3 variables mentioned above used to compute this index. In this case, β_3 would represent the highest percentage change in the violence rate that is explained by the drug dealers' highest level of military expenditure on drug war ($I_{DW}=1$). As in the previous cases, if I wanted to determine the change in the violence rate's growth rate explained by moving I_{DW} from one eradication level I_{DW}^i to a higher one I_{DW}^j , I would again simply perform the algebraic operation $\beta_3(I_{DW}^j - I_{DW}^i)$.

Finally, it should be pointed out that all those variables might be correlated because they occur in municipalities where there is an insufficient central government presence, its rule of law is very scarce and there are huge economic opportunities to produce narcotics without the pressure of enforcement. I include as controls for the central government's presence the square kilometers per capita of a municipality^{18 19}, the logarithm of its population, its distance²⁰ to Bogotá and to its capital of *departemento*.

¹⁸The idea behind this instrument is that a larger area per capita indicates a smaller police presence, which reduces the efficiency of the government's enforcement activities. As a result, a larger area per capita signifies a worse institutional presence, which implies a better location for producing illegal narcotics with a smaller probability of capture.

¹⁹An alternative measure would be the local government's public expenditure. However, that information is not available at the municipality level, avoiding me to use it as an instrument.

²⁰The distances expressed in miles or kilometers are not available for every municipality. Moreover, for some municipalities their distances changed because roads were built or improved during our period of analysis as a policy response to cocaine production. As a result, I use the coordinate system of every municipality expressed in degrees to construct a measure of distance for each of them. As such, this system does not take into account the possible natural barriers that make a

These two last variables do not vary across years, which makes them not the best control variables for a panel. Additionally, it is untrue that distance captures correctly the institutional strength of a region. Given the centralized structure of Colombian military expenditure²¹, there are regions with larger economic power that attract more resources on security from the central government. Thus, I computed the following two variables:

$$dbogota_i = 1 - \left(\frac{1}{1 + dbogotamun_i} \right) * \frac{DepGDP}{BogotaGDP} \quad (4.7)$$

$$dcapitals_i = 1 - \left(\frac{1}{1 + dcapitalsmun_i} \right) * \frac{DepGDP}{BogotaGDP} \quad (4.8)$$

where $dbogotamun_i$ and $dcapitalsmun_i$ are the distances of municipality i to Bogotá and the capital of *departemento* in which municipality i is located, respectively. $BogotaGDP$ is the Bogotá's 2010 real GDP and $DepGDP$ is the 2010 real GDP of the *departemento* in which municipality i is located both measured by DANE²².

The values of $dbogota_i$ and $dcapitals_i$ are between 0 and 1. The *closer* a municipality is to Bogotá and its capital city of departamento, the closer $dbogota_i$ and $dcapitals_i$ are to 0. To define *proximity*, these measures take into account the economic importance of the *departemento* in which municipality i is located relative to that of Bogotá. For instance, when I look at figures (A.23) and (A.24)²³ in appendix (A.3), I realize that a municipality in the southern *departemento* of Amazonas is as far away from Bogotá than a municipality located in the northern *departemento* of La

municipality inaccessible. However, it still can capture the relative distance of a municipality to the main capitals, where most of the military bases are, and from which military attacks are planed and executed, which is precisely what I want to control for.

²¹See Avella, 2009 for an analysis on the historical Colombian public expenditure levels and institutional organization.

²²DANE(Departamento Administrativo Nacional de Estadísticas) is the official center that collects colombian socio-economic information.

²³The maps presented in figure (A.24) were taking from SIGOT (Sistema de Información Geográfica para la Planeación y el Ordenamiento Territorial) website, which is the official site where the Colombian central government publishes the country's spatial and geographical information. The GDP information at the municipality level is not available for all the municipalities of the country for the period of analysis, and the average of the rural property size per municipality is only available for 1101 municipalities (out of 1122) for 2007 and 2009. Due to this lack of information, I was not able to include these two variables as instruments to control for the potential of a municipality to produce coca crops.

Guajira. However, La Guajira is economically richer than Amazonas. My measures are able to differentiate the relative importance of those two municipalities through the relative weight that La Guajira's and Amazonas' GDPs have on that of Bogotá²⁴.

It is clear that the distance measures computed in equations (4.7) and (4.8) are not the best proxies to capture the institutional strength of a municipality relative to Bogotá or its capital of *departemento*, which is assumed to determine its assignment of security forces to eradicate coca leaves by the Colombian central government. The reason is that accessibility might also be an important factor to determine whether a municipality is good for the production of coca leaves, and to determine whether the Colombian central government dedicates resources to eradicate coca crops in that municipality. Unfortunately, there is not a good measure of accessibility for every municipality of the country, and a radial distance seems not to be a bad instrument to capture institutional presence within a *departemento* and the country. At least, that seems to be true for coca crops production in Colombia and the prosecuting activities that the government has followed to eradicate this production.

Coca production in Colombia has historically taken place in municipalities with large rural opportunities for the crop. These municipalities are usually located far away from the capital cities where the rural property size is larger and income lower relative to those of the main capital cities. The latter can be seen when we compare the average of the rural property size in figure (A.24a) and the GDP by *departemento* in figure (A.24b) with the drug dealers war index²⁵ in figure (A.26c) in appendix (A.3), where we realize that coca production is mainly taking place far away from the main capital cities of the country where the average of the rural property size is larger and in *departamentos* with a smaller GDP relative to that of Bogotá's.

²⁴In the regression results presented below, the distance variables were used as indicated in this section. However, several alternatives were pursued. One alternative is to compute them only using the GDP ratios. As there is only GDP information by *departemento*, one solution is to assume that all the municipalities of a single *departemento* had the same GDP. This alternative provided statistically insignificant estimates for the unique distance variable computed because all the variability gained using the distance variables proposed in the text is lost within a single *departemento*. As a result, it losses explanatory power because it is useless to explain the huge differences that exist within a single *departemento* in terms of cocaine production and violence.

²⁵This index is mainly determined by the production of coca leaves and the number of accidents and incidents with mine fields.

Additionally, the *pattern* of the average of the rural property size indicates that the average of the rural property size in a municipality increases in a sort of radial way the farther the municipality is from the main capital city of the *departamento* in which the municipality is located as well as the farther it is from Bogotá. As a result, if a municipality's rural property size average and income are good predictors for its potential to have coca production, the distance variables computed in equations (4.7) and (4.8) also seem a good alternative to capture that potential because they capture the radial development that take place in most of the *departamentos* of the country, which also increase the potential for the production of coca crops. In fact, when I run a simple OLS regression of the logarithm of coca crops size against the distance variables computed in equations (4.7) and (4.8), the following results are obtained²⁶:

$$\log(crops) = -5.15^{***} + 2.49^{**}dbogota + 5.64^{***}dcapitals \quad (4.9)$$

If equation (4.9) adequately captures the relationship between the logarithm of coca crops and the distance variables²⁷, it indicates the percentage in which the coca crops production increases in municipalities that are far way from Bogotá and their capital of *departamento*. Thus, the most distant municipalities from Bogotá have a 2.49% more coca crops production and the most distant municipalities from their capital of *departamento* have a 5.64% more coca crops production. In this sense, coca production seems to be taken place in distant municipalities from the main capital cities. Consequently, if the government also follows a similar logic with respect to the eradication of narcotics as the one followed by coca producers, I argue that the distance variables might also help determine the assignment of security forces by the Colombian central government to eradicate and control the production of narcotics on a municipality because the military machinery and tactics used by the government

²⁶(***) indicates that the estimated parameter is statistically significant at 1% and (**) indicates that the estimated parameter is statistically significant at 5%.

²⁷It is obvious that the estimated parameters of equation (4.9) are not perfectly estimated because there is an omitted variable bias in their estimation. A similar regression analysis is performed in table (A.6) controlling for this omitted variable bias. The result obtained in that table (not shown in the table) is similar to the one obtained in equation (4.9). Thus, the results of equation (4.9) are indicative of the positive correlation between coca production and distance from capital cities in Colombia.

can be applied to most of the country, without having accessibility a determining influence on the decision whether to eradicate or not on a municipality difficult to access.

Table (A.2) in appendix (A.3) presents a summary table for the variables used in this study. Two points are worth noting about table (A.2). On the one hand, the values presented on the table are averages of the variables for the period 1999 – 2010. When I observe the 5 *summary numbers* for the three indices, which summarizes their distributions, two characteristics are observed: first, the distributions of the eradication (I_E) and drug-dealers-war (I_{DW}) indices are both positively skewed. This implies that most of the Colombian municipalities are categorized as being of low-enforcement and low-drug-dealers-war levels. I also can observe that the maximum values in the average distributions of I_E and I_{DW} are 0.81 and 0.71, which implies that there was *not* a single municipality that received central government's drug-enforcement and drug-dealers-war activities in every year of the data set. Consequently, there were municipalities in which those drug outcomes were more common, while for most of the municipalities, those drug activities took place rather intermittently during the period of my data set. Second, the distribution of I_{AE} is, in contrast, negatively skewed, with a median value of zero. Besides, the maximum value in the I_{AE} average distribution is 1. Consequently, anti-eradication activities were concentrated in a reduced amount of municipalities, while for most of the municipalities, those drug activities never took place.

On the other hand, I do not include variables that control for income or labor market variables because the information on these variables is deficient or nonexistent. Sometimes, the proxies used in some studies are endogenous to the homicide rate or of poorer quality than normal. To overcome such a deficiency in information, I will run a panel data Spatial Durbin Model (SDM) with fixed and temporal effects. This model helps control for omitted variables not included in the regressions, which can be useful to explain the violence in Colombian municipalities. In the next subsection, I argue that spatial methods are necessary to run these regressions and in section (4.4), I present my identification strategy to test my hypotheses.

4.3.2 A spatial correlation

An extensive literature documents the spatial correlation of the homicide rate and the existence of drugs in Colombia (Mejia and Rico, 2010, Díaz and Sanchez, 2004, Holmes et al., 2006; & Gootenberg, 2008). Figures (A.25) and (A.26) in appendix (A.3) show averages for the main variables used in this paper. On the top of each graph, I present the average of the logarithm of the homicide and displacement rates per municipality for the period 1999 – 2010. A first characteristic I can observe on these maps is that not all municipalities present homicides or forcefully displaced people during this period. On all maps, the blue color represents a value of zero for the variable under examination. The small cluster of southern municipalities close to the Amazon region²⁸ and another on the west coast are the only ones with zero homicides during the period. The same happens with the rate of displaced people, which exhibits a smaller cluster of southern municipalities with zero values. These regularities might occur because those municipalities are mostly uninhabited. Most of the terrain of those municipalities comprises natural reserves and, in some cases, is difficult to access.

Second, in general I observe that the country presents both high homicide and displaced people rates in almost its entire territory. However, there are municipalities in which the situation is worse. In figures (A.25a) and (A.25b), the red color indicates a spatial concentration of the violence variables in specific regions of the country. The most problematic ones are close to Venezuela, Panamá, and Buenaventura Port, located on the Pacific coast, which are all exit points used by irregular groups to smuggle cocaine overseas²⁹.

