Three essays on the economics and strategic interactions of drug trafficking

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Three essays on the economics and strategic interactions of drug trafficking

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To my mother Maria Cristina and my nine-month-old son Gianmarco.

Curriculum Vitae

I was born in Cali and went to the German School (Deutsche Schule) in this city.

I am a full-time Faculty Full Professor in the Department of Economics at Universidad del Valle, Cali, Colombia. I have a Master's degree in Applied Economics. I am a member of the Research Group of Conflict, Learning and Game Theory of Universidad del Valle, and of the Research Group of Economic Development, Growth and Labor Market of the same university. I am an Associate Researcher and academic pair recognized by Minciencias. During the period 2011-2013, I served as the Director of the Master Program in Economics of Universidad del Valle.

I have been researching on the topic of drug trafficking for more than a decade, in the context of various research projects. My lines of research are the economics of crime, international trade, and economic growth. I have published several academic articles on these topics, all of which can be accessed and downloaded from my Google Scholar, Researchgate, Ideas-Repec, or Academia profiles.

Currently, I am a member of the following academic networks: the Society for the Advancement of Socio-Economics (SASE), the Latin American Studies Association (LASA), and the Network of Economics Researchers of the Central Bank of Colombia (Banco de la República). In addition, I have been a member of the Social and Economic Observatories Network-Valle del Cauca (Red de Observatorios Regionales del Mercado de Trabajo (ORMET-Valle del Cauca) (2014-2017).

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I also want to thank the helpful comments of all the participants in the III Network of Quantitative Methods, organized by AFADECO, Universidad Santo Tomás, Universidad Pontificia Bolivariana, Universidad Colegio Mayor de Cundinamarca, and Universidad Militar de la Nueva Granada on 24th February 2022.

The other two chapters were also presented at diverse academic events. Previous versions of them were presented at the Workshop of Industrial Organization and the Workshop of Applied Microeconomics of Universidad del Rosario. I thank the suggestions of professors Guillem Roig and Jorge Hernán Florez of the same university. I am also thankful for the comments of Renzo Clavijo and Josá Astaiza. I also want to thank the valuable comments of Professor Luis Eduardo Sandoval of Universidad Militar de la Nueva Granada and to all the participants in the V Network on Microeconomics organized by Afadeco and Universidad Militar de la Nueva Granada, celebrated virtually on 6th May 2021 at this University. Finally, I want to thank the insightful comments of Professor Tomás Rodríguez of Universidad de los Andes during the presentation of the first paper in the IV National Colloquium of doctoral students, celebrated virtually on 3th December 2021 at Universidad del Norte.

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Resumen

La presente disertación doctoral pretende hacer una investigación amplia sobre los mecanismos que diseñan e implementan los narcotraficantes para evadir la ley en el mundo contemporáneo. Se trata de un conjunto sofisticado de dispositivos de defensa, coerción y de corrupción que tienen como propóstico debilitar la persecución y el control de las autoridades, en el contexto de represión mundial contra las drogas que ha configurado la llamada guerra contra las drogas desde hace más de seis décadas. El resultado principal de este accionar delictivo ha sido la creación de poder —tanto económico, como militar, político y social— al margen de los estados nacionales.

Las preguntas que surgen en este contexto son: ¿Qué tan efectivas son realmente las políticas de represión a las drogas que se han venido implmentanto en este contexto desde hace mpas de seis décadas? ¿Qué mecanismos estratégicos implementados por los narcotraficantes explican la ineficacia de estas políticas? ¿Qué alternativas de política —económica, criminal o de incentivos— existen? ¿Cuáles son sus fortalezas y debilidades?

Para atacar esta problemática, esta investigación hace un análisis amplio —tanto teórico como empírico— de la cadena productiva del narcotráfico en sus diferentes eslabones. Este contribuye a la comprensión de las dinámicas del narcotráfico en el mundo contemporáneo, desde el análisis de la evoluación de los cultivos de coca durante la década anterior, hasta las dinámicas de violencia para-estatal que implementan las organizaciones ilegales en las zonas urbanas con el propósito de ganar poder territorial.

La presente disertación doctoral consta de tres ensayos distintos pero íntimamente concatenados en su principal propósito de estudiar a profundidad las estrategias y dinámicas que caracterizan el accionar de las organizaciones ilegales de narcotráfico en la actualidad.

El primer capítulo analiza empíricamente el impacto (de corto plazo) sobre los cultivos de coca que tuvo la suspensión del programa de fumigación

aérea con glifosato en Colombia en el año 2015. Con este propóstico es estima un modelo de diferencias en diferencias que logra captar una relación causal entre la suspensión de las fumigacioes aéreas y la evolución del los cultivos de coca para el periodo 2016-2018. Se trata del primer trabajo que intenta hacer una análisis riguroso de los efectos de esta medida legal que fue impulsada por la Corte Constitucional de Colombia.

El segundo capítulo propone un modelo analítico de teoría de juegos —en el contexto de un juego secuencial en dos etapas— con el propósito de explicar las estrategias de violencia, corrupción y coerción usadas por los narcotraficantes en contextos con poder territorial para debilitar la persecucón que ejercen las autoridades de control. Tal es el caso de la forma específica como se desenvuelven las organizaciones ilegales en el contexto del microtráfico en las ciudades latinoamericanas.

Este segundo ensayo parte de hacer una reflexión profunda sobre la estructura de poderes y dispositivos (en el sentido filosófico amplio de Foucault) que configuran las organizaciones ilegales con el propósito de reproducirse en un contexto de represión en su contra.

El tercer artículo propone otro modelo analítico para explicar los procesos de corrupción que impulsan los traficantes en los eslabones intermedios de la cadena productiva del narcotráfico, con el propósito de transportar y traficar drogas a escalas grandes y medianas a nivel transnacional. Este tercer ensayo hace una contribución a la comprensión del reciente auge que hatenido el tráfico de cocaína a Europa, consolidando una problemática que hasido denominada por algunos investigadores como un “cancer de la corrupción”.

Introduction

The present doctoral dissertation pretends to develop a broad and deep investigation of the mechanisms drug traffickers design and implement to evade law enforcement in the contemporary world. These mechanisms consist of a sophisticated set of defense, coercion, and corruption devices, which pretend to weaken the control and persecution exerted by the law enforcement authorities in the context of world repression against drugs configured in the war on drugs for over six decades. The main result of this performance has been the production and reproduction of power —both economic, military, political, and social— outside the national states.

The questions arising in this context are: ¿How effective are the drug-repression policies implemented over more than six decades? What strategic mechanisms implemented by drug traffickers explain the ineffectiveness of these policies? ¿What other —economic, criminal or incentives— policy alternatives exist? ¿What are their strengths and weaknesses?

To attack this problematic situation, the present research develops a broad analysis —both theoretically and empirically— of the drug-trafficking value chain at its different stages. It contributes to the comprehension of drug trafficking dynamics in the contemporary world, going from the evolution of coca crops over the past decade to the para-statal violence dynamics implemented by illicit organizations in urban zones to gain territorial control.

The present doctoral dissertation consists of three different but intimately interconnected essays, all of which aim to understand the strategies and dynamics shaping the performance of illegal organizations nowadays.

The first chapter empirically analyzes the effects of the ban of the aerial spraying policy that took place in Colombia in 2015. The main goal is to analyze the (short-run) impact of the aerial spraying banning of coca plantations and estimate its average treatment effect (ATE) on the coca-crops' levels. With that purpose, I estimate a difference-in-differences model using municipal information on the coca crops for the period 2011-2018, which exploits the exogenous governmental decision to ban the spraying, as well as the variability of the intensity of fumigation between municipalities during the past decade.

The main finding is that the ban on aerial spraying led to a statistically significant but modest rise in coca-growing after its interruption, explaining only a small percentage of the dramatic surge it exhibited since 2014. I also find that structural factors explain, to a great extent, the mechanisms behind the effects of the spraying ban. The findings imply that the spraying banning explains only a small percentage of the dramatic increase of coca crops during the period 2014-2018. They also confirm the ineffectiveness of aerial spraying during the period 2011-2014. Hence, in terms of public policy, this study implies that drug policy should focus more on public investments in infrastructure in the coca-producing municipalities.

The second chapter paper presents a game-theoretical model to analyze the strategies used by traffickers to weaken law enforcement. The chapter's main goal is to analyze the strategies of coercion and bribery used by traffickers to weaken the interdiction and prosecution efforts of law enforcement authorities. With this purpose, I model the strategic interactions between traffickers and law enforcement authorities in a context where the former uses a conjugation of bribes and violence to influence the latter's actions in their favor, preventing the possibility of bargaining over the amount of bribes. These strategies hamper and neutralize the prosecution and interdiction efforts of control authorities. The model shows that despite the conditioning trafficker's moves, the law enforcement effort's fundamental determinant is prosecution and interdiction technology. The model also shows that the seizure probability depends positively on the premium rate received by officers in retribution for their effectiveness and that higher premium rates strengthen the bribery's deterrence, but coming to certain levels can unleash more violence.

This second essay departs from a profound reflection on the structure of powers and devices (in the broad philosophical sense of Foucault) configured by illegal organizations to reproduce themselves in a context of repression.

The third chapter proposes another analytical model to explain the corruption processes traffickers boost at the midstream stages of the illicit value chain, with the pretension to transport and trafficking illegal drugs at medium or large scales at a transnational level. This third essay contributes to comprehending the recent upsurge of cocaine trafficking from Latin America to Europe, which has consolidated a problematic situation named by some researchers as a " cancer of corruption".

The analytical framework of the " cancer of corruption" constitutes a three-stage sequential game in which traffickers and officers interact, determining the probability of successful bribery, the equilibrium levels of bribes, as well as the equilibrium quantity of drugs sold and the proportion of traffickers entering to illegal markets.

This latter model proves several findings, among them that drug-market size is the most powerful force encouraging the performance of illicit organizations and weakening corruption deterrence. Concerning anti-drug policy, the model corroborates that, in general terms, traditional criminal policy instruments tend to be effective in deterring the entry of more traffickers to illicit markets in the presence of corrupt agents. However, it also shows that a premium rate given to the officers in retribution for their achievements in interdiction provides an alternative effective instrument to combat drug trafficking at the wholesale level. This alternative policy tends to be a powerful instrument for low premium rate levels.

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Foreword

This thesis is a collection of three solo essays on the value chain of drug trafficking at its different stages and the impact of repression policies that have been (and could be) implemented to control the performance and development of these activities in the shadow of the illegal world.

The first chapter is an empirical investigation of the impact on the evolution of coca crops of the banning of aerial spraying that took place in Colombia in 2015 due to legal prescriptions. The second chapter is a theoretical investigation of the joint mechanisms of violence and corruption that illegal agents perform at the final stages of the illicit industry, especially for the distribution and sales of illegal drugs in Latin American cities, in the context of micro-trafficking. The third chapter is a theoretical investigation of corruption mechanisms criminal organizations apply to transport and trafficking illegal drugs transnationally at the midstream levels of the illicit value chain.

Chapter 1

The impact of the interruption of aerial spraying in Colombia: What does it imply?

1.1 Introduction

The present article is the first to analyze rigorously the impact of the sudden suspension of an important policy program in Colombia in 2015: the aerial spraying program, which was banned after a pronouncement of the Constitutional Court of Colombia and the Council of State of this country the previous year. Going beyond the contribution of this work to the analysis of drug policy in Colombia, it contributes to the literature that examines sudden changes in economic policy, i.e., policy bans originated by legal prescriptions. Several empirical works in economics have analyzed the impacts of diverse policy programs on economic or social variables. Still, fewer have tackled the impact evaluation of the banning of policy programs or campaigns as a result of legal issues or judgements. This is a promising topic to study deeply in economics and social sciences.

In other fields, such as health sciences, for instance, many works have quantitatively analyzed the impact of law judgment on health promotion policy, health systems, or patients' health conditions (see Campostrini et al.

(2006), Ogilvie et al. (2006), Xu et al. (2022), among others). In the area of educational studies, many works have broadly examined the influence of diverse legal prescriptions and proscriptions on education policy and students' academic performance (see for example, the works of Craig and Martin (2023), Hashim et al. (2018), Wang (2022)). However, fewer economic researchers have focused on the analysis of legal interventions (see, for instance Beneito and Vicente-Chirivella (2022), Besedeš et al. (2017) Holland et al. (2021), Maurin and Navarrete (2022), Roe et al. (2020)) conducing to policy bannings. Let's first consider the problematic situation to be empirically analyzed in the present article, to understand the impact of a concrete juridical intervention in Colombia on a policy implementation.

During the period 2014-2018 coca crops grew dramatically in Colombia, after a phase of continuous decrease between 2008 and 2013. Once again, this country became the main producer of coca crops and cocaine worldwide (UNODC, 2016a, 2017, 2018, 2019, 2020). In fact, during the period 2014-2018 the total number of hectares (ha) cultivated with coca increased by 144,49%, reaching a peak of 171.495 ha in 2017, 102,362 more than in 2014 (data from the Colombian Drugs Observatory (ODC by its Spanish acronym, 2020).

The rebound coincided with the redirection of the anti-drug policy during the government of President Juan Manuel Santos. On the one hand, the enforcement efforts shifted from an approach centered on the forced eradication of coca-crops —both on aerial spraying and manual eradication, but to a larger extent on the first one— to a model focused on the interdiction of cocaine base and hydrochloride. On the other hand, a new strategy of rural development based on the National Comprehensive Program for the Substitution of Illicit Crops (PNIS)[1], which implementation began in 2017, replaced the programs of alternative development implemented during the first decade of the century (Rocha-García, 2019; Salazar-Valencia et al., 2017). In October 2015, another crucial turn represented an inflection point for anti-drug policy: after pronouncements of the Council of State (in February

[1]See section 6 for a discussion of PNIS and its implications for the analysis.

2014) and the Constitutional Court of Colombia (in March 2014) about the eventual wrongful damage to the environment and human health caused by the glyphosate use, aerial spraying was suspended in the country by orders of the National Narcotics Council (Consejo Nacional de Estupefacientes (CONSEP)) and of the National Authority of Environmental Licenses (Autoridad Nacional de Licencias Ambientales (AMLA)).

Two years after, the White House declared its concern about the increase in coca crops, and then the U.S. Secretary stated that Colombia should revive the aerial spraying. In this context, former President of Colombia Ivan Duque, opened the doors to restructure the anti-drug policy again, considering the possibility of reviving the aerial spraying around the country. Since then, the debate on the viability and effectiveness of aerial spraying in Colombia has been open and burning again. Part of the discussion has been centered on the consequences of the policy implementation on the environment, human health, and violence (Abadie et al., 2015; Camacho and Mejía, 2017; Dávalos et al., 2016; Rincón-Ruiz et al., 2016; Rozo, 2014; Van Bruggen et al., 2018). In fact, this is one of the most debated questions by researchers, politicians, and journalists nowadays.[2] Other works point out the negative effects of the deforestation policies and the damage to ecosystems (Dávalos et al., 2016; Rincón-Ruiz et al., 2016; Van Bruggen et al., 2018).

Moreover, several works have analyzed the effectiveness of aerial spraying on coca planting.[3] Recently, a few articles have tackled this question in the context of the surge in coca plantations between 2015 and 2018 (see Ladino et al. (2021), Prem et al. (2021)), though not as their main research focus, while more works have stated diverse hypotheses and arguments to explain the same phenomenon.[4] Instead, the present work empirically analyzes

[2]For instance, Rozo (2014) examines the effects of herbicides on the treated areas' welfare conditions. She finds they have several unintended negative consequences on poverty, school dropout, infant mortality, and homicide rates.

[3]See Avila-Ceron et al. (2018), Abadie et al. (2015), Gallego and Rico (2013), Mejía and Restrepo (2016), Mejía et al. (2017), Moreno-Sanchez et al. (2003), Ortiz (2009), Raffo (2010), Raffo et al. (2016), Rincón-Ruiz et al. (2016), Rocha-García (2018, 2019).

[4]See Bargent (2015), Cabrera (2016), Cote (2019), Ladino et al. (2021), Orjuela-Santodomingo (2019), Posada-Salazar et al. (2019), Prem et al. (2021), Rico-Valencia

another concern not addressed until now as the main research question: What has been the (short-run) impact of the halt of aerial spraying on the evolution of coca crops?

This paper empirically analyzes the effects of the ban on the aerial spraying policy implemented in Colombia during the second decade of the present century. The main goal is to analyze the (short-run) impact of the interruption of the aerial spraying of coca plantations and so to estimate its average treatment effect (ATE) on the coca-crops' levels. With that purpose, I estimate a difference-in-differences model using municipal information of the coca crops for the period 2011-2018, which exploits the exogenous decision of government agencies to ban the spraying, as well as the variability of the herbicide's spraying between Colombian municipalities during the past decade.

My hypothesis —to be empirically examined— is that the ban on aerial spraying led to a modest rise in the coca-growing after its interruption. As a consequence, the upsurge of coca crops may be probably explained by the confluence of diverse factors —that I will mention in the next section.

The article finds several interesting results: The main finding is that the ban on aerial spraying led to a statistically significant but modest rise in the coca-growing after its interruption, explaining only a small percentage of the dramatic surge it exhibited since 2014. The estimated ATE of the interruption of aerial spraying in Colombia is around 0.1, so that the decrease of one hectare sprayed led to a marginal increase of only 0,1 hectares (both areas sprayed and planted measured as the share of municipal area per 1,000 hectares) during the period 2016-2018 (post-treatment). This increase represents only 2,6% of a standard deviation and 6% of the sample mean of coca growing for the pre-treatment year (2014).

This finding unveils that the suspension of aerial spraying *ceteris paribus*

(2017), Rocha-García (2018, 2019), Sáenz (2018), Santos (2019), Vargas (2019) and Zuleta (2017).

is not one of the leading causes of the rise of coca crops during the period studied. This means that other factors posited in other works or their conjugation may have also unleashed statistically significant but more relevant effects in quantitative terms. This is consistent with my initial hypothesis, which implies that the confluence of diverse factors may probably explain the upsurge in coca crops.

Secondly, the event study corresponding to the baseline model provides evidence supporting the fulfillment of the main identification assumption: The parallel trends assumption. It implies that, though the ban on aerial spraying had a small impact on coca crops during the post-treatment period, it was ineffective to reduce coca crops during the pre-treatment period. As I will show, this goes in the same direction as Mejía et al. (2017), who find that spraying one additional hectare reduces coca crops only by 0.02 to 0.03 hectares. As a consequence, there seems to be an asymmetry between the effects aerial spraying had on coca crops and the impact of its suspension.