Third, figures (A.25c), (A.25d), (A.26c), and (A.26d) present the drug war indices as defined in the previous sub-section. On the maps, I observe that the indices are also spatially concentrated with a larger proportion of Colombian municipalities exhibiting a value of zero in all three indices. In this case, a key point can be noted: both the Eradication Index (figure (A.25c)) and the Drug Dealers War Index (fig-

²⁸See figure (A.23) for a detailed map of Colombia and its main international frontiers.

²⁹See the Moran I's tests below.

ure (A.26c)) are more spatially concentrated around the areas in which most of the homicides and displacements take place; whereas the Anti-Eradication Index is less scarcely concentrated around the same areas. However, all three indices are spatially correlated with both endogenous variables to a certain degree³⁰. This fact is confirmed when I analyze table (A.3) in appendix (A.3), where I rank the main variables of this study by *departamento*. In this table, I observe that there are *departamentos* with high values in both endogenous variables and all three indices; for example, Guaviare, Caqueta, Arauca and Putumayo, among others.

It is worth noticing that the indices' maps confirm the intuition about the indices average distributions laid out in section (4.3.1). On the one hand, it is clear on the maps that anti-eradication activities are taking place on clusters of municipalities. Those clusters are located in the South –Meta, Guaviare, Caquetá and Putumayo *departamentos*–, Northeast –Arauca, Norte de Santander and Cesar *departamentos*–, Northwest –Bolívar, Sucre, Córdoba and Antioquia *departamentos*–, and Southwest –South of Choco, Valle del Cauca, Cauca and Nariño *departamentos*. Additionally, when I compare those clusters with the altitude per municipality shown in figure (A.26d), it seems as if Colombian anti-eradication activities were geographically located at the bottom of the main mountain chains that crosses Colombia³¹. On the other hand, Eradication and Drug Dealers War Indices are scattered around over almost the entire country, both exhibiting many small municipalities on the top of the mountain chains with zero values. It is also clear on the maps that these last two indices are also geographically distributed relative to the Colombian mountain chains. It seems that the altitude and distance to Bogotá are good exogenous sources of variation to explain all three indices' variability. In the next section, I explain how to exploit them to

³⁰If we compute Moran I's tests to tests whether these variables are spatially correlated, the following results are obtained: 0.14, 0.12 and 0.13 for the correlation between the logarithm of homicide rate and the eradication, anti-eradication and drug dealers war indices respectively, and 0.26, 0.17 and 0.28 for the correlation between the logarithm of the displacement rate and the eradication, anti-eradication and drug dealers war indices, respectively, being all these tests statistically significant at 1%. In order to compute these indices, I use the 5-nearest neighbors contingent matrix. The numbers obtained for the Moran I's tests indicate that there is a spatial correlation between the dependent variables and the drug war indices.

³¹One chain goes from Nariño (South) to Santander and Norte de Santander (Northeast), and the other from Nariño to Antioquia (Northwest).

obtain exogenous proxies for the drug war indices.

Finally, I observe that all those variables exhibit a high spatial autocorrelation. In table (A.2) in appendix (A.3), I compute Moran I's test³² for each of the variables used in this study. This test indicates that when determining the causal correlation among those variables, I must also include controls for the spatial autocorrelation that they exhibit. In the following section, I also explain how I perform that task.

4.4 The Empirical Strategy

My main interest is to test whether drug enforcement has an effect on violence in Colombia. To attain that, my empirical strategy consists of three stages: first, I run the following model under the same idea proposed in equation (A.24):

$$v = \beta_0 + \rho Wv + X\beta + WX\theta + \epsilon \quad (4.10)$$

where v represents a $(N \times T) \times 1$ vector containing any of the two endogenous variables used in this study: the logarithm of the homicide or the (forcefully) displaced people rates, both per 100,000 inhabitants. $N = 1122$ is the number of Colombian municipalities and $T = 12$ is the number of years used for estimation. X is a $(N \times T) \times 7$ matrix containing the following variables: I_E , the Eradication Index proposed in equation (4.2); I_{AE} , the Anti-Eradication Index proposed in equation (4.4); and I_{DW} , the Drug Dealers War Index proposed in equation (4.5). X also contains some institutional controls such as the logarithm of the population, municipality area per capita, and the “distance” of each municipality to Bogotá and its capital of *departamento* as defined by equations (4.7) and (4.8) respectively. Following Anselin, 1988 and LeSage and Pace, 2009, I include in the estimations Wy and WX to proxy for omitted variables that might help explain the variability of the endogenous variables but for which there is not information available. W is a spatial weight matrix constructed using the 5 nearest neighbors of each municipality³³.

³²I also use the 5-nearest neighbor contingent matrix to compute these tests.

³³A common problem in spatial econometrics is the choice of the aggregation level used to con-

As all the variables in X vary across time, equation (4.10) can be estimated including fixed or time effects, where the parameters associated to the indices ³⁴ are the main parameters of interest. However, in this specification some of the variables used to compute all three indices are endogenous. Specifically, the number of military attacks initiated by the central government against irregular groups, which is one of the main variables used to compute I_E , is endogenous to the violence rates. These attacks are performed by the army and police, who consider the level of violence as well as the required level of coca eradication in each municipality, to perform their enforcement activities in a municipality. This is in contrast to the other 5 variables used to compute I_E , which are performed by Policía Antinarcótics³⁵. Mejia and Restrepo, 2011 argue that coca crops, which is one of the variables used to compute I_{DW} , are also endogenous to the level of violence. I argue that massacres and incidents and accidents with mine fields, the other two variables used to compute I_{DW} , are also endogenous to the levels of violence in Colombia. Following Mejia and Restrepo, 2011, I must find an exogenous source of variation that helps explain those variables but at the same time is uncorrelated with either the homicide or displacement rates.

These authors use the altitude per municipality to proxy for the existence of illegal markets for cocaine in Colombia. They point out that, for technological reasons related to soil and climate conditions, coca plants provide larger concentrations of

struct the weight matrices. I tried three different combinations of weight matrices: 5, 10, and 15 nearest neighbors. My results show that when I increase the number of neighbors considered, the estimated first- and second-order effects of section 4.2.2 above become slightly stronger for all three indices. These results might be explained by the fact that the municipalities with the worse drug war and violence outcomes tend to be in *departamentos* with large extensions of territory and few municipalities, such as Guaviare (4), Putumayo (13), Vichada (4), Arauca (7), and Guainía (9). All these municipalities are more likely to be close neighbors in econometric terms, when the number of neighbors considered to construct the weight matrix increases. Consequently, throughout the presentation of the econometric model and the results, I always refer to or use the 5-neighbor contingent matrix. This matrix allows me to capture the neighbors' influence on a municipality, without taking into account neighbors from distant *departamentos* for those special cases.

³⁴The parameters β_1 , β_2 and β_3 of 4.1.

³⁵Antinarcoitics police. This is a police unit that follows a source of information different to the amount of homicides or displaced people to plan and perform their tasks. They use the number of crops captured by SIMCI, which are values that are available when coca crops are almost ready for harvesting, which occurs at least six months after the coca trees are planted (See SIMCI web-site for technical issues regarding possible delays in coca crops satellite data collection). In that sense, Antinarcoitics police plan their enforcement activities based on a database that might be *lagged at least six months*.

cocaine at lower altitudes. As a result, municipalities located at lower altitudes have more coca crops and more violence associated to the illegal markets for cocaine that results from these crops. Mejia and Restrepo, 2011 argue that there is no reason why the altitude might be correlated with violence other than through its effect on cocaine production. According to the model laid out in section (A.3.1), this conclusion is imprecise because cocaine production is also endogenous to the eradication and anti-eradication military expenditures performed by the central government and drug dealers in each municipality.

I argue that a municipality's distance to its capital of *departamento* and Bogotá, the measures computed in equations (4.7) and (4.8), also help explain the productivity of coca production in Colombia for two reasons. First, it is more difficult and expensive to produce coca crops in capital cities or near them due to a stronger police presence. In these municipalities, the most important economic and public administrative activities of each *departamento* take place. This leads the central government to allocate relatively more resources on police to these capital cities. Second, the Colombian central government organizes and executes its military operations using strategically-positioned military bases. These military bases are located near or within the capital cities of the most important *departamentos*³⁶. These two features suggest that the distance of a municipality to its capital of *departamento* is a good source of exogenous variation to capture the opportunity costs of cocaine production in Colombia. The spatial analysis laid out in section (4.3.2) indicates that the distance to Bogotá is also a good source of variation.

Those exogenous sources of variation are used to determine the *potential* intensity of attacks targeted to a municipality by drug dealers and the government to perform anti-eradication and eradication activities as follows:

$$y = \beta_0 + \rho W y + X\beta + WX\theta + \epsilon \quad (4.11)$$

where y is a $(N \times 1)$ vector that contains either of the following two endogenous

³⁶See Dube and Naidu, 2012 for an analysis of the Colombian military operations, the location of its military bases, and the possible consequences of these military operations on violence.

variables: the number of attacks initiated by the government against irregular groups or the number of attacks initiated by irregular groups against the central government's security forces. X is a $(N \times T) \times 3$ matrix containing my exogenous sources of variation. As the altitude per municipality does not vary over time, I cannot include fixed or time effects to estimate equation (4.11), because they are perfectly correlated with my instrument. To control for omitted variables that might help explain any of these two variables, I also include Wy and WX .

I use $\hat{y} = \hat{\beta}_0 + X\hat{\beta}$ as a proxy for drug enforcement and anti-enforcement activities of the government and irregular groups. These variables measure the *potential* intensity of attacks a municipality might have due to its *potential* for coca production, given by its own geographical and spatial position. Notice that I do not include any of the spatial effects to compute the proxies. Thus, every $\hat{y}_i$ is computed only using the information contained in X for municipality i and the β 's are computed net of possible omitted variables that also help explain why a municipality receive military attacks by any of the groups considered.

In turn, I use the proxies obtained in the previous step to estimate the following model:

$$y = \beta_0 + \rho Wy + X\beta + WX\theta + \epsilon \quad (4.12)$$

where in this case y is a $(N \times T) \times 1$ vector containing either the logarithm of hectares of coca crops captured by SIMCI, the number of massacres committed by irregular groups in their areas of influence or the number of incidents and accidents with mine fields, which are known to be used to protect the coca crops from being eradicated. X in this case contains the exogenous sources of variation used in equation (4.11), along with the proxies for drug enforcement and anti-enforcement activities computed from the same equation. Again, I include Wy and WX to proxy for omitted variables that might help explain any of the last three variables used to compute I_{DW} .