Thirdly, the analysis of mechanisms points out that structural factors seem to explain the impact of the spraying banning. Hence, the "banning effect" may be conceived as a *rebound effect* linked to structural determinants and the lack of a new consolidated policy strategy that would have replaced the precedent model focused on forced eradication and alternative development policies after their de-escalation (Rocha-García, 2019). I find evidence that two types of structural determinants explain the "banning effect": 1) The remoteness of wholesale markets to sell agricultural products; 2) Geographical characteristics inherent to the diverse natural regions of Colombia.

To be concrete, I find that a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha), when interacted with the mean value of a distance index to the principal wholesale food market, causes a marginal increase of 0.56 hectares of coca planted (as a share of municipal area over 1,000 ha) after the spraying banning, which —as I will show— corresponds to an economically relevant but still small amount when compared with the huge increase in coca plantations between 2014 and 2018. Regarding geographical characteristics, I also find that the altitude of municipalities has a positive non-linear effect when interacting with the treatment variable —though only statistically significant at the 10% percent level—: a decrease of one hectare sprayed, when interacted with the mean value of altitude squared, causes a marginal increase of 0.13 hectares of coca planted after the spraying banning.

Concerning geographic heterogeneous effects, I find that the regions pushing the impact of the spraying banning are, in its order of magnitude, the Amazon region, the Andean Region, and the Caribbean Region. Regressions at a more disaggregated level indicate that departments of the same natural regions explain the impact of the treatment variable: Putumayo Department for the case of the Amazon Region; Bolivar, Cordoba, and Antioquia —i.e., the Uraba Antioqueño— for the Caribbean Region; and Antioquia, Nariño and Valle del Cauca both for the Andean Region and the Pacific Region.

Further robustness checks corroborate that all the results are stable and robust under different sampling choices and alternative specifications. Moreover, I run a set of placebo tests to check that with "fake" ban years, the treatment variable is not statistically significant and produces trivial effects. Lastly, I ran the models under an alternative negative-binomial setting, confirming that the same results persist.

Lastly, regarding drug policy, this study finds additional empirical evidence confirming the ineffectiveness of aerial spraying during the 2011-2014 period. I suggest that drug policy should be more focused on public investments in infrastructure in the coca-producing municipalities, as indeed was suggested in Section 1 of the Peace Agreement between the Colombian government and the Fuerzas Armadas Revolucionarias de Colombia-Ejército del Pueblo (FARC-EP), in the context of an "integral rural reform". In this vein, the article concludes that the shift in drug policy developed between 2011 and 2018, during the government of President Santos, went in the right direction, even if there was a *rebound effect* caused by the suspension of aerial spraying.

The article relates to three strands in the literature on anti-drug policies concerning illicit crops. Firstly, a series of studies examining the effectiveness of forced eradication policies. Most of them use diverse econometric methods to examine the effect of forced eradication policies, i.e., of aerial spraying or manual eradication on coca crops (Avila-Ceron et al. (2018), Abadie et al. (2015), Gallego and Rico (2013), Mejía et al. (2017), Moreno-Sanchez et al. (2003), Raffo et al. (2016), Rincón-Ruiz et al. (2016), Rocha-García (2018, 2019)). Yet, others develop theoretical models to analyze or simulate their impact (see Mejía and Restrepo (2016), Ortiz (2009), Raffo (2010)), among others.

Most empirical works find that aerial spraying has a negative moderate or modest but statistically significant effect on coca crops, inducing reductions after its implementation. For instance, Rozo (2014) and Rocha-García (2018, 2019) find moderate and statistically significant effects. Studying the impact of the aerial spraying campaign implemented in Colombia between 2000 and 2010, Rozo (2014) concludes that, although involuntary eradication programs tend to induce moderate reductions in coca crops, i.e., a quarter of the reduction in coca grown per hectare sprayed, they negatively affect the welfare conditions of the people living in the treated areas. Rocha-García (2018) shows that while the coca harvested area changes in -0.32 hectares in response to the increase of one hectare sprayed, the sowed area changes in -0.38 ha. These are quantitatively closed values to the mentioned results of Rozo (2014). Rocha (2019) finds that the total long-run marginal effect of aspersion on coca crops is from -0.2 ha, as a result of the sum of a direct effect on the sprayed municipalities of -0.37 ha and an indirect positive effect of spatial spillovers of 0.17 ha. Rocha explains that this makes evident the presence of rebound or balloon effect for this policy.

On the other hand, Abadie et al. (2015) and Mejía et al. (2017) find modest but statistically significant effects. Abadie et al. (2015) make an econometric evaluation of Plan Colombia. In the context of dynamic panel data models, Abadie et al. (2015) find that, on average, the marginal increase of sprayed coca crops reduces the coca crops between 11% and 12% of an acre. Mejía et al. (2017) develop an impact evaluation of the aerial spraying in Colombia using information of coca crops for a 10 km band around the frontier with Ecuador. Unlike Rozo's findings, they conclude that spraying is more costly and has smaller effects on coca cultivation: spraying one additional hectare reduces coca crops only by 0.022 to 0.03 hectares. The present work focuses on examining the impact of the spraying banning, not on analyzing the impact of aerial spraying. Nevertheless, as I will show in Section 5, it also sheds light on testing the latter concern: my results go in the direction of Abadie et al. (2015) and Mejía et al. (2017).

A second and more relevant related strand of works concerns the analysis of diverse hypotheses and arguments explaining the upsurge of coca plantations for the 2014-2018 period. Many hypotheses and arguments have been considered in recent works to understand the huge increase in coca crops between 2014 and 2018. Following Bargent (2015), Cabrera (2016), Cote (2019), Ladino et al. (2021), Orjuela-Santodomingo (2019), Posada-Salazar et al. (2019), Prem et al. (2021), Rico-Valencia (2017), Rocha-García (2018, 2019), Sáenz (2018), Santos (2019), Vargas (2019) and Zuleta (2017) there can be identified at least seven different hypotheses that explain these trends:

1) The trend in the gold price during these years (Bargent, 2015; Rico-Valencia, 2017; Sáenz, 2018; Santos, 2019). This possible causal relationship hinges on the actual possibility of substituting one activity with the other, depending on their relative returns. It is based on the fact that if the relative price of gold increases (decreases), the opportunity cost of planting coca increases (falls), so that illegal crops tend to decrease (increase) (Bargent, 2015; Rico-Valencia, 2017; Sáenz, 2018). 2) The depreciation of the Colombian currency (the Peso) as a result of the fall in the international oil price (Cabrera, 2016; Orjuela-Santodomingo, 2019; Posada-Salazar et al., 2019; Santos, 2019). According to this hypothesis, the Peso depreciation would have made cocaine exports more attractive in the consumer countries, in the same way as depreciation positively affects legal exports (Cabrera, 2016; Santos, 2019). Only a few researchers and papers have paid attention to this factor until now (see Cabrera (2016), Orjuela-Santodomingo (2019), and Posada-Salazar et al. (2019)). 3) The possible pressure the FARC

or other criminal bands may have exerted on their controlled territories (Prem et al., 2021; Santos, 2019). Rocha-García (2019) points out that there is evidence that during the announcement of the demobilization of the FARC guerrillas, new armed groups and FARC dissidents tried to gain control over the "cocaleros" territories.[5] 4) The upturn in the crops has been fueled by sales of coca derivatives –as bazuco[6] or coca base– in a context of increasing consumption of hallucinogens at a domestic or international level.[7] 5) The increase in the crops responds to the increase in seizures.Zuleta (2017) explains clearly this hypothesis: "[As] interdiction's processes make that lower proportions of cocaine reach de consumption markets, it is necessary to produce more to satisfy the demand of international markets (p. 8)".[8]

6) The peace negotiations in Havana between the Colombian government and the FARC guerrillas engendered subsidy expectations and created economic aid to the families involved in illicit crops, which triggered incentives for coca planting. Mejía et al. (2019) (see also Prem et al. (2021)) show that the huge increase in coca crops during these years is the result of the public announcement of the implementation of a voluntary crop substitution policy,

[5]Actually, during the period 2013-2015, the increase in the illegal plantations took place in municipalities with the presence of one or more illegal armed groups and where poverty was more salient (Zuleta, 2017; Rocha-García, 2019).

[6]The bazuco or basuco is a low-cost and extremely impure drug produced from the coca base using diverse kinds of precursors, some of them very dangerous for human health. These include sulfuric acid, kerosene, and methanol, but may include other dangerous inputs used to process and "cut" the drug: gasoline, brick dust, insecticides, and even death-human bones. Due to the precursors used to manufacture it, it has a devastating effect on human —physical and mental health—. It has a sweet penetrating smell and produces only short-run effects, the reason why it is very addictive. It is well known as the "drug of the poor people" in Latin American cities, and it is sold in the urban slums (as the so-called "ollas").

[7]Zuleta (2017) shows in detail why this hypothesis seems to fail. He argues that this hypothesis faces two problems: First, Following the National Department of Planning (DNP by its Spanish acronym), the domestic market represents a small proportion (20%) of the total demand, so that likely this factor explains an increase in the area cultivated with coca close to 100%. Second, there is no evidence of an increasing trend in domestic consumption of cocaine, except for one of its derivatives (bazuco), during this period. However, the prevalence of bazuco consumption is markedly lower than for cocaine (Zuleta, 2017).

[8]Nonetheless, following Cote (2019), Zuleta (2017) adduces that contrary to this hypothesis, the interdiction of cocaine (cocaine hydrochloride, cocaine salts or cocaine base) negatively impacts the coca crops of the following year.

the National Program of Crop Substitution (PNIS by its Spanish acronym), once a final peace agreement between the government and the FARC guerrillas had been reached.[9]

7) The suspension of aerial spraying explains the increase in the cultivated area. This is just the hypothesis examined in this paper. Zuleta (2017) argues that the chronology of events does not seem to support this hypothesis. Although the number of eradicated hectares began to fall in 2006 and the manual eradication in 2008, between 2007 and 2012 the planted area did not increase but shrank. Instead, it began to grow after some years in 2014.

Besides that, Mejía et al. (2019) remark that their explanation based on the PNIS policy announcement's effect is inconsistent with an explanation based on the halt of aerial spraying.[10] But their work does not center the analysis on the study of the impact of the suspension of aerial spraying as I do in this work, which is the first attempt centering the empirical analysis in examining this hypothesis.

As Rocha (2019) explains, a key issue for understanding the recent trends in coca crops is that as a preamble to the implementation of the new strategy intensive in rural development –the PNIS– both eradication and alternative development were descaled, so that any transition strategy filled the gap during the changing policy regimes.

Considering the state of the art on this matter, it makes sense to hypothesize that the ban on aerial spraying led to a statistically significant but modest rise in the coca-growing after its interruption. As a consequence, the confluence of diverse factors may probably explain the upsurge of coca crops.

[9] The announcement took place in May 2014 through a press release during the peace negotiations.

[10] In a set of estimations of their model, they include as a control variable the cumulative share of municipal area exposed to aerial eradication interacted with year fixed effects during the period 2011-2014, the years before the ban. They show that the point estimate is unchanged both in terms of magnitude and significance; indeed, the differential effect of the announcement on coca planting in the municipalities that expect large benefits from growing coca rises slightly.

The third strand of relevant works studies structural factors determining the presence and persistence of illicit crops in Colombia over more than six decades. Diverse works —some of them more recent than the others—, conceived from different disciplines and approaches as economics (Rocha-García (2015)), political science (Garzón et al. (2019), Mejía-Hidalgo (2021), Mantilla et al. (2021), Rico-Valencia (2017)), historical research (Molano (1987)), and a human rights approach (Salazar-Valencia et al. (2017)) constitute this strand. I address this fundamental discussion when analyzing mechanisms behind the "banning effect" (see Section 5), understanding it as a *rebound effect* originated in the structural problems of the coca-producing municipalities.

Therefore, the article contributes to the literature on the matter in many ways: First, it is to the best of my knowledge, the first paper focusing on the examination of the impact of the interruption of aerial spraying on the coca-crops' trends in Colombia. Second, as other recent (mentioned) works on the topic, it advances in the analysis of the factors explaining the upsurge of coca plantations during the 2014-2018 period. Third, though not its main concern, this article also contributes to the literature examining the effectiveness of aerial spraying in Colombia, in our case for the period 2011-2015. Last but not least, this paper advances in the comprehension of the structural determinants shaping the evolution of coca crops. Apart from Rocha-García (2015), any article has addressed this issue for the past years from a quantitative-economic approach, although some studies have done it using other approaches (see Garzón et al. (2019), Mejía-Hidalgo (2021), Mantilla et al. (2021), Rico-Valencia (2017), Salazar-Valencia et al. (2017) among others).

The rest of the paper proceeds as follows: Section 2 presents the data sources and descriptive statistics. Section 3 describes the empirical strategy. The next section presents the results, including the main findings, the analysis of the fundamental identifying assumption, and further robustness checks. Section 5 analyzes the potential mechanisms behind the impact of the spraying banning. Finally, Section 6 concludes and proposes some final reflections.

1.2 Data and main statistics

1.2.1 Available data

I built a panel data set at a municipal level for the period 1999-2018 assembling information from different sources: The Conflict Data Base of Universidad del Rosario, several variables of the CEDE Conflict and Violence Panel Data, other variables of the CEDE Panel Data of Health and Services, the CEDE Panel Data of Good Government and the CEDE Panel Data of General Characteristics (CEDE (2020)). Furthermore, it was merged with coca crops and eradication information of the Colombian Drugs Observatory (ODC (2020)).

Coca crops: The information on coca crops comes from the Colombian Drugs Observatory (ODC (2020)) and the CEDE Conflict and Violence Panel Data (CEDE (2020)). In both cases, its primary source is The Integrated System for Illicit Crop Monitoring (SIMCI by its Spanish Acronym) of the United Nations Office on Drugs and Crime (UNODC). The main outcome variable is the area cultivated with coca measured as the share of total municipal area with coca plantation per 1,000 hectares. Hence, the official area of the municipalities in hectares (extracted from the CEDE Panel Data of General Characteristics (CEDE (2020))) was also used to calculate this variable.

Forced eradication of coca crops: Data of eradication (aerial spraying and manual eradication) was also extracted from the Colombian Drugs Observatory and the CEDE Conflict and Violence Panel Data (ODC (2020), CEDE (2020)). This information comes from the Colombian Antinarcotics Police (DIRAN). The main variables are the treatment variables constructed from the variable of aerial spraying: area of coca crops sprayed (measured as the share of total municipal area with spraying per 1,000 hectares).

Conflict Data: A variable accounting for the presence of conflict events in municipalities is included in the models as a covariate. It is a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period. This variable was taken from the Conflict Data Base of Universidad del Rosario, which was originally compiled by Restrepo et al. (2004) and updated by Juan Vargas' team at Universidad del Rosario. This data set records diverse conflict events extracted from Noche y Niebla Review provided by NGO CINEP.

Geographical variables: Other geographic covariates interacted with yearly dummies were included: the natural logarithm of the height of municipalities (meters above sea level), the natural logarithm of the linear distance to the main wholesale food market (in kilometers), the logarithm of the linear distance to Bogotá (in kilometers) and regional dummies.[11] The latter comprehend five variables capturing the different natural regions of the continental territory in Colombia: the Amazon Region (gamazonia), the Andean Region (gandina), the Caribbean Region (gcaribe), the Pacific Region (gpacifica) and the Orinoco Region (gorinoquia).[12] An index of the linear distance to the principal wholesale food market and the regional dummies are also analyzed as potential mechanisms behind the magnitude of the impact resulting from the ban on aerial spraying.

All these data were provided by the CEDE Panel Data of General Characteristics (CEDE (2020)). The primary sources of the data are the following: Instituto Geográfico Agustín Codazzi (IGAC) for the altitude variable; CEDE calculations based on IGAC data for the variables of distance to the departmental capital and the principal wholesale food market; and Divipola for the regional dummies.

Other variables: Furthermore, the models include other covariates as an

[11]In all the cases continuous variables were summed to one to avoid their indeterminacy in the zero cases when transformed into logarithms.

[12]According to Instituto Geográfico Agustin Codazzi (IGAC), Colombia has six different natural regions with diverse geographic characteristics such as relief, distance to the sea, soil conditions, and average rainfall. The six regions are the Amazon Region, the Andean Region, the Caribbean Region, the Pacific Region, the Orinoco Region, and the Insular region. The latter region consists of all the Colombian islands and archipelagos. Since only the continental territory is relevant in the present analysis, the Insular region is not considered.

Unsatisfied Basic Needs index (UBN) for the year 2011, the natural logarithm of the urban population in 2011, and the natural logarithm of the rural population in 2011. All of them come from the CEDE Panel Data of General Characteristics (CEDE (2020)), and their primary source is DANE. Also, a series of the price of gold and the Colombian nominal exchange rate for the period of study were added to the data set to analyze alternative potential mechanisms. While the first one was extracted from the World Gold Council (WDC) (WDC, 2020), the second one was taken from the Data Storage of the Central Bank of Colombia (Banco de la República de Colombia).

1.2.2 Main trends of coca crops and forced eradication

This subsection presents some basic trends concerning coca crops and forced eradication, i.e., aerial spraying and manual eradication for the period 1999-2018.[13] This enables us to have a broad picture of the main trends during the present century.

Figure 1.1 depicts the trends of coca crops, aerial spraying, and manual eradication for the period 1999-2018. It clearly shows a tipping point in the trend of coca crops by the year 2013. Even though coca crops decreased steadily during the period 2007-2013, from that year on they began to grow dramatically reaching a level even higher than in 2000, when Plan Colombia barely began to impact their level. This means that while during the period 2000-2013 planted hectares decreased at an implicit annual growth rate of -9.4%, during the period 2013-2018, they increased at an implicit annual growth rate of 25.1%. In 2018 they decreased by 1.44% in comparison to 2017, but they continue to be at a high level of 169,018.19 ha, still higher than in 2000.

As aerial spraying was forbidden in May 2015, our post-treatment period goes from 2016 to 2018. But, during 2014-2018 coca crops exhibited a huge growth: they increased by 144.49%, while through the period 2015-2018,

[13] Although manual eradication is not included as a covariate in the econometric models, it is important to describe its evolution during the last decades, because it is an important component of forced eradication.

they rose at a rate of 75.9%, with implicit annual growth rates of 22.34% and 18.83%, respectively. However, it is analytically relevant to examine the crops' evolution during the previous years since the government of President Santos redirected the anti-drug policy. Hence, our period of interest is 2011-2018.