Using equation (4.12), I use $\hat{y} = \hat{\beta}_0 + \hat{X}\hat{\beta}$ as instruments to proxy for the variables used to compute I_{DW} . $\hat{X}$ does not contain any of the proxies for drug en-

forcement and anti-enforcement activities computed from equation (4.11). As a result, the computation of I_{DW} is net of those enforcement activities. Also, $\hat{X}\hat{\beta}$ is a measure that resembles the drug dealers war' instrumentalized proxy computed by Mejia and Restrepo, 2011. Thus, my results are directly comparable with those found by them.

Then, the final stage involves recomputing all indices as explained in equations (4.2), (4.4), and (4.5), using the proxies found in equations (4.11) and (4.12), with a slight difference that the vector a in those equations is now composed of the entire array of values of the computed proxies without a priori division of every array between zero and positive values. With these recomputed indices, I run again the model laid out in equation (4.10), concluding my empirical strategy. Before analyzing the results, two points are worth noting: first, the measurement units of the recomputed indices are entirely comparable with those of the original indices; as a result, the interpretation of the estimated coefficients associated to these new indices is the same. Second, my methodology to recompute the indices do not bias the estimated results in any systematic way. The recomputed indices reorganize municipalities according to their estimated potential to have drug war military expenditures, resulting from their geographical and spatial location, which is a priori unrelated to violence. As a consequence, any correlation between these indices and the proxies for violence can be understood as a causal correlation.

4.5 Results

4.5.1 Initial Results

The lack of information associated to income or labor market variables for the Colombian municipalities forces me to rely on indirect methods to control for a potential omitted-variable bias in our estimations. This section is based on Elhorst, 2003 and Elhorst, 2012, who formally present the rationale behind running a Panel Data Spatial Durbin Model to control for this econometric problem. They also present the

empirical application where they indicate the different existing alternatives to test whether the spatial and panel data effects controlled for with this model are really of statistical significance.

A good feature of spatial econometrics methods is that they also allow to use a municipality's neighbors information to estimate the effects of the municipality's drug war indices on its *own* violence outcomes. This interrelation also allows to determine the effect of a municipality's drug war indices on its *neighbors'* violence outcomes. These effects are called the direct and indirect effects of the drug war indices on violence, respectively. It is worth noticing that these two effects are conceptually and quantitatively different from the drug enforcement's first- and second-order effects defined in the introduction. The first-order effect of drug enforcement includes the direct and indirect effects of I_E and I_{AE} on violence. The second-order effect includes the direct and indirect effects of I_{DW} .

The estimation results of equation (4.10) are presented in tables (A.4) and (A.5) in the appendix (A.3). Table (A.4) presents the estimation results for the logarithm of the homicide rate; table (A.5) does it for the logarithm of the displacement rate. In the first column of each table, I present the estimated coefficients provided by MATLAB without including fixed or time effects. LeSage and Pace, 2009 argue that these estimated coefficients are not the main interest of the spatial econometric analysis, but the direct, indirect and total effects computed from them. Even though I analyze the estimated spatial effects, which were computed as explained by Elhorst, 2003, I follow Elhorst, 2012 in presenting these estimated regression coefficients for the sake of results completeness.

On columns 2 to 4 of each table, I present the estimated direct, indirect, and total effects of equation (4.10). In turn, from column 5 to 12 of each table, I present the same types of results as in the first four columns including fixed, time, and fixed and time effects, respectively. I also present in each table the tests to ascertain whether a Panel Data Spatial Durbin Model is the correct specification to estimate equation (4.10), as explained by Elhorst, 2012. According to Elhorst, 2012, there are two alternatives to test whether the correct model to run is a panel data Spatial Durbin

Model(SDM), Spatial Autoregressive Model (SAR) or a Spatial Error Model (SEM). There is a common argument underlying both alternatives: the SDM model can be reduced to either the SAR model or the SEM model. The main difference between the two alternatives is that one compares the performance of the particular model (SAR or SEM) with the general model (SDM), and the other compares the performance of the general model (SDM) with the particular model (SAR or SEM).

The alternative that goes from the particular model to the general model uses simple LM tests to determine which model better explains the variability of the data. There are two types of tests to use with this alternative: One type compares the SAR (or SEM) model with the SDM model without controlling for the possibility that the data also follows a SEM (or SAR) model jointly with the SAR (or SEM) model. These tests are labeled *LM_spatial_lag* in tables (A.4) and (A.5) in appendix (A.3) for the comparison between the SAR model with the SDM model and *LM_spatial_error* for the comparison between the SEM model and the SDM model. The other type of tests to use with this alternative compares the SAR (or SEM) model with the SDM model controlling for the possibility that the data also follows a SEM (or SAR) model jointly with the SAR (or SEM) model. These tests are labeled *Rob.LM_spatial_lag* in tables (A.4) and (A.5) in appendix (A.3) for the comparison between the SAR model with the SDM model and *Rob.LM_spatial_error* for the comparison between the SEM model and the SDM model.

In turn, the alternative that goes the general model to the particular model uses either Wald or LR tests to determine which model better explains the variability of the data. In this case, these tests are labeled *Wald_spatial_lag* or *LR_spatial_lag* in tables (A.4) and (A.5) in appendix (A.3) for the comparison between the SDM model with the SAR model and *Wald_spatial_error* or *LR_spatial_error* for the comparison between the SDM model with the SEM model. In both testing alternatives, the null hypothesis is that the data does not follow the SDM model (either the SAR or SEM models) against the alternative hypothesis that it does follow the SDM model. As a result, a large value in any of the latter tests indicate that the SDM model better explains the variability of the data.

Several results can be derived from table (A.4). First, following Elhorst, 2012, all tests indicate that the best specification to run equation (4.10) is a Panel Data Spatial Durbin Model. In other words, there are omitted variables that help explain violence in Colombia, which are properly captured by Wy and WX in equation (4.10). All the estimated values of ρ in table (A.4) indicate that there is a positive correlation between municipality i 's homicide rate and the homicide rate of municipality i 's surrounding municipalities. As a result, there are geographical factors not controlled for with the fixed or time effects that also help explain the homicide rate in Colombia in the period 1999–2010. Second, regardless of whether I include fixed, time, or both effects together, there is a positive correlation between the Eradication Index (I_E) and both the logarithm of the homicide and displaced people rates in Colombia. The estimated impact of the Colombian government's military eradication activities is very stable across specifications. In section (4.3.1), the interpretation of the estimated results associated to these indices is explained. There, it is said that β_1 ³⁷ represents the percentage change of the violence rate resulting from drug enforcement. As I consider spatial effects, β_1 is estimated by the total spatial effects, composed of the sum of the direct and indirect effects of I_E on v .

Second, tables (A.4) and (A.5) indicate that the government's drug enforcement activities generated a total increase in the homicide rate between 1.14% and 2.47% and a total increase in the displacement rate between 1.02% and 2.84%. According to these results, the total effects appear to be mainly driven by the direct effects of enforcement. In other words, it appears that coca eradication activities generate violence in the municipalities in which they are performed. However, I cannot give these results a causal interpretation because I_E is endogenous to both the levels of violence and the production of narcotics.

Third, the attacks of irregular groups against the government's security forces do generate homicides and displaced people in Colombia. According to table (A.4), the estimated impact of the irregular groups' activities on violence is also very stable across specifications. These activities generate an estimated total increase in

³⁷The parameter associated to the drug enforcement military expenditures of equation (4.1).

the homicide rate between 0.53% and 1.33% and an estimated total increase in the displaced people rate between 0.76% and 1.84%. According to these results, when irregular groups attack a municipality, their actions also affect contiguous municipalities. These attacks are most likely targeted to gain control of the territory. However, I_{AE} is endogenous to several factors apart from the simple production of cocaine. As a result, I cannot yet ascertain if these attacks only respond to the interests that irregular groups have on the territory for cocaine production or other factors, such as the availability of petroleum or gold.

Finally, the drug war among dealers, captured by I_{DW} , is also positively correlated with the violence in Colombia, as Mejia and Restrepo, 2011 argue. According to my preliminary results, the drug dealers' war generates a total increase in the homicide rate between 0.61% and 2.77% and a total increase in the displaced people rate between 2.69% and 7.53%. It is interesting to note that the indirect effects of the drug dealers' war is not as stable for the homicide rate than as for the displacement rate. My preliminary results indicate that the drug dealers' war affect more heavily the homicide rate of the municipality where it takes place than the homicide rate of its surrounding municipalities. In contrast, the drug dealers' war not only affects directly the displacement rate of the municipality in which it takes place, but also the displacement rate of those municipalities around it. Consequently, according to my preliminary results, people seem to abandon their homes when drug dealers attack each other in their municipalities of residence, or when they do it in the surrounding municipalities. However, I cannot give these results a causal interpretation because I_{DW} is endogenous to the levels of violence, the production of narcotics and the government's eradication activities.

To provide a causal interpretation, I perform a 2SLS analysis that is presented in the next section. Before entering in that discussion, an important point is noted here: if I_E , I_{AE} and I_{DW} really capture the Colombian drug war military expenditures of all participants in the drug war during the period 1999 – 2010, there were substantial first- and second-order effects of enforcement in Colombia. The estimated first-order effect of enforcement derived from tables (A.4) and (A.5) is between 2.27% and 3.00%

for the homicide rate and between 2.12% and 3.83% for the displaced people rate. The estimated second-order effect of enforcement is between 0.61% and 2.77% for the homicide rate and between 2.69% and 7.53% for the displacement rate.

4.5.2 2SLS Results

The results of the first stage of the IV estimations are presented in table (A.6) in appendix (A.3), which is divided in two parts. The upper part of table (A.6) presents the estimation results for the number of attacks initiated by the government against irregular groups and the number of attacks initiated by irregular groups against the government's security forces. Thus, it presents the results of equation (4.11) in section (4.3.1). In turn, the lower part of table (A.6) presents the estimation results for the logarithm of coca crops, the number of accidents and incidents with mine fields, and the number of massacres perpetrated by irregular groups in their areas of influence. These are the results of equation (4.12) in section (4.3.1).

The first column of each set of regression results in table (A.6) presents the estimated coefficients provided by MATLAB. The other 3 columns present the direct, indirect, and total effects, which were also computed as explained by Elhorst, 2003 and Elhorst, 2012. I also present the tests to determine whether a Panel Data Spatial Durbin Model is the correct specification to estimate equations (4.11) and (4.12), as explained by Elhorst, 2012. The estimation results in table (A.6) do not control for any of the panel data fixed or time effects. The latter is due to two reasons: first, fixed effects are perfectly correlated with the altitude per municipality, one of the instruments in those estimations. Second, time effects resulted statistically insignificant.

From table (A.6), several insightful results can be obtained. A first general result is that a Spatial Durbin Model is the correct specification to estimate equations (4.11) and (4.12). The latter can be concluded from the tests indicating that these estimations cannot be reduced to either a panel data SAR or SEM models. This result might indicate that the government attacks irregular groups not only because

they are producing narcotics, but also because of their criminal activities, such as robberies, kidnappings, and the like. The same can be said from irregular groups' attacks. These groups have an interest in the territory that goes beyond the sole production of narcotics.

Additionally, the number of attacks perpetrated by both groups is explained by the altitude in the expected sign. If the altitude really captures the coca crops productivity, the number of attacks of both groups is explained to some extent by the *potential* that municipalities have for cocaine production. In regards to these attacks, I obtain two interesting results: on the one hand, the direct and indirect spatial effects of the distance variables are statistically insignificant, but the total effects are weakly significant for the number of attacks initiated by the government against irregular groups. It seems that distances to capital cities and Bogotá do not entirely capture the government's military attacks against irregular groups. However, the distance of municipalities to capital cities has some influence on that decision: the *farther* municipalities were to Bogotá and the *closer* they were to capital cities, the more the government attacked irregular groups in these municipalities.

On the other hand, the distance variables are statistically significant for the irregular groups' number of attacks; however, the results are mixed. The total effects of the distance variables indicate that the number of attacks of irregular groups increased when the municipalities were *farther* from Bogotá and *closer* to their capital cities of *departamento*. These latter results are explained by the estimated direct and indirect effects of the distance variables. The direct effects indicate that the number of attacks of irregular groups increased when the municipalities were both *closer* to Bogotá and their capital of *departamento*. The indirect effects indicate that the municipalities' neighbors were less likely to be attacked when the municipalities were *closer* to Bogotá and their capital cities of *departamento*. This result might indicate that municipalities that were jointly close to capital cities and Bogotá had fewer attacks by these groups. This latter result is confirmed by the spatial analysis laid out in section (4.3.2), where we observe that the number of irregular groups' attacks have a concentration at the bottom of the mountain chains that crosses Colombia

from South to Northwest and Northeast. However, in those municipalities that are really far away from the mountain chains or at the top of them, near to Bogotá, the attacks were zero during the entire period under examination. That is illustrated, for example, in the South of Colombia, in spite of being a region entirely dedicated to the production of coca crops, as indicated in figure (A.25c).

Based on the empirical strategy explained in section (4.4) for equation (4.11), I use $\hat{y} = \hat{\beta}_0 + \hat{X}\hat{\beta}$ to obtain exogenous proxies for the government and irregular groups' drug war military expenditures on the Colombian municipalities. As explained in section (4.4), I use the latter $\hat{y}$'s in the estimations of equation (4.12) to obtain net exogenous measures of the Colombian drug dealers' war. The regressions of equation (4.12) are presented in the lower part of table (A.6), where *govconthat* and *irreconthat* represent the proxies for the government and irregular groups' drug war military expenditures obtained from equation (4.11).

In regards to the results for the variables used to compute I_{DW} , the total effects of the altitude indicate that it negatively affects all three variables. That concurs with the results obtained by Mejia and Restrepo, 2011, who also found out that cocaine production is negatively related to the altitude per municipality in Colombia. This result also confirms my intuition that the number of incidents and accidents with mine fields and massacres are also associated with the altitude in the expected sign. If the altitude really captures a municipality's cocaine productivity potential, my results indicate that mine fields and massacres also seem to respond to the drug dealers' war that Mejia and Restrepo, 2011 attempt to control for only using coca crops as a proxy.

The results also confirm my intuition that the military actions of the government to eradicate narcotics, captured by *govconthat*'s total effects, have also an effect on the three variables. Additionally, they show that these actions *reduced* the number of hectares of coca produced, *reduced* the number of mine fields used by irregular groups, and *increased* the number of massacres in the country. All the latter results can be interpreted as follows: first, coca crops showed a downward tendency during the

period of analysis³⁸. This was clearly the response of the tougher drug enforcement policy initiated with “Plan Colombia”.

Second, *govconthat*’s total effects on the number of incidents and accidents with mine fields are mostly influenced by *govconthat*’s indirect effects. The *govconthat*’s direct effect indicates that the government’s direct actions to eradicate coca crops in the affected municipalities *increased* the incentives of irregular groups to use mine fields to protect the coca cultivated areas from eradication. The *govconthat*’s indirect effect indicates that once an area was totally controlled by the government, this territorial control reduced the total amount of mine field cases. Finally, *govconthat*’s total effects on massacres are weakly statistically significant. This result is mainly influenced by the *govconthat*’s direct effects. Thus, it seems that coca eradication military attacks also increased the incentives for irregular groups to commit massacres on the municipalities where eradication took place.

When I analyze the total effects of the anti-eradication activities, the results are less clear-cut to understand. First, *irreconthat*’s total effects indicate that the irregular groups’ anti-eradication activities *reduced* the coca crops in Colombia. That result is influenced by *irreconthat*’s indirect effects, which implies that when a municipality was more attacked, their neighbors produced fewer coca crops. This might indicate that irregular groups made more attacks in those municipalities near to coca production centers subjected to eradication. As *irreconthat*’s direct effects are statistically insignificant for coca production and coca production was reduced in the whole period, it seems that the overall effect was that the irregular groups’ attacks did not attain what they intended to.

Second, *irreconthat*’s total, direct, and indirect effects on the number incidents and accidents with mine fields are all either statistically insignificant or weakly significant. This result might indicate that anti-eradication military actions and mine fields are *substitute inputs* to protect the coca fields. Finally, *irreconthat*’s total ef-

³⁸For a thorough analysis of coca crops in South America, see the United Nations Office for Drugs and Crime (UNODC) website on crops monitoring in the world: UNITED NATIONS OFFICE ON DRUGS AND CRIME, 2013.

fects on massacres are statistically significant. This result is mainly influenced by *irreconthat*'s indirect effects and can be interpreted as that of coca crops. It seems that irregular groups' anti-eradication attacks increased the number of massacres in the municipalities where they attacked, which were in territories where they were losing influence.

In general, it appears that my empirical strategy gives sound proxies to be used in the second stage of the IV strategy. I compute these proxies using $\hat{y} = \hat{\beta}_0 + \hat{X}\hat{\beta}$ and the estimated coefficients from table (A.6). Table (A.2) in appendix (A.3) shows summary statistics for the re-computed indices and figure (A.27) presents their maps. A quick comment is in order: it seems that the procedure to recompute the indices do not bias in any systematic way their values. However, these new indices have a slightly different distribution, being I_E 's distribution the most similar to the original one. Even though, it does not appear that the new indices are re-computed in a way that favors my hypothesis.

The second IV stage is presented in tables (A.7) and (A.8) in appendix (A.3), which replicates equation (4.10) and tables (A.4) and (A.5) using the new indices obtained from equations (4.11) and (4.12) to proxy for the drug war military expenditures. From tables (A.7) and (A.8), several results are also obtained. First, the tests to ascertain the type of model to run again indicates that a Spatial Durbin Model is the best specification for our data. There are omitted factors that help explain the violence in Colombia different from the drug war variables, which are properly captured by Wv and WX terms in equation (4.10).

Second, my results seem to indicate that the government's drug enforcement activities *do generate* violence in Colombia. Based on $\hat{I}_E$'s total effects on the logarithm of the homicide and displacement rates, the estimated impact of these actions is positive. According to tables (A.7) and (A.8), the government's eradication activities *increased* the homicide rate between 0.75% and 1.84% and the displacement rate between 0.99% and 5.82%. All these estimates are statistically significant at common significant levels.

Third, $\hat{I}_{AE}$'s estimated total effects indicate that anti-eradication activities by ir-

regular groups *increased* violence in Colombia. However, these estimated effects are not stable across specifications, especially for the homicide rate. My results indicate that the sign and statistical significance of the effect of the irregular groups' anti-eradication activities varies when I include fixed effects in the estimations. It seems that the activities that these groups perform on the territory they are fighting for influence the way in which their actions affect the homicide rate. Fixed effects might be capturing structural homicides that occur in the territory. There must be structural homicides that are controlled and determined by these groups. My results indicate that when these structural homicides are not controlled for, the irregular groups' attacks have a statistically insignificant positive direct effect on the municipalities in which they attack and a statistically significant negative indirect effect on the surrounding municipalities where they attack. This result can be interpreted as implying that once these groups have gained a sufficient important territorial control over a set of contingent municipalities, their military actions against the government to control the territory with the intention to produce cocaine reduce the homicide rate of the entire area, except where they are attacking. In contrast, when I control for these structural homicides, their actions to control the territory only affect positively the homicide rate on the territories where they attack. The latter is not true for the displacement rate where the effect of the irregular groups' anti-eradication activities is always positive across specifications.

Finally, $I_{DW}^{\wedge}$'s total effects indicate that the drug dealers' war have mixed effects on violence in Colombia, especially for the displacement rate. According to my results, this war generated a change in the homicide rate between 2.29% and 4.37%. $I_{DW}^{\wedge}$'s direct and indirect effects are also rather stable across specifications. They indicate that the drug dealers' war increased the homicide rate in the municipalities where this war took place and the surrounding municipalities as well. The latter is not true for the displacement rate. In this case, the inclusion of fixed effects also affects the sign and statistical significance of the drug dealers' war effects on violence. It seems that there are structural phenomena that are intertwined with the drug dealers' war in the Colombian municipalities which obscure the pure effect of the drug dealers'

war actual influence on the displacement rate. Once these structural variables are controlled for with the fixed effects, the total, direct and indirect effects of the drug dealers' war on the displacement rate become statistically insignificant and with a contrary sign to one expected.

In all the results presented in tables (A.7) and (A.8), the inclusion of fixed effects affected the value of the estimated results. If I assume that the models containing these effects provide us with the most accurate estimations, as the F tests at the bottom of tables (A.7) and (A.8) indicate, our results show that drug enforcement has had important effects on violence in Colombia. Tables (A.7) and (A.8) indicate that the government's eradication military expenditure generated an increase of 1.84% in the homicide rate and 0.99% in the displacement rate. The drug dealers' war generated an increase of 4.00% in the homicide rate and 0.16% in the displacement rate. And, the irregular groups' anti-eradication activities generated an increase of 0.14% in the homicide rate and an increase of 0.25% in the displacement rate. My results indicate that there were substantial first- and second-order effects of enforcement in Colombia. The first-order effect is 0.98% for the homicide rate and 1.24% for the displacement rate. The second-order effect is 4.00% for the homicide rate and 0.16% for the displacement rate.

4.6 Conclusion

In this paper, I argue that drug enforcement in a source country does generate violence, where the latter is measured as rate of homicides or displacement per 100,000 inhabitants. I use data on drugs from Colombia during the period 1999–2010 to test this hypothesis. I find that drug enforcement has two effects: first- and second-order effects. The first-order effect refers to the direct violence generated by the drug war between the government and drug dealers. When the government spends on military activities to control the production of narcotics, there are eventually victims that results from that expenditure. Drug enforcement might also have an impact on the feeling of security of the inhabitants of the areas where the drug war take place,

forcing them to move to safer regions where they are not affected by these activities.