Figure 1.1 also depicts the evolution of manual eradication during the last couple of decades. There can be seen that manual eradication was slightly increasing during the first years of Plan Colombia but then began to grow at a higher rate, particularly in 2005, as a result of the beginning of the manual eradication program. This program was initially conceived as a project to complement aerial eradication efforts, especially in areas where the latter was more problematic, such as borders, rivers, and Special Management Areas. Manual eradication peaked in 2008, the year after which it began to decrease again, until 2014, when manual eradication began to increase once again as a consequence of the reforms implemented by the Santos government. During 2014 and 2018, manual eradication grew from 11,703 ha to 59,978 ha, which means an increase of 413%.

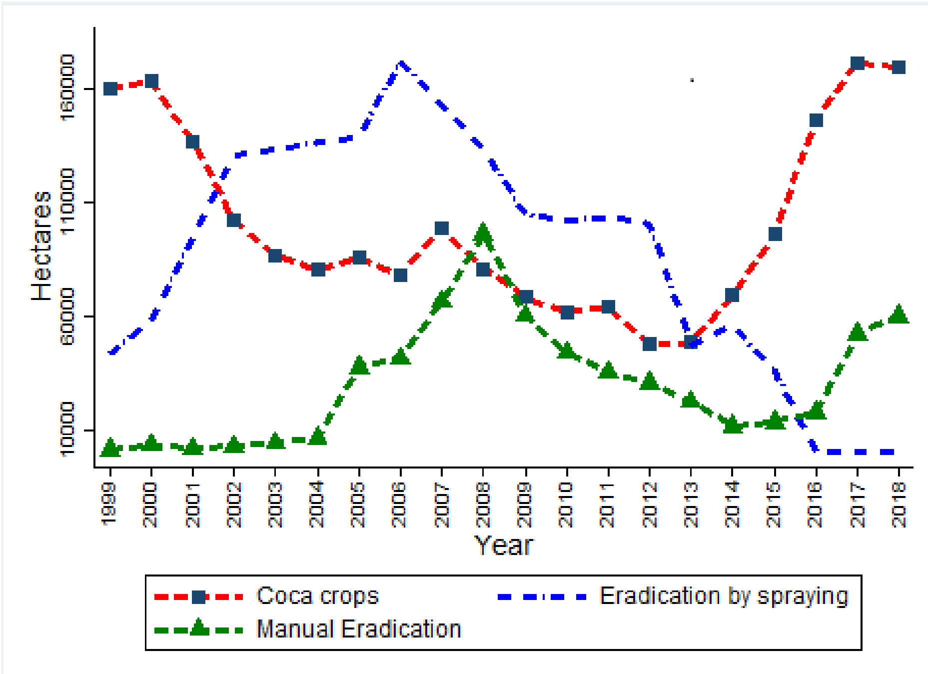


Figure 1.1: Coca crops, aerial spraying and manual eradication (2000-2018).

1.2.3 Summary statistics

Table 1.1 presents the summary statistics. Panel A exhibits the summary statistics of the main variables of interest for the baseline models and the corresponding baseline sample. These are the outcome variable, the treatment variables, and the time-varying variables used to calculate the latter (see details in the Table). All of them are measured for the period 2011-2018, omitting 2015. There can be seen that while the mean of coca crops (outcome of interest) for the baseline sample and the whole period was 411. 97 ha , the mean of the hectares sprayed for the same period was 176.07 ha. The corresponding standard deviations were high: 1309.11 and 704. 7 respectively. Expressing these variables as a share of the municipal area per 1,ooo ha (see the baseline models ahead), it can be observed that the mean of coca crops is 2,79, whereas the mean of spraying is 0.97. The treatment variable used for all the baseline models, $Treatment_i$, corresponds to the sum of hectares of coca crops sprayed (as a share of the municipal area per 1,000 hectares) during the pre-treatment period (2011-2014). It had a mean of 6.89 and a standard deviation of 17.79 for the baseline municipalities during the period of interest (omitting 2015).

Table 1.1 shows the differences between the means and standard deviation of the outcome variable for the treated and control municipalities. The treated corresponds to the municipalities where aerial spraying was performed for at least one year during the pre-treatment period and presented positive levels of coca crops for at least a year of that period. The discrete version of the treatment is denoted by the variable $Treated_i$. On the other hand, the control group corresponds to the municipalities that were never sprayed during the same period, but presented positive levels of coca crops at least for a year during that period. The evolution of the crops' trends in these regions can be conceived as a counterfactual. Hence, $Treated_i$ is one for the municipalities belonging to the treatment group or zero for the control group (see main statistics in Table 1.1). Table 1.2 also exhibits the differences of both statistics for the pre-tratment period (before the spraying banning) and the post-tratment period (after the spraying banning). Variable $Post$ in Table 1.1 captures the temporal dummy variable.

Although one would expect a lower mean of the outcome for treated municipalities —as long as the impact of spraying over coca crops during the pre-treatment period is expected to be negative— it is higher (3.726 against 1.598). What explains this surprising result —as we will explain ahead— is the magnitude and statistical significance of the impact of this variable over crops during that period and the confluence of other factors shaping the crops' evolution. Furthermore, the mean of the outcome for the treated municipalities after the ban of spraying (6.227) is substantially higher than before this policy's sudden stop (1.851). These descriptive statistics give insights on the possible positive impact of the spraying ban on coca crops for the post-treatment period —i.e., for the period 2016-2018—, which I will analyze in detail in what follows.

Figure 1.2 depicts a scatter plot for the outcome variable against $Treatment$ for the year 2017. The figure does not show a clear relationship between both variables but a dispersed cloud of points. Similar plots can be obtained by scattering the outcome variable for the other post-treatment years against the treatment.

Table 1.1: Summary statistics

	Panel A: Main Variables				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Obs.	Mean	Std. Dev.	Min	Max
Coca crops (in hectares)	1,736	411.97	1309.11	0	23147.95
Hectares of coca crops sprayed	1,736	176.07	714.70	0	9678.21
Municipal area in hectares	1,736	297733.47	614133.24	7300	6567400
Share of coca cultivation per 1,000 ha	1,736	2.79	7.74	0	98.44
Share of coca sprayed per 1,000 ha	1,736	0.98	4.23	0	71.64
Treatment	1,736	6.89	17.79	0	166.91
Treated	1,736	0.56	0.50	0	1.00
Post	1,736	0.43	0.50	0	1.00
	Panel B: Covariates				
	Obs.	Mean	Std. Dev.	Min	Max
Attacks by armed groups	992	1.53	6	0	94
Clashes between armed groups	992	0.12	0.57	0	9
Dist. to the main wholesale food market (in kms)	248	187.63	125.32	0.00	678.74
Urban Population in 2011	248	16217.87	54069.28	0	603540
Rural Population in 2011	248	12735.72	10728.85	851	86698
UBN2011	248	0.61	0.22	0.19	1
Linear Distance to Bogota (in kms)	248	390.19	139.23	96.88	752.44
Altitude (in meters above the sea level)	248	663.25	735.13	2	2897
gandina	248	0.33	0.47	0	1
gpacifica	248	0.29	0.45	0	1
gorinoquia	248	0.08	0.27	0	1
gamazonia	248	0.19	0.40	0	1
gcaribe	248	0.11	0.32	0	1
Gold price (in U.S dollars per troy once)	8	1.36	0.18	1.16	1.67

Notes: Panel A presents the summary statistics for the main variables of interest for the baseline models. All of them are measured for the period 2011-2018, omitting 2015. The share of coca cultivation is the outcome variable. It corresponds to the hectares of coca planted as a share of the municipal area per 1,000 hectares. *Treatment* is the treatment variable used for all the regressions. It corresponds to the sum of hectares of coca crops sprayed (as a share of the municipal area per 1,000 hectares) during the pre-treatment period (2011-2014). *Treated* is the discrete version of the treatment. It is one for municipalities where aerial spraying was performed at least for one year during the pre-treatment period and presented positive levels of coca crops for at least a year of that period, and zero for the municipalities that were never sprayed during the same period, but presented positive levels of coca crops at least for a year during that period. The original number of observations of the two latter variables is 248 as they are time-invariable. *Post* is the temporal dummy variable, which is 0 for the pre-tratment period (2011-2014 omitting 2015) and 1 for the post-tratment (2016-2018). Panel B presents the summary statistics for the covariates included in the baseline models. It reports the original number of observations of these variables. Variable *Atacks* by armed groups measures the number of attacks performed by armed groups in Colombia during the pre-treatment period 2011-2014. *Clashes* measures the number of clashes between a pair of armed groups or triad of them in Colombia during the same period. *Distance to the main wholesale food market* corresponds to the linear distance for each municipality to the main wholesale food market (in kilometers). *Urban Population in 2011* is the total number of inahabitants living in the urban area of each municipality in year 2011. *Rural Population in 2011* is the total number of inahabitants living in the rural urban area of each municipality in year 2011. *UBN2011* is an Unsatisfied Basic need index for the year 2011 (divided by hundred). textitLinear Distance to Bogotá is the linear distance from every municipality to the capital city of Colombia, Bogotá. *Altitude* is the height of each municipality (meters above sea level). *gandina*, *gpacifica*, *gorinoquia*, *gamazonia*, and *gcaribe* are the regional dummy variables. *Gold Price* is the international price of gold for the period 2011-2018 measured in U.S. dollars per thousandth of troy once.