However, this is not the only effect of enforcement. As narcotics are supplied by decentralized markets, drug dealers have the monetary and the military power to fight back against the government's drug enforcement activities and against other drug gangs, with which a pacific resolution of conflicts seems to be simply impossible. Our results also indicate that Colombian violence derives from factors other than the country's drug war. Colombian drug dealers also generate violence not associated to cocaine production. This happens when drug dealers gain sufficient military power to control a territory, which generates spillover effects over other activities on which violence is also used. This is true, for instance, when irregular groups use the profits of narcotics to fight territorial control in regions with other natural resources such as gold or petroleum. This also occurs when these groups use their military power to position themselves as the ultimate regulators of their regions of influence.

A meaningful conclusion reached in this paper is that in Colombia the use of mine fields is explained by the production of cocaine and the drug enforcement activities of the central government. As a result, one of the worst consequences of the Colombian conflict is actually incentivized by the Colombian drug war. Another conclusion is that Colombian data show that there existed first- and second-order effects of drug enforcement in the period 1999 – 2010: my results indicate that the first-order effect is 0.98% for the homicide rate and 1.24% for the displacement rate in the period 1999-2010 and the second-order effect is 4.00% for the homicide rate and 0.16% for the displacement rate.

As a final conclusion, I cannot claim that the military tactics are the best methods to completely control the existence of drugs in Colombia. Despite the strength gained by the Colombian army and police from "Plan Colombia", there are still Colombians interested in participating in the production of cocaine. Given the existence of an international market providing these individuals with funds to fight back the central government's security forces, the result is that *more Colombians* are dying every day for the war against drugs.

Chapter 5

Conclusions

This dissertation presents three cases in which crime is manifested. In chapter 2, I extend a model of property crime by incorporating a market for illegal goods. The secondary market is formed by individuals who rationally decide to become criminals, steal durable goods, and sell them in this market, and by non-criminals that demand stolen goods. The model develops a few additional elements. First, criminal activities take place because individuals target durable goods either for re-selling or for consumption. Second, criminals activities take place because there is a potential demand for stolen property. This demand is composed of individuals buying stolen property willingly. Finally, I assume that the government performs two crime control activities: street control and control on illegal transactions taking place in secondary markets.

In this simplified framework, I obtain the following results. First, under certain conditions individuals with low preferences for the durable good may have incentives to engage in criminal activities: they would steal goods and sell them in the secondary market. Second, depending on the combination of law enforcement activities put in place by the government, individuals with a “low-middle” preference for the durable good would become criminals, steal goods, but keep them for their own consumption. Finally, some non-criminals that are subject to crime and lose their property may have incentives to replace the stolen good by purchasing it in the secondary illegal market. This last conclusion is consistent with the fact that even though individuals

openly complain about property crime, if the price of stolen goods is low enough, they may have incentives to purchase illegal goods supporting and encouraging indirectly illegal activities and more crime.

In chapter 4, I argue that drug enforcement in a source country does generate violence, where the latter is measured as rate of homicides or displacement per 100,000 inhabitants. I use data on drugs from Colombia during the period 1999–2010 to test this hypothesis. I find that drug enforcement has two effects: first- and second-order effects. The first-order effect refers to the direct violence generated by the drug war between the government and drug dealers. When the government spends on military activities to control the production of narcotics, there are eventually victims that results from that expenditure. Drug enforcement might also have an impact on the feeling of security of the inhabitants of the conflictive areas, forcing them to move to safer regions where they are not affected by these activities.

However, this is not the only effect of enforcement. As narcotics are supplied by decentralized markets, drug dealers have the monetary and the military power to fight back the government's drug enforcement activities and other drug gangs, with which a pacific resolution of conflicts seems to be simply impossible. Our results also indicate that Colombian violence derives from factors other than the country's drug war. Colombian drug dealers also generate violence not associated to cocaine production. This happens when drug dealers gain sufficient military power to control a territory, which generates spill over effects over other activities on which violence is also used. This is true, for instance, when irregular groups use the profits of narcotics to fight territorial control in regions with other natural resources such as gold or petroleum. This also occurs when these groups use their military power to position themselves as the ultimate regulators of their regions of influence.

Finally, I construct in chapter 3 a crime model in which there is a sub-set of the population who are attracted to drugs, and have a minimum drug consumption requirement. The numerical results of this chapter indicate that when the government does not face a budget constraint, the best strategy is to spend only on capturing thieves and not on seizing drugs. The reason is that drug control policies increase the

equilibrium drug prices, which increases the addicts' incentives to engage in property crime. By spending nothing on controlling drugs, the government keeps the economic incentives of addicts to engage in criminal activities at its minimum levels. This occurs because the government is not able to induce an equilibrium drug price that makes drug addicts become more risk-neutral with changes in p_d .

In contrast, when the government faces a budget constraint, and there is a minimum expenditure requirement, the best strategy for the government is to control a positive percentage of drugs in the market. The reason is that the government is able to supplement its budget with the income obtained from captured addicts engaged in crime. When the government has sufficient funds to control the optimal percentage of thieves in equilibrium, the best strategy of the government is to subsidize the consumption of drugs. This occurs because income improvements increase the equilibrium price of drugs, but it does not occur to a point in which individuals become risk-neutral so that the economic incentives of enforcement have a larger influence on individual's criminal decisions. At the equilibrium values encountered for p_d , people are incentivized to commit crime. Hence, it is optimal for the government to reduce those incentives through increasing the availability of drugs in the market.

This dissertation contributes to the economic literature in at least three aspects. First, it constructs a model with which the relationship between durable goods and crime can be formally analyzed. This model can be extended in a diversity of ways. For example, it can incorporate more complicated relationships between different vintages of a durable good and the incentives that individuals have to steal those vintages. It can also be extended to analyze the optimal response of a durable good's producer who produces a good that is targeted by thieves.

Second, this dissertation constructs a model with which the criminal incentives of addicts are studied. This model shows that when the economy is inhabited by individuals with lexicographic preferences with respect to the single composite drug commodity in the economy, drug control policies operate in an environment of risk-lover individuals who can be induced to crime by their addiction. This model can be extended to incorporate the dynamic decisions of the same addict in order to study

the optimal dynamic response of the government to control narcotics when these individuals make different criminal decisions throughout their lifetime. It can also be extended to incorporate the optimal response of drug dealers with respect to the level of addiction in the economy. This analysis might provide with the conditions under which drug dealers find profitable to either increase or reduce the addiction levels of the narcotics they produce. It can also be extended to incorporate the response of the same drug dealers with respect to the diversification of narcotics in the economy. Finally, this dissertation introduces a set of valid exogenous sources of variation to test whether drug enforcement increases violence or not. This analysis allows to test whether a policy targeted to reduce an externality might create another one. This methodology can be adjusted to study other phenomena that depend on the altitude per municipality, and the distance from capital cities as explanatory variables.

APPENDIX

A.1 Appendix: Property Crime and Durable Goods

(a) Extensive Form Representation of Criminals' Decisions

(b) Extensive Form Representation of Non-Criminals' Decisions

Figure A.1: Extensive Form Representation of the Game

Figure A.2: Non-criminal i's demand for a New Durable Good at the Third Round of Decisions

Figure A.3: Possible Sub-Perfect Nash Equilibria organized along the domain of α

Figure A.4: Aggregate Supply of Stolen Durable Goods

Figure A.5: Aggregate Supply of Stolen Durable Goods

Figure A.6: Possible Social Configurations of the Economy

where,

$$\begin{aligned} a_1 &= \frac{p - p'}{(1 - \beta)[q - (1 - \pi_2)q']} \\ a_2 &= \frac{p}{(1 - \beta)q} \\ a_3 &= \frac{p'}{(1 - \beta)(1 - \pi_2)q'} \end{aligned}$$

and,

$$\begin{aligned} b_1 &= \frac{\lambda_{nc}^r(1 - \pi_1)p}{[\beta + (1 - \beta)\pi_2\lambda_{nc}^r(1 - \pi_1)]q} \\ b_2 &= \frac{p - (1 - \lambda_{nc}^r(1 - \pi_1))p'}{(1 - (1 - \beta)(1 - \pi_2)\gamma - (1 - \beta)(1 - \gamma)\lambda_{nc}^r(1 - \pi_1)(1 - \pi_2))q} \\ b_3 &= \frac{p}{[1 - (1 - \beta)\lambda_{nc}^r(1 - \pi_1)(1 - \pi_2)]q} \end{aligned}$$

$$d = \frac{(1 - \pi_2)p' - \pi_2 f_2}{(1 - \beta)q'}$$

Figure A.7: Relationship between π_2 and π_1 faced by the government for a given value of $\lambda_{nc}^r = nc$

(a) Equilibrium Crime Rates for $p = 0.10$ and $p = 0.12$

(b) Equilibrium p' for $p = 0.10$ and $p = 0.12$

(c) Percentage of criminals who keeps the stolen property

(d) Percentage of criminals who sells the stolen property

Figure A.8: Equilibrium Values of λ_{nc}^* and p' for different values of π_1 and π_2

A.2 Appendix: Optimal Drug Supply Control

A.2.1 Graphs

Figure A.9: The Extensive-Form Representation of the Game

Figure A.10: Population Distribution Organized by Income (w_i) and Drug Preferences (ϵ_i)

Figure A.11: Multiple Equilibria of Percentage of Thieves (N_T) Figure A.12: Multiple Equilibria of Percentage of Thieves (N_T)

Figure A.13: Optimal Aggregate Drug Demand given $\{p_d, N_T\}$

Figure A.14: Aggregate Total Percentage of Thieves

(a) Equilibrium Percentage of Heavily Addicted Thieves

(b) Equilibrium Percentage of Lightly Addicted Thieves

(c) Equilibrium Percentage of Thieves with Zero Addiction

Figure A.15: Splitting The Total Percentage of Thieves into Addiction Groups

Figure A.16: Aggregate Total Percentage of Thieves for Different Values of $\{f, t\}$

Figure A.17: Equilibrium Prices for Different Values of $\{f, t\}$ Figure A.18: Government's Budget Optimal Constraints for Different Values of $\{f, t\}$

Figure A.19: Government's Budget Optimal Constraints for Different Values of $\{f, t\}$ Figure A.20: Eq. Values for the Control Variables of the Government ($\{\pi_c, \pi_T, f, \tau\}$)

Figure A.21: Eq. Values for the Control Variables of the Government ($\{\pi_c, \pi_T, f, \tau\}$)

Figure A.22: Eq. Values for the Control Variables of the Government ($\{\pi_c, \pi_T, f, \tau\}$)