Table 1.2: Descriptive statistics on coca crops by treatment status

				Treat	
	All	Treated	Control	After	Before
Share of coca cultivation per 1,000 ha	(1)	(2)	(3)	(4)	(5)
Mean	2.791	3.726	1.598	6.227	1.851
Std. Dev.	7.744	8.509	6.454	11.980	3.319
Obs.	1736	973	763	417	556

Notes: The relevant variable is the outcome variable measures the hectares of coca planted as a share of the municipal area per 1,000 hectares. Column (1) presents the mean and the standard deviation for the whole baseline sample of municipalities. Column (2) presents the mean and the standard deviation for the treated municipalities. Column (3) presents the same statistics for the treated municipalities after the spraying banning. Column (4) presents them before the spraying banning.

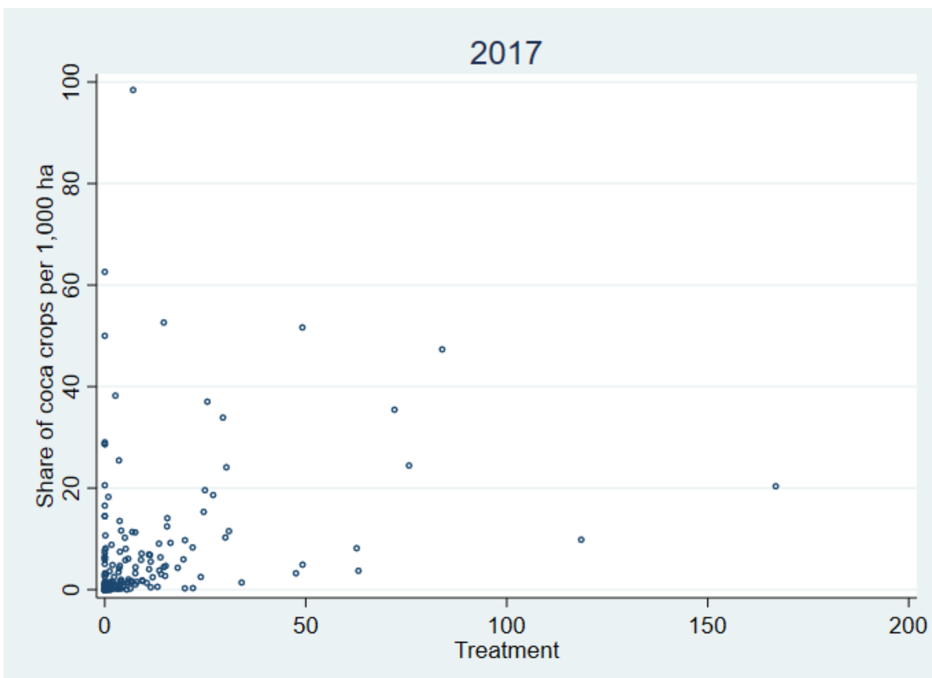


Figure 1.2: coca crops vs. Treatment.

Notes: Hectares of coca planted as a share of municipal area per 1,000 ha vs. Treatment.

1.3 Empirical Strategy

1.3.1 Main specification

The baseline model corresponds to a difference-in-differences model for the period 2011-2018, in which significant changes were consolidated in the anti-drug police in Colombia. The model exploits the exogenous Colombian government's decision — i.e., of the CONSEP and ANLA— to ban the spraying from October 2015 onward, as well as the variability of the herbicide's spraying between municipals during the past decade.

Following some works (see Rozo (2014), Rocha-García (2018, 2019), among others) the baseline sample includes only the municipalities that historically have produced coca.[14] In concrete, the sample was limited to the municipalities growing coca for at least a year during the period 2011-2014, the pre-treatment period. They represent a sample of 248 municipalities and 1,736 observations.

This sampling choice is supported by the fact that the coca crops tend to be concentrated in a few municipalities. Yet this group has been changing over the years due to the fulfillment of *the balloon effect* and the high variability of crops over time. From a total of 1,122 municipalities,[15] due to climatic and geographic conditions, it is possible to plant coca crops only in 819 of them (79%) (UNODC-SIMCI (2019)). However, only a fraction of them tend to plant coca and concentrate most of their plantations for a certain year. For instance, in 2017 only ten municipals represented 44% of the coca crops registered in Colombia.[16]

[14]Other works use the majority of Colombian municipalities. See for example Prem et al. (2021) or Abadie et al. (2015), among others.

[15]Strictly speaking, Colombia has only 1,103 municipalities including 9 special districts that are also considered as municipalities. Also, there are other 18 non-municipalized areas and the capital district (Bogotá), which are contemplated as municipalities too. All of them sum a total of 1122 municipalities.

[16]For that year the ten municipalities with the largest quantity of coca planted in Colombia were in their order Tumaco (11 % of the national total), Tibú (8 %), Puerto Asis (6 %), El Tambo (4 %), El Charco (3%), Barbacoas (3%), El Tarra (3%), Valle del Guamez (2%), Sardinata (2%), and Orito (2%).

Moreover, taking into account only municipalities that historically have produced coca enables us to work with a balanced sample between treatments and controls. Hence, this will be relevant for the fulfillment of the identifying assumption of the model.

The outcome variable is the amount of hectares planted per municipality (as the share of municipal area with coca plantation per 1,000 hectares), while the temporal treatment variable is a Dummy variable, $Post_t$, which equals 1 for the years of treatment, the first three years after spraying was forbidden (2016, 2017, 2018), or 0 in other case. As spraying was interrupted in October 2015, actually the post-treatment exactly began on that date. For this reason, as we deal with annual data, to get more precision in the definition of the temporal treatment variable I omit the year 2015 for the baseline estimations.

The analysis will be centered on the intensive-margin-analysis using a continuous variable, a more fine-tuned way to capture the whole variability between treated and non-treated. Let $Treatment_i$ be this treatment variable, whose value corresponds to the sum of the hectares of coca crops sprayed (as a share of municipal area per 1,000 hectares) for the period 2011-2014 by each municipality with coca crops at least for a year during the same period.

The baseline model can be written simply as:

$$Y_{it} = \alpha_i + \lambda_{dt} + \theta(Treatment_i * Post_t) + \sum_{c\in\mathbf{X},j\in J} \gamma(c \times \delta_j) + \epsilon_{idt} \tag{1.1}$$

where subindex i denotes the municipalities, d the departments and t time, from 2011 to 2018 but omitting the year 2015. Y_{it} represents the coca crops planted in municipality i in time t (as a share of municipal area per 1,000 ha). $Treatment_i$ is the continuous treatment variable capturing the intensity of spraying by each municipality. $Post$ is a temporal dummy being equal to 1 in the period 2016-2018 and 0 in other case. $\mathbf{X}$ is a vector of control variables capturing municipal characteristics, including a conflict variable, geographical aspects, and an UBN index, all of them measured for the pre-treatment period and interacting with yearly dummy variables. α_i corresponds to fixed effects at the municipal level and λ_{dt} to department-year fixed effects. Lastly, ϵ_{idt} is the error term, which I generally cluster at the municipality level.

In this setting, θ is the estimated average treatment effect of the interruption of aerial spraying for the treatment period (2016-2018). It corresponds to the change in the coca crops (as a share of municipal area per 1,000 hectares) caused by a decrease of one unit in aerial spraying (as a share of municipal area per 1,000 hectares) after its suspension.

1.3.2 Alternative specifications

What happens if we include in the treatment group the municipalities sprayed in 2015 just after the prohibition of the spraying campaign? Do we get the same results from the previous models? To answer these questions, I run another set of models without omitting the year 2015. In this setting, the treatment group includes the municipalities sprayed at least for a year over the period 2011-2015 and which also had coca crops at least for a year during this period. The control group includes municipalities never sprayed over the same period but with positive levels of coca crops at least for a year in that period. This means that in the intensive-margin-analysis, the continuous treatment now adds the hectares of coca crops sprayed for the year 2015 (as a share per 1,000 ha of municipal area) to the sum of them for the period 2011-2014, by each municipality with coca crops at least for a year during the longer period 2011-2015. This extended sample includes a total of 2.032 observations and 254 municipalities. The model continues being stated by Eq. (1.1), except for the extended sample and the treatment amplification.

What would happen if one introduces time trends in the model? To see if the results persist, I also run the baseline model and the latter alternative model including a time trend.

1.3.3 Identifying assumption

The relevant assumption supporting the identification of the model is that in the absence of the suspension of aerial spraying, the treated municipalities would have followed a similar trajectory to non-treated municipals. The validity of the "parallel trends" assumption can be partially assessed by estimating a dynamic version of the baseline model of the following type:

$$Y_{it} = \alpha_i + \lambda_{dt} + \sum_{j \in J} \beta_j (Treatment_i \times \delta_j) + \sum_{c \in \mathbf{X}, j \in J} \gamma (c \times \delta_j) + \epsilon_{idt} \quad (1.2)$$

where J includes the sample years except 2015 and 2014, the year before the ban on spraying. The parameters β_j can be interpreted as the differential coca production in the treated municipalities on the intensive margin, in year j relative to the year before the interruption of aerial spraying.

I estimate an equivalent regression to examine the validity of parallel trends for the alternative specification (which includes 2015), including 2014 but not 2015 in Eq.(1.2).

1.3.4 Additional robustness checks

Different sampling choices and treatments

To have a broader picture of the banning of aerial spraying on coca crops and check the results of the main models, I run additional sets of models with different sampling choices.[17] This modification will imply reformulating the treatment variable. Firstly, I run the baseline model with a looser specification of the treatment variable, which does not require sampled municipalities to have planted coca at least for a year during the pre-treatment period but to have historically produced coca. Then I run another set of models for a much larger sample, including the majority of the 1,122 municipalities of

[17] Some empirical studies have analyzed robustness using this procedure. One interesting example is Duggan et al. (2016), who study the market impacts of pharmaceutical product patents for the case of India

Colombia, most of them not having produced coca historically.