A.2.2 Equations

Equations of Section 3.3.3

$$A_0(p_d; \epsilon_i) = \frac{\left[(1 - \epsilon_i)^{\frac{1}{1-\theta}} p_d^{\frac{\theta}{1-\theta}} + \epsilon_i^{\frac{1}{1-\theta}} \right]^{\left(\frac{1-\theta}{\theta}\right)}}{p_d} \quad (\text{A.1})$$

$$A_1(p_d; \epsilon_i) = \frac{\epsilon_i^{\frac{1}{\theta}}}{p_d} \quad (\text{A.2})$$

$$A_2(\epsilon_i) = a_\epsilon \epsilon_i^{\frac{1+\theta}{\theta}} \quad (\text{A.3})$$

$$U_{1,i}^e = [I_i^1 - p_d a_\epsilon \epsilon_i] \left[A_0(p_d; \epsilon_i) + p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)(1-f)})(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \right] \quad (\text{A.4})$$

$$U_{2,i}^e = [I_i^2 - p_d a_\epsilon \epsilon_i] \left[A_0(p_d; \epsilon_i) + p(w_i \leq \frac{p_d a_\epsilon \epsilon_i - \eta \bar{w}}{(1-\tau)})(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \right] \quad (\text{A.5})$$

$$U_{3,i}^e = [I_i^0 - p_d a_\epsilon \epsilon_i] \left[A_0(p_d; \epsilon_i) + p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)})(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \right] \quad (\text{A.6})$$

$$U_{4,i}^e = [I_i^0 - p_d a_\epsilon \epsilon_i] \left[A_0(p_d; \epsilon_i) + p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)})(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \right] \quad (\text{A.7})$$

$$U_{5,i}^e = [I_i^3 - p_d a_\epsilon \epsilon_i] \left[A_0(p_d; \epsilon_i) + p(w_i \leq \frac{p_d a_\epsilon \epsilon_i + \eta \bar{w}}{(1-\tau)})(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \right] p(w_i \geq \frac{\eta \bar{w}}{(1-\tau)}) - A_2(\epsilon_i) p(w_i < \frac{\eta \bar{w}}{(1-\tau)}) \quad (\text{A.8})$$

$$U_{6,i}^e = [I_i^1 - p_d a_\epsilon \epsilon_i] \left[A_0(p_d; \epsilon_i) + p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)})(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \right] \quad (\text{A.9})$$

$$B_0 = A_0(p_d; \epsilon_i) \left[\lambda_{gr}(1 - \pi_T) p(w_i \leq \frac{\eta \bar{w}}{(1-\tau)}) - (1 - \lambda_{gr}) \pi_T f \right] + \quad (\text{A.10})$$

$$(A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \left\{ (1 - \lambda_{gr}) \pi_T (1 - f) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)(1-f)}) + (1 - \lambda_{gr})(1 - \pi_T) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i - \eta \bar{w}}{(1-\tau)}) - (1 - \lambda_{gr}(2 - \pi_T)) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)}) - \lambda_{gr}(1 - \pi_T) p(w_i > \frac{\eta \bar{w}}{(1-\tau)}) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i + \eta \bar{w}}{(1-\tau)}) \right\}$$

$$B_1 = A_0(p_d; \epsilon_i) \lambda_{gr}(1 - \pi_T) p(w_i \leq \frac{\eta \bar{w}}{(1-\tau)}) + (A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \left\{ (1 - \lambda_{gr}) \pi_T p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)(1-f)}) \right. \quad (\text{A.11})$$

$$+ (1 - \lambda_{gr})(1 - \pi_T) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i - \eta \bar{w}}{(1-\tau)}) - (1 - \lambda_{gr}(2 - \pi_T)) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i}{(1-\tau)}) - \lambda_{gr}(1 - \pi_T) p(w_i > \frac{\eta \bar{w}}{(1-\tau)}) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i + \eta \bar{w}}{(1-\tau)}) \left. \right\}$$

$$B_2 = \eta \bar{w}(1 - \pi_T) \left[A_0(p_d; \epsilon_i) (1 - \lambda_{gr} p(w_i \leq \frac{\eta \bar{w}}{(1-\tau)})) + (A_1(p_d; \epsilon_i) - A_0(p_d; \epsilon_i)) \left\{ (1 - \lambda_{gr}) p(w_i \leq \frac{p_d a_\epsilon \epsilon_i - \eta \bar{w}}{(1-\tau)}) \right. \right. \quad (\text{A.12})$$

$$+ \lambda_{gr} p(w_i \leq \frac{p_d a_\epsilon \epsilon_i + \eta \bar{w}}{(1-\tau)}) p(w_i > \frac{\eta \bar{w}}{(1-\tau)}) \left. \right\} \right] + \lambda_{gr}(1 - \pi_T) A_2(\epsilon_i) p(w_i \leq \frac{\eta \bar{w}}{(1-\tau)})$$

Exogenous Parameter Values for the Numerical Exercise

Addiction Parameters	$\underline{\epsilon}$	$\bar{\epsilon}$	$n_{\epsilon_i=0}$	$n_{\epsilon_i=\underline{\epsilon}}$	$n_{\epsilon_i=\bar{\epsilon}}$	a_ϵ
Values	0.25	0.75	0.70	0.20	0.10	3
Income Parameters	$\alpha_{1,w}$	$\alpha_{2,w}$	w_{max}	η	$\bar{w}$	
Values	1.4	4	25	0.02	7.3641	
Mixed Parameters	A_s	σ_s	θ	a_c	a_T	α_T
Values	3	0.8	0.55	1	2	0.5

Table A.1: Parameter Values for the Numerical Exercise

A.3 Appendix: The Effects of Drug Enforcement on Violence in Colombia 1999–2010

A.3.1 The model

The problem

Let us use the following simple model which is based on the paper written by Mejia, 2008. Let us assume that there are N municipalities in a country. This country is assumed to have a central government authority that determines the set of rules that each of the N municipalities must follow¹. There are N_g groups who, have already decided to produce cocaine² and are willing to engage in an anti-predatory game (or anti-prohibition activities) against the government, if it decides to engage in a predatory game (prohibition activities) against these groups. Each of the N_g are also willing to fight their share in the drug market violently given the contractual environment in which they have to operate. The government is assumed to have decided to prosecute the production of cocaine, and it's willing to engage in a predatory

¹Colombia is a presidential regime with a single legislature making policy decisions for the entire country.

²These N_g might be purely drug dealers, who produce drugs to simply gain a revenue, or irregular groups who decide to seek a quick revenue in the production of drugs to supplement their other sources to accomplish their political objectives. What matters in the sequel is that both drug dealers and irregular groups spend military resources to produce cocaine, regardless of their objective at wanting to produce narcotics.

game to enforce such decision³

In this scenario, if group i decides to produce cocaine in municipality j , it has to spend M_j^r dollars on military activities against the government and $M_{i,j}^{ir}$ dollars on military actions against the other rival groups in order to seize territory in the following way:

$$L_{i,j} = (1 - \rho_j^g) \rho_{i,j}^{ir} L_j \quad (\text{A.13})$$

where L_j is the amount of territory in municipality j ,

$$\rho_j^g = \frac{M_j^g}{M_j^g + \phi_j M_j^r} \quad (\text{A.14})$$

is the proportion of land gained by the government when it spends M_j^g dollars on military actions in municipality j against all groups who are willing to spend resources on military actions on the same municipality, and

$$\rho_{i,j}^{ir} = \frac{M_{i,j}^{ir}}{M_{i,j}^{ir} + \sum_{k \neq i=1}^{N_g} M_{k,j}^{ir}} \quad (\text{A.15})$$

is the proportion of land gained by group i when it spends $M_{i,j}^{ir}$ dollars on military actions in municipality j against all groups that are seeking to produce on the same municipality. Equations A.14 and A.15 are called Contest Success Functions, which are functions widely used in the economic analysis of conflict (see Skaperdas, 1996).

Equation A.14 assumes that $\frac{dM_j^g}{dM_j^r} = \phi_j \frac{M_j^r}{M_j^g}$. As a result, a larger ϕ_j implies a larger military efficiency of group i 's military expenditure on municipality j relative to the government's. In contrast, equation A.15 assumes that each group has the same military efficiency than the rest in all municipalities of the country. This simplification is assumed because a priori each regular group can settle down in every municipality,

³For the sake of our argument, it does not matter whether the government reached this decision following the median voter preference or the lobby of a single group within the country. What matters is the government's willingness to use the army to prosecute the production of cocaine, and the amount of money it is likely to invest in this activity. Hence, we also assume that the economy has already solved the social problem of cocaine prohibition, and that there are people who find profitable to join cocaine "*firms*", even if it is illegal, and follow the rules they impose to solve their internal social problem for coordinating the production of cocaine.

whereas the colombian government uses military bases to position its military forces to attack. Not all municipalities have military bases. See Dube and Naidu, 2012 for an analysis on the way colombian government performs its military operations, the location of its military bases and the possible consequences of these military operations on violence.

Using equations A.13–A.15, group i 's maximization problem is:

$$\max_{I_{i,j}, M_j^r, M_{i,j}^{ir}} \pi_i(I_{i,j}, M_j^r, M_{i,j}^{ir}) = \sum_{j=1}^{N_p} [p_d \theta_j I_{i,j}^\alpha L_{i,j}^{1-\alpha} - I_{i,j} - M_j^r - M_{i,j}^{ir}] \quad (\text{A.16})$$

where $I_{i,j}$ is the amount of resources invested by group i in inputs for the production of cocaine in municipality j , p_d is the international price of cocaine, and N_p is the number of municipalities in which all cocaine producers have decided to invest military resources to produce cocaine ⁴.

The solution

Equation A.16 can be solved in several ways. By its consistency characteristics, we will find the sub-perfect nash equilibrium of this problem. For an analysis of the characteristics of a sub-perfect nash equilibrium solution, see Fudenberg and Tirole, 1991. To attain that, we will first determine the optimal value of $I_{i,j}$ and then determine the values of M_j^r to finally find the values of $M_{i,j}^{ir}$ for every group i and for every municipality j , in which cocaine producers decide to produce. Thus, we want to determine the optimal amount of resources in inputs that every group is willing to invest in the production of cocaine after having already (optimally) invested in war.