For the first set of models, I limited the sample to municipalities producing coca for at least a year during the period 1999-2018. This historical period was established by the fact that municipal data on coca crops are only available from this year onwards.[18] The treated are now the municipalities sprayed at least for a year during the pre-treatment period and which planted coca crops at least for a year from 1999 to 2014. On the other hand, the controls are municipalities not sprayed during the pre-treatment period but having had plantations at least for a year from 1999 to 2018. This set of treated and controls represents a sample of 327 municipalities and 2,289 observations when omitting year 2015 (or 2,616 including that year).

As before, the models will be focused on the intensive margin analysis. The treatment variables for this larger sample are denoted as $Treatment3$ or $Treatment4$ (see section 4). The first one is used for the models omitting year 2015, and the second one for the ones including that year. Thus, $Treatment3$ measures the sum of the hectares of coca crops sprayed (as a share of municipal area per 1,000 hectares) for the period 2011-2014 by each municipality of this larger sample (including municipalities historically planting coca). $Treatment4$ captures the sum of the hectares of coca crops sprayed (as a share of municipal area per 1,000 hectares) for the period 2011-2015 by each municipality of the larger sample.

The second set of models includes all the municipalities except special districts and non-municipalized areas without coca crops, aerial spraying, or manual eradication for the period 1999-2018 or the sample period 2011-2018. Also, the capital district, Bogotá, and the two Caribean islands, San Andrés and Providencia, are excluded from this sample too. The treated are now the municipalities having been sprayed at least for a year during the pre-treatment period. The rest of the municipalities perform as controls. This means a sample of 1,110 municipalities and 7,770 observations excluding the year 2015 (or 8,880 without omitting that year).

[18]The SIMCI began to operate in 1999.

Placebos

To examine the empirical robustness of my hypothesis and the baseline model's identification, I also contrast it with a set of *placebo models* capturing a different hypothesis about the timing of the impact of the reduction in aerial spraying on coca crops. It could make sense as coca crops began to increase in 2014, a year before the fumigation ban (see Figure 1.1 and Section 1.2.2). In addition, aerial spraying was already progressively diminishing during the whole pre-treatment period, from 2011 until 2015, before it was suspended.

However, the impact of this progressive reduction in spraying on crops is expected to be quantitatively smaller or negligible compared to the effect of its ban in 2015. This means that the decrease in crops in 2014 and, to a large extent, in 2015 (remember that spraying was suspended late in that year) may be explained by factors different from the evolution of aerial spraying.

In addition, these placebo models are also relevant to examine the possible presence of pre-trends originated in the existence of the anticipation effects related to the spraying banning. ¿Could it be the case? Most probably not! While the pronouncements of the Council of State and the Constitutional Court of Colombia about the negative consequences of glyphosate on the environment and human health were publicly stated between February and March of 2014, the suspension of its use by the CONSEP and the AMLA was finally established more than a year later, in October 2015. Nonetheless, both subsequent pronouncements were unexpected by the public opinion and even coca farmers. The key consideration here is that anybody had anticipated a total and permanent stop of the fumigation before it occurred in October 2015. As a result, one of the reasonable conditions for anticipation effects does not hold in this case: individuals have access to information on future treatment (Malani and Reif, 2015).[19]

[19]Malani and Reif (2015) formulate three conditions to be satisfied to become the anticipation of a treatment a reasonable diagnosis: 1) Individuals behave as forward-looking agents; 2) they have access to information on future treatment, and 3) there are

To analyze these alternative kinds of effects, I run a set of placebo models cutting the sample in 2014 or 2015 and using as "fake" ban years 2014 and 2014-2015 respectively. The treatment variable is now the intensity of spraying for the period 2011-2013: the sum of hectares sprayed during the placebo pre-treatment period for the municipalities with at least one year with positive levels of coca plantations for the period 2011-2014.

Considering that coca-crops data tend to exhibit overdispersion and a large number of zero values —even in the baseline model but to a lesser extent —, the negative binomial data approach constitutes an interesting modeling alternative. Indeed, in our samples the variance is greater than the mean (see Table 1.1 of summary statistics in Section 1.2.3). To compare estimations and the estimated average treatment effect under this specification, I run a set of models under this alternative setting. Appendix C presents the statement of this model and the corresponding results.

1.3.5 Potential mechanisms

I also analyze heterogeneous effects linked to socioeconomic and geographical characteristics of municipalities that give insights into the mechanisms behind the impact of the ban on aerial spraying on coca crops. In concrete terms, —as I will show and explain in the following section— the distance to each municipality's principal wholesale food market constitutes a potential mechanism explaining the impact of the aerial spraying suspension on coca crops. Furthermore, there are statistically significant and quantitatively large differential effects originated in the concrete geographical region where the municipality is located. The enhanced models are of the following type:

$$\begin{aligned} Y_{it} = \alpha_i + \lambda_{dt} \quad & + \phi_1(Z_i * T_i * Post_t) + \phi_2(Z_i * Post_t) \\ & + \phi_3(T * Post_t) + \sum_{c \in \mathbf{X}, j \in J} \gamma(c \times \delta_j) + \epsilon_{idt} \end{aligned} \tag{1.3}$$

where T_i is the treatment variable, Z_i the municipal characteristic working

benefits associated with taking actions before the treatment is implemented.

as a potential mechanism, and the rest of the variables enter as in the former models. Within these models ϕ_1 captures the estimated ATE of the triple interaction corresponding to the treated municipalities that also exhibit characteristic Z_i relative to the rest of municipalities. It offers an estimation of the heterogeneous impact of the treatment under the influence of characteristic Z_i.

1.4 Results

1.4.1 Main findings

I have a strongly balanced panel data set with 1,736 observations for the main models. The difference in means test for treated municipalities before and after the spraying banning corroborates the descriptive findings of Table 1.2, reason why the dif-in-dif model constitutes a appropriate framework to examine the impact of the sudden stop of aerial fumigation on coca plantations. Table A1 in Appendix A presents the results of the test.

Table 1.3 shows the estimations for the models of Eq. (1.1). The regression of Column (1) does not include controls, while the other two in Columns (2) and (3) do (see details in the notes below the table). The errors are clustered by municipalities in the first two columns and bootstrapped in the third one. In the three models the treatment variable is statistically significant and has a positive but modest effect on the coca crops: the estimated ATE of the interruption of aerial spraying for the period 2016-2018 is between 0.101 and 0.125. Taking as a more precise estimation the models with controls, the results imply that the estimated ATE is around 0.1. This means that a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha) causes only an increase of 0.1 hectares coca planted (as a share of municipal area over 1,000 ha) after the fumigation banning. This increase is statistically significant at a range between 0.01% and 0.05 % but economically modest: it represents only 2,6% of a standard deviation and 6% of the sample mean of coca growing for the pre-treatment year (2014). Hence, the aerial spraying banning explains only a small percentage of the dramatic increase of 144,45% in coca crops between 2014 and 2018.

Table 1.3: Coca production and suspension of aspersion.

Dependent variable: Share of coca cultivation over 1,000 hectares.

VARIABLES	(1)	(2)	(3)
Treatment*Post	0.125***	0.101**	0.101***
	(0.046)	(0.045)	(0.026)
Observations	1,736	1,736	1,736
R-squared	0.680	0.730	0.730
Municipalities	248	248	248
Municipality FE	YES	YES	YES
Dept-Year FE	YES	YES	YES
Controls	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)

Notes: The year 2015 is omitted from the baseline sample, which includes a total of 248 municipalities. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and department-year fixed effects. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1) and (2) present robust standard errors clustered by municipalities in parenthesis, while Column (3) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

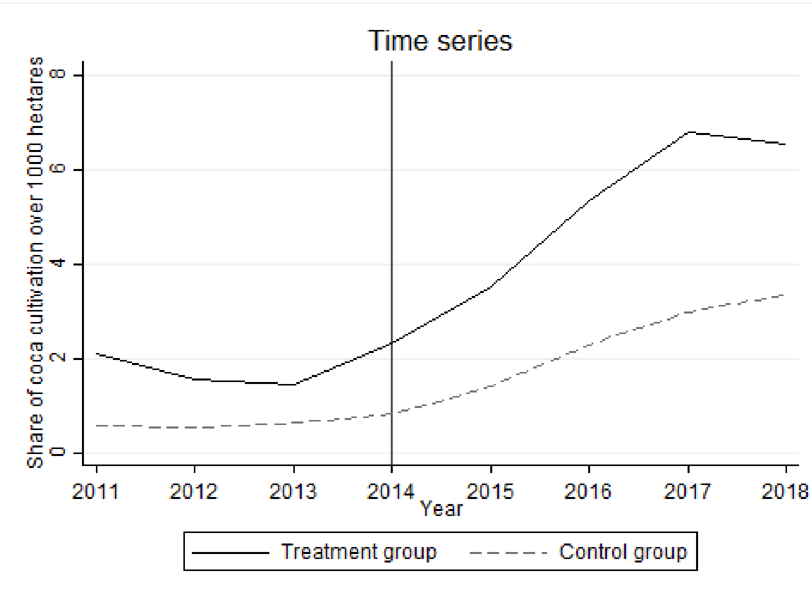
During the period 2014-2018 there was a huge growth of 102,362.92 ha in coca plantations. Meanwhile, there was a total decrease of 55,532 ha in the area sprayed (between 2014 and 2016). However, the model predicts only an increase in the coca plantations of around 5,553 ha as an effect of the aerial spraying banning, which represents only about 5.4% of the number of additional plantations. As a result, the baseline model gives empirical evidence supporting the hypothesis that the ban on aerial spraying led to a statistically significant but modest rise in the coca-growing after its interruption, which explains only a small percentage of the dramatic surge it exhibited since 2014. Therefore, this factor *ceteris paribus* is not one of the leading causes of the rise of coca crops during the period 2014-2018. This finding implies that other factors suggested in other works —mentioned in Section 2— or the conjugation of them may have also provoked a statistically significant but more relevant effect in economic and quantitative terms. Again, this goes in the direction of the initial hypothesis stated, which implies that the upsurge of coca crops may be probably explained by the confluence of diverse factors —including the interruption of aerial spraying—.

Moreover, these results have to be understood with caution when analyzing the effects of aerial spraying on coca crops: They do not imply that aerial spraying has had at least a small impact —i.e. an estimated average treatment effect around 0.1— on coca crops during the pre-treatment period. Instead, there seems to be an asymmetry between the effects aerial spraying had on coca crops during the pre-treatment period and the impact of its suspension on them. I will explain this argument in the following section.

1.4.2 Identifying assumption: Parallel trends

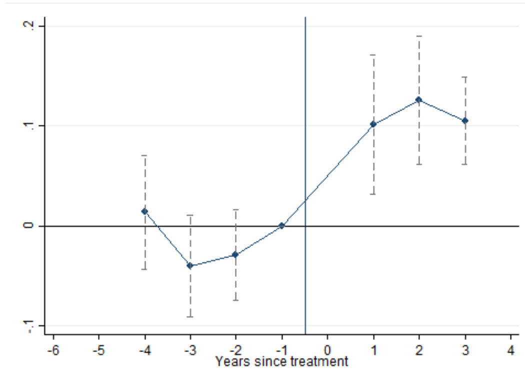
Figure 1.3 depicts the "parallel trends" graph. It shows at a graphical level that there seems to be partial evidence of its fulfillment. This figure shows that the two lines became clearly divergent after 2015, the year prior to treatment, though they began to diverge in 2014. Table A2 (see Appendix A) presents the estimation of the dynamic version of Eq. (1.1) given by Eq. (1.2).

Figure 1.3: Collapsed series for treated and non-treated.

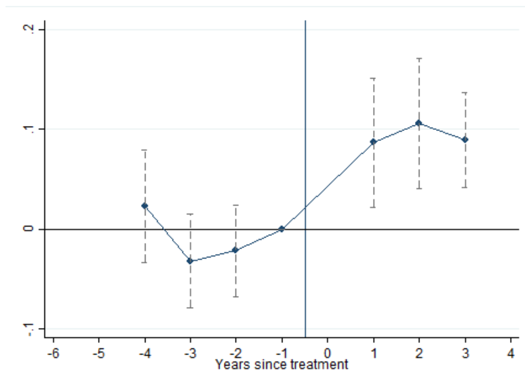


The models give evidence supporting the fulfillment of the parallel trends assumption. This can be confirmed in Figure 1.4, which depicts de corresponding event study. Regressions in Table A2 clearly show that the coefficients associated with the dummy variables interacted to the treatment for the post-treatment period are all statistically significant at the 1% level, but economically modest. In contrast, the coefficients for the pre-treatment years are not statistically significant.

Figure 1.4: Event study baseline model



(a) Regression without controls.



(b) Regression with controls.

Notes: These figures present the point estimates of the regressions and the confidence interval at the 95%

The event study corroborates that the yearly impact of the treatment during the pre-treatment is not statistically significant and relatively close to zero. Although the estimated coefficients for $Treatment$ interacted with the yearly dummies for 2012 and 2013 are negative, with values of -0.032 and -0.022 (see Column (2) in Table A2 in Appendix A), respectively, they are not statistically significant nor quantitatively relevant. On the other hand, the estimated coefficient for $Treatment$ interacted with the yearly dummy for 2011 is not statistically significant and gives a value of 0.023 (see Column (2) in Table A2) —an unexpected positive but close to zero value—. These results go in the same direction as the work of Mejía et al. (2017), who find that spraying one additional hectare reduces coca crops only by 0.02 to 0.03 hectares.

This finding has a crucial implication for the analysis too: it corroborates that, although the ban of aerial spraying had a small impact on coca crops during the post-treatment period, it was ineffective to reduce coca crops during the pre-treatment period. Hence, there seems to be an asymmetry between the effects aerial spraying had on coca crops and the impact of its suspension. This implies that the latter constitutes, to a great extent, a *rebound effect* linked structural factors and to the lack of a new consolidated anti-drug policy strategy that would have replaced the eradication and alternative development policies after their de-escalation during the period 2013-2015 (Rocha-García, 2019). As I will show in section 1.5, one of the structural determinants behind the impact of the aerial spraying banning is the lack of legal economic alternatives for the farmers and the limitations in the means to transport and sell legal agricultural production. Two determinant factors of the latter are the availability of roads to sell production and the remoteness of wholesale markets in the coca-producing regions. The distance to each municipality's principal wholesale food market captures the second determinant.

1.4.3 Additional results

Table 1.4 presents the estimations of the models with the larger sample including year 2015. The results are the same of the baseline model: the estimated average treatment effect of the aerial spraying banning is 0.1. For the three models the estimated coefficients associated with the treatment variable are statistically significant at the 1% level. As a consequence, the initial hypothesis is also confirmed when including the amount of hectares sprayed immediately after the fumigation's suspension, in 2015. These ultimate fumigated hectares are included in the alternative treatment variable, $Treatment2$.

Table 1.4: Coca production and suspension of aspersion for the whole period.

Dependent variable: Share of coca cultivation over 1,000 hectares.

VARIABLES	(1)	(2)	(3)
Treatment2*Post	0.116***	0.100***	0.100***
	(0.038)	(0.039)	(0.027)
Observations	2,032	2,032	2,032
R-squared	0.704	0.749	0.749
Municipalities	254	254	254
Municipality FE	YES	YES	YES
Dept-Year FE	YES	YES	YES
Controls	NO	YES	YES
Years	2011-2018	2011-2018	2011-2018

Notes: The models use the extended baseline sample including year 2015 and a total of 254 municipalities. Hence, the treatment variable now, $Treatment2$, is the sum of the hectares of coca crops sprayed for the period 2011-2015 (as a share per 1,000 ha of municipal area), by each municipality with coca crops at least for a year during the longer period 2011-2015. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and department-year fixed effects. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1) and (2) present robust standard errors clustered by municipalities in parenthesis, while Column (3) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Furthermore, Table 1.5 presents the results of the baseline model of Eq. (1.1) and the latter model (without omitting 2015) including time trends. The same results as before are obtained, corroborating the robustness of the model.

Table 1.5: Coca production and suspension of aspersion with time trends.

Dependent variable: Share of coca cultivation over 1,000 hectares.

	(1)	(2)	(3)	(4)
VARIABLES				
Treatment*Post	0.125***	0.101**		
	(0.046)	(0.045)		
Time trend	0.656***	-10.268***	0.535***	-6.976**
	(0.155)	(3.125)	(0.168)	(3.306)
Treatment2*Post			0.116***	0.100***
			(0.038)	(0.039)
Observations	1,736	1,736	2,032	2,032
R-squared	0.680	0.730	0.704	0.749
Municipalities	248	248	327	327
Municipality FE	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES
Controls	NO	YES	NO	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018

Notes: Columns (1) and (2) omit 2015 from the baseline sample, including a total of 248 municipalities. Columns (3) and (4) include 2015 from the baseline sample, so that they incorporate a total of 327 municipalities. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and department-year fixed effects. All the regressions include time trends. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. All the Columns present robust standard errors clustered by municipalities in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

1.4.4 Further robustness

The models with different sampling choices and treatments

Table 1.6 gives indications about the robustness of the main findings for a larger sample of municipalities with a looser specification of the continuous treatment variable, as explained in Section 1.3.4, which can be the variable *treatment*3 when omitting the year 2015, or the variable *treatment*4 when including it. The corresponding models with controls (see Columns (2) and (4) of Table 1.6) exhibit estimated average treatment effects close to the ones estimated for the baseline models, of 0.115 and 0.106, respectively; in both cases the variables of interest are statistically significant at the 5% or 1% level.

Table 1.6: Coca production and suspension of aspersion for a larger sample of municipalities.

Dependent variable: Share of coca cultivation over 1,000 hectares.

VARIABLES	(1)	(2)	(3)	(4)
Treatment3*Post	0.137***	0.115**		
	(0.047)	(0.045)		
Treatment4*Post			0.126***	0.109***
			(0.039)	(0.038)
Observations	2,289	2,289	2,616	2,616
R-squared	0.683	0.723	0.706	0.743
Municipalities	327	327	327	327
Municipality FE	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES
Controls	NO	YES	NO	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018

Notes: These models use the larger sample with municipalities producing coca at least for a year during the period 1999-2018, which includes 327 municipalities. The treatment variable does not require sampled municipalities to have planted coca at least for a year during the pre-treatment period, but to have historically planted it. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and department-year fixed effects. In Columns (1) and (2) the year 2015 is omitted from the sample, while in Columns (3) and (4) it is included. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. All