Taking first order conditions with respect to $I_{i,j}$ in equation A.16, we get the following condition:

⁴For simplicity, we assume that if a group i decides to invest military resources in municipality j , all (N_g-1) remaining groups will also invest military resources in the same municipality. An alternative derivation would consider the case in which a subset of the N_g invest in municipality j ; however, for our purposes, it is innocuous to assume that all groups behave similarly in terms of investing in the same municipality j or not.

$$I_{i,j} = (p_d \theta_j \alpha)^{\frac{1}{1-\alpha}} L_{i,j} = (p_d \theta_j \alpha)^{\frac{1}{1-\alpha}} (1 - \rho_j^g) \rho_{i,j}^{ir} L_j \quad (\text{A.17})$$

Inserting equation A.17 in equation A.16, we obtain the following expression:

$$\pi_i(M_j^r, M_{i,j}^{ir}) = \sum_{j=1}^{N_p} [(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma L_{i,j} - M_j^r - M_{i,j}^{ir}] \quad (\text{A.18})$$

where $\sigma = (\alpha^{\frac{\alpha}{1-\alpha}} - \alpha^{\frac{1}{1-\alpha}})$. Using equation A.18, we can determine the optimal value of $M_{i,j}^{ir}$. Taking first order conditions to equation A.18 with respect to $M_{i,j}^{ir}$, we get the following expression:

$$M_{i,j}^{ir} = \sqrt{(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma (1 - \rho_j^g) L_j \sum_{k \neq i=1}^{N_g} M_{k,j}^{ir} - \sum_{k \neq i=1}^{N_g} M_{k,j}^{ir}} \quad (\text{A.19})$$

Equation A.19 applies for every group i who decides to produce cocaine in municipality j . As a result, equation A.19 can be solved for a symmetric value of $M_{i,j}^{ir}$ for which $M_{k,j}^{ir} = M_{i,j}^{ir} = M_j^{ir}$ for all groups $k \neq i = 1, 2, \dots, N_g$. Then, $M_{i,j}^{ir}$ becomes:

$$M_j^{ir} = \frac{(N_g - 1)(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma (1 - \rho_j^g) L_j}{(N_g)^2} \quad (\text{A.20})$$

Inserting equation A.20 in equations A.13 and A.18, we obtain the following expression for the optimal revenue of group i :

$$\pi_i(M_j^r) = \sum_{j=1}^{N_p} \left[\frac{(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma (1 - \rho_j^g) L_j}{N_g^2} - M_j^r \right] \quad (\text{A.21})$$

Finally, from equation A.21 we can obtain the optimal value for M_j^r . Deriving this expression with respect to M_j^r , we get:

$$M_j^r = \frac{\sqrt{(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma L_j \phi_j M_j^g}}{\phi_j N_g} - \frac{M_j^g}{\phi_j} \quad (\text{A.22})$$

I can use equation A.22 to obtain the following expression for M_j^{ir} in terms of M_j^g :

$$M_j^{ir} = \frac{(N_g - 1)(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma L_j}{(N_g)^2} - \frac{(N_g - 1)}{N_g} \sqrt{\frac{(p_d \theta_j)^{\frac{1}{1-\alpha}} \sigma L_j M_j^g}{\phi_j}} \quad (\text{A.23})$$

Digression

If the most worrisome consequence in the war against drugs is violence generated by the government's and drug producers' drug military expenditure, the model presented in section A.3.1 provides one insightful result. If we had perfect information about military expenditures made by all parties on municipality j to produce or avoid the production of narcotics and the violence rate in the same municipality associated to the drug war, we could split municipality j 's violence rate in the following way:

$$v_j = \beta_1 M_j^g + \beta_2 M_j^r + \beta_3 M_j^{ir} + \text{rest} \quad (\text{A.24})$$

where $\beta_1 M_j^g$ represents the violence rate explained by the government's drug enforcement military expenditure. $\beta_2 M_j^r$ represents the violence rate explained by drug dealers' anti-enforcement military expenditure. $\beta_1 M_j^g + \beta_2 M_j^r$ is what we called the first-order effect of enforcement in the introduction. Finally, $\beta_3 M_j^{ir}$ represents the violence rate due to the drug dealers' war when they fight over the control of the territory to produce drugs. This is the second-order effect of enforcement.

A.3.2 Figures and Tables

Figure A.23: Map of Colombia: Administrative Division

(a) Rural Property Size Average

(b) 2005 GDP by *Departamento*

Figure A.24: Rationale behind using the distance variables

Logarithm of Colombian Homicide Rate 1999-2010

(a) Logarithm of Homicide Rate

Logarithm of Colombian Displacement Rate 1999-2010

(b) Logarithm of Displacement Rate

Index of Military Expenditure on Cocaine Eradication 1999-2010

(c) Index of Cocaine Eradication

Index of Military Expenditure against Cocaine Eradication 1999-2010

(d) Anti-Eradication Index

Figure A.25: Endogenous Variables VS Eradication and Anti-Eradication Indices

Logarithm of Colombian Homicide Rate 1999-2010

(a) Logarithm of Homicide Rate

Logarithm of Colombian Displacement Rate 1999-2010 (b) Logarithm of Displacement Rate
Altitude of Colombian Municipalities**Index of Military Expenditure on War among Dealers 1999-2010**

(c) Dealers War Index

(d) Altitude

Figure A.26: Endogenous Variables VS Dealers War Index and Altitude

Instrumentalized Index of Military Expenditure on Drug Enforcement 1999-2010

(a) Instrumentalized I_E

Instrumentalized Index of Military Expenditure against Drug Eradication 1999-2011

(b) Instrumentalized I_{AE}

Instrumentalized Index of Military Expenditure on War among Dealers 1999-2010

(c) Instrumentalized I_{DW}

Figure A.27: Instrumentalized Drug War Indices

Variables	loghrate	logdrate	I_E	I_{AE}	I_{DW}	dbogota	dcapitals	logpop	altitude	$\hat{I}_E$	$\hat{I}_{AE}$	$\hat{I}_{DW}$
mean	2.83	4.68	0.069	0.09	0.072	0.94	0.89	9.56	1142.03	0.20	0.66	0.66
std	1.71	2.74	0.16	0.27	0.15	0.06	0.11	1.10	917.37	0.17	0.26	0.16
min	0	0	0	0	0	0	0	4.81	2	0.02	0.14	0.21
prctile. 25%	1.94	3.32	0.019	0	0.01	0.89	0.86	8.88	180	0.11	0.33	0.56
prctile 50%	3.27	5.30	0.069	0.083	0.074	0.96	0.94	9.48	1103.5	0.153	0.66	0.66
prctile 75%	4.11	6.63	0.81	1	0.71	0.98	0.96	10.15	1850	0.23	0.1	0.78
max	7.20	11.36	1	1	1	1	1	15.81	3300	0.92	1	1
Moran Coef.	0.37	0.55	0.43	0.20	0.43	0.73	0.87	0.33	0.82			
p-value	0	0	0	0	0	0	0	0	0			

Correlation Coefficients												
loghrate	1	0.33	0.24	0.23	0.23	0.11	0.15	0.33	-0.07	0.2033	0.11	-0.04
logdrate		1	0.37	0.23	0.40	-0.12	-0.07	0.22	-0.39	0.375	0.06	0.041
I_E			1	0.30	0.67	-0.10	-0.10	0.19	-0.19	0.851	-0.066	0.08
I_{AE}				1	0.38	-0.03	-0.002	0.31	-0.08	0.222	-0.05	-0.07
I_{DW}					1	-0.05	-0.05	0.19	-0.21	0.597	-0.035	0.061
dbogota						1	0.85	0.07	0.31	0.017	-0.64	-0.02
dcapitals							1	0.15	0.24	-0.004	-0.672	0.411
logpop								1	-0.18	0.01	-0.14	0.09
altitude									1	0.198	0.125	-0.191
$\hat{I}_E$										1	0.085	0.068
$\hat{I}_{AE}$											1	-0.059
$\hat{I}_{DW}$												1

Table A.2: Summary Statistics

Position	loghrate	logdrate	I_E	I_{AE}	I_{DW}	altitude
1	RISARALDA	CAQUETA	GUAVIARE	ARAUCA	GUAVIARE	BOYACÁ
2	VALLE DEL CAUCA	GUAVIARE	PUTUMAYO	PUTUMAYO	CAQUETA	NARIÑO
3	ARAUCA	ARAUCA	CAQUETA	CAQUETA	ARAUCA	C/MARCA*
4	CAQUETA	PUTUMAYO	ARAUCA	CAUCA	PUTUMAYO	CALDAS
5	CALDAS	META	VICHADA	META	META	QUINDÍO
6	GUAVIARE	CESAR	META	GUAVIARE	VAUPES	RISARALDA
7	QUINDÍO	CHOCÓ	NARIÑO	RISARALDA	VICHADA	CAUCA
8	META	BOLIVAR	CAUCA	NORTE DE SANTANDER	BOLIVAR	SANTANDER
9	HUILA	MAGDALENA	NORTE DE SANTANDER	CASANARE	NORTE DE SANTANDER	ANTIOQUIA
10	CASANARE	ANTIOQUIA	ANTIOQUIA	HUILA	CAUCA	NORTE DE SANTANDER
11	ANTIOQUIA	LA GUAJIRA	BOLIVAR	NARIÑO	ANTIOQUIA	VALLE DEL CAUCA
12	PUTUMAYO	CASANARE	AMAZONAS	VALLE DEL CAUCA	GUAINA	HUILA
13	TOLIMA	SUCRE	CHOCÓ	ANTIOQUIA	NARIÑO	TOLIMA
14	CESAR	CAUCA	CESAR	LA GUAJIRA	AMAZONAS	PUTUMAYO
15	LA GUAJIRA	HUILA	LA GUAJIRA	TOLIMA	CHOCÓ	CASANARE
16	NORTE DE SANTANDER	VICHADA	CORDOBA	CESAR	LA GUAJIRA	META
17	CAUCA	NORTE DE SANTANDER	CALDAS	QUINDÍO	CESAR	CAQUETA
18	NARIÑO	CORDOBA	VALLE DEL CAUCA	CALDAS	CORDOBA	CESAR
19	C/MARCA*	RISARALDA	SANTANDER	CHOCÓ	VALLE DEL CAUCA	GUAVIARE
20	CORDOBA	CALDAS	CASANARE	SUCRE	CALDAS	ARAUCA
21	SUCRE	VALLE DEL CAUCA	TOLIMA	VAUPES	SANTANDER	VAUPES
22	ATLÁNTICO	NARIÑO	MAGDALENA	MAGDALENA	CASANARE	CHOCÓ
23	SANTANDER	TOLIMA	GUAINÍA	BOLIVAR	MAGDALENA	AMAZONAS
24	MAGDALENA	QUINDÍO	RISARALDA	VICHADA	HUILA	LA GUAJIRA
25	VICHADA	C/MARCA*	BOYACÁ	ATLÁNTICO	TOLIMA	VICHADA
26	BOLIVAR	GUAINÍA	HUILA	C/MARCA*	RISARALDA	MAGDALENA
27	CHOCÓ	ATLÁNTICO	VAUPES	SANTANDER	SUCRE	GUAINÍA
28	SAN ANDRÉS	AMAZONAS	C/MARCA*	GUAINÍA	C/MARCA*	SUCRE
29	BOYACÁ	SANTANDER	QUINDÍO	BOYACÁ	QUINDÍO	CORDOBA
30	AMAZONAS	BOYACÁ	SUCRE	CORDOBA	BOYACÁ	BOLIVAR
31	VAUPES	VAUPES	ATLÁNTICO	AMAZONAS	SAN ANDRÉS	ATLÁNTICO
32	GUAINÍA	SAN ANDRÉS	SAN ANDRÉS	SAN ANDRÉS	ATLÁNTICO	SAN ANDRÉS

* CUNDINAMARCA

Table A.3: Ranking of *Departamentos* by Variable

Dependent Variable: loghrate												
Variables	SDM,FE			SDM,FE			SDM,FE			SDM,FE		
	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total
Intercept	-0.98***											
I_E	1.20***	1.20***	-0.06	1.14***	0.90***	0.91***	0.34	1.27***	1.25***	1.28***	0.44	1.71***
I_{AE}	0.35***	0.41***	0.93***	1.33***	0.33***	0.38***	0.62***	1.00***	0.34***	0.38***	0.68***	1.05***
I_{DW}	0.62***	0.63***	0.14	0.77***	0.90***	0.95***	1.37***	2.32***	0.62***	0.62***	-0.003	0.61**
$\rho W y$	0.49***				0.26***				0.46***			0.19***
Obs.	13464				13464				13464			13464
σ^2	1.94				1.46				1.94			1.44
R^2	0.34				0.54				0.34			0.55
Corrected R^2	0.34				0.50				0.34			0.51
Log L	-23870.63				-21182.04				-23828.04			-20983.06
LM_Spatial_Lag	3482.58***				652.42***				3096.99***			324.83***
LM_Spatial_Error	3345.32***				589.87***				2968.76***			265.66***
Rob.,LM_Spatial_Lag	193.37***				101.58***				179.66***			132.19***
Rob.,LM_Spatial_Error	56.11***				39.03***				51.42***			73.02***
Wald_Spatial_Lag	N.A.				75.79***				59.86***			75.50***
LR_Spatial_Lag	70.27***				83.05***				59.88***			81.64***
Wald_Spatial_Error	286.00***				108.09***				184.59***			112.83***
LR_Spatial_Error	186.31***				118.69***				182.98***			123.05***
Hausman_Test					57.67***							71.62***
F_Effects					4.96***				0.04			5.28***

*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%

Table A.4: Regressions without Controlling for Endogeneity

Dependent Variable: logdtrate																
Variables	SDM_FE				SDM_F_E				SDM_FE				SDM_FE			
	No Fixed or Time Effects		Fixed Effects		Time Effects		Fixed and Time Effects		Time Effects		Fixed and Time Effects					
	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total
Intercept	0.40*															
I_E	1.40***	1.45***	0.78	2.23***	0.40***	0.55***	2.30***	2.84***	1.38***	1.41***	0.32	1.72***	0.32**	0.35**	0.66**	1.02***
I_{AE}	0.21***	0.30***	1.30***	1.60***	0.23***	0.27***	0.49**	0.76***	0.24***	0.34***	1.50***	1.84***	0.30***	0.33***	0.78***	1.12***
I_{DW}	2.27***	2.60***	4.93***	7.53***	0.68***	0.98***	4.86***	5.84***	2.28***	2.57***	4.48***	7.05***	0.54***	0.64***	2.06***	2.69***
$\rho W y$	0.66***				0.55***				0.62***							
Obs.	13464				13464				13464							
σ^2	3.42				2.09				3.41				2.00			
R^2	0.55				0.75				0.55				0.76			
Corrected R^2	0.54				0.72				0.55				0.73			
Log L	-28019.55				-23906.12				-27905.98				-23326.37			
LM_Spatial_Lag	9514.34***				5486.69***				7950.10***				1530.30***			
LM_Spatial_Error	9054.52***				5145.10***				7451.19***				1456.17***			
Rob_LM_Spatial_Lag	661.69***				408.77***				632.91***				122.05***			
Rob_LM_Spatial_Error	201.87***				67.18***				133.99***				47.92***			
Wald_Spatial_Lag	N.A.				79.19***				21.21***				43.86***			
LR_Spatial_Lag	20.70***				85.51***				21.71***				47.93***			
Wald_Spatial_Error	206.71***				149.28***				202.27***				68.88***			
LR_Spatial_Error	186.31***				161.51***				238.63***				74.49***			
Hausman_Test					40.74***								44.18***			
F_Effects					8.68***				0.07				9.63***			

*** Statistically significant at 1%. ** Statistically significant at 5%. * Statistically significant at 10%

*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%

Table A.5: Regressions without Controlling for Endogeneity

Variables	Dependent Variable: govcont					Dependent Variable: irrecont				
	SDM					SDM				
	Estimates	Direct	Indirect	Total	No Fixed or Time Effects	Estimates	Direct	Indirect	Total	No Fixed or Time Effects
Intercept	0.70***					-1.50***				
Alt	-0.0002***	-0.0002***	-0.0002***	-0.0004***		-0.00042***	-0.00041***	0.00003	-0.0002***	
dbogota	-0.50	-0.23	3.48	3.25*		-4.09***	-4.09***	11.48***	7.39***	
dcapital	-1.03	-1.11	-0.65	-1.77*		-7.64***	-7.39***	3.71**	-3.69***	
ρW_y	0.53***					0.43***				
Obs.	13464					13464				
σ^2	7.21					9.01				
R^2	0.21					0.13				
Corrected R^2	0.21					0.13				
Log L	-32767.22					-34131.02				
LM_Spatial_Lag	2916.38***					1671.90***				
LM_Spatial_Error	2909.45***					1730.14***				
Rob. LM_Spatial_Lag	8.31***					95.08***				
Rob. LM_Spatial_Error	1.34					153.32***				
LR_Spatial_Lag	34.50***					54.59***				
Wald_Spatial_Error	87.04***					88.80***				
LR_Spatial_Error	89.88***					91.65***				
Variables	Dependent Variable: logcrops					Dependent Variable: mines				
	SDM					SDM				
	Estimates	Direct	Indirect	Total	No Fixed or Time Effects	Estimates	Direct	Indirect	Total	No Fixed or Time Effects
Intercept	-0.23					2.55***				
govcont	0.10	-0.06	-2.48***	-2.54***		0.66***	0.48***	-3.69***	-3.21***	
Irrecont	0.08	0.05	-0.55***	-0.50***		0.03	0.04	0.16	0.20*	
Alt	-0.001***	-0.001***	-0.001***	-0.002***		0.0002	0.0001	-0.0012***	-0.0011***	
ρW_y	0.67***					0.36***				
Obs.	13464					13464				
σ^2	13.32					20.69				
R^2	0.50					0.22				
Corrected R^2	0.50					0.22				
Log L	-37207.15					-38652.23				
LM_Spatial_Lag	8019.02***					625.79***				
LM_Spatial_Error	7799.96***					391.96***				
Rob. LM_Spatial_Lag	275.98***					595.99***				
Rob. LM_Spatial_Error	56.92***					362.15***				
LR_Spatial_Lag	184.64***					625.67***				
Wald_Spatial_Error	336.03***					863.29***				
LR_Spatial_Error	344.02***					874.97***				
*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%										

Table A.6: Regressions Controlling for Endogeneity: first-step regressions

Dependent Variable: loghrate																
Variables	SDM_FE				SDM_FE				SDM_FE				SDM_FE			
	No Fixed or Time Effects		Fixed Effects		Time Effects		Fixed and Time Effects		Fixed and Time Effects		Total					
	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total
Intercept	-1.03***															
I_E	0.92***	0.94***	0.42***	1.36***	0.34***	0.35***	0.40**	0.75***	0.94***	0.99***	0.73***	1.71***	0.47***	0.51***	1.32***	1.84***
$\hat{I}_{AE}$	0.17	0.11	-1.15***	-1.04***	0.51**	0.53**	0.07	0.60	0.17	0.11	-1.19***	-1.08***	0.46**	0.45*	-0.30	0.14
I_{DW}	0.43**	0.53**	1.84***	2.38***	0.61	0.74	3.63**	4.37***	0.40*	0.50**	1.79***	2.29***	0.58	0.70	3.31**	4.00***
ρWy	0.48***				0.29***				0.46***				0.23***			
Obs.	13464				13464				13464				13464			
σ^2	1.96				1.49				1.95				1.47			
R^2	0.33				0.53				0.33				0.54			
Corrected R^2	0.33				0.49				0.33				0.50			
Log L	-23930.63				-21322.64				-23871.02				-21142.68			
LM_Spatial_Lag	3096.11***				729.49***				2699.83***				404.46***			
LM_Spatial_Error	2757.92***				2786.14***				698.66***				2346.68***			
Rob..LM_Spatial_Lag	339.15***				65.89***				353.25***				35.54***			
Rob..LM_Spatial_Error	0.96				35.06***				0.11				16.00***			
Wald_Spatial_Lag	N.A.				69.62***				115.31***				66.17***			
LR_Spatial_Lag	109.54***				75.02***				114.75***				72.51***			
Wald_Spatial_Error	188.37***				69.88***				223.22***				74.71***			
LR_Spatial_Error	199.97***				74.53***				223.97***				81.98***			
Hausman_Test					102.75***								91.96***			
F_Effects					4.80***				0.06				5.09***			

*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%.

*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%

Table A.7: Regressions Controlling for Endogeneity: second-step regressions

Dependent Variable: logdurate																
Variables	SDM_FE				SDM_FE				SDM_FE				SDM_FE			
	No Fixed or Time Effects		Fixed Effects		Time Effects		Fixed and Time Effects		Time Effects		Fixed and Time Effects					
	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total	Estimates	Direct	Indirect	Total
Intercept	-7.65***															
I_E	1.70***	1.96***	3.85***	5.82***	0.21**	0.33***	2.04***	2.38***	1.73***	1.97***	3.70***	5.67***	0.15	0.18*	0.81***	0.99***
I_{AE}	0.04	0.12	1.10***	1.22***	-0.09	0.09	3.02***	3.10***	0.04	0.10	0.89***	0.98***	-0.36	-0.33	0.58	0.25
I_{DW}	0.83***	1.15***	1.10***	1.22***	0.46	0.19	-5.03*	-4.84	0.87***	1.20***	4.98	6.17***	0.87	0.79	-0.63	0.16
ρWy	0.66***				0.56***				0.61***				0.38***			
Obs.	13464				13464				13464				13464			
σ^2	3.47				2.09				3.45				2.01			
R^2	0.54				0.74				0.54				0.76			
Corrected R^2	0.54				0.72				0.54				0.73			
Log L	-28111.11				-23938.97				-27970.03				-23386.91			
LM_Spatial_Lag	9361.42***				5240.21***				7678.88***				1497.87***			
LM_Spatial_Error	8459.49***				5026.45***				6733.06***				1416.11***			
Rob. LM_Spatial_Lag	934.70***				231.58***				951.81***				141.05***			
Rob. LM_Spatial_Error	32.76***				17.81***				5.99**				59.29***			
Wald_Spatial_Lag	N.A.				46.82***				85.05***				18.05**			
LR_Spatial_Lag	78.91***				59.71***				87.81***				19.18***			
Wald_Spatial_Error	338.01***				69.94***				263.37***				18.31***			
LR_Spatial_Error	328.95***				103.13***				373.81***				19.26***			
Hausman_Test					119.38***								69.72***			
F_Effects					8.91***				0.08				9.75***			

*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%

*** Statistically significant at 1%; ** Statistically significant at 5%; * Statistically significant at 10%

Table A.8: Regressions Controlling for Endogeneity: second-step regressions

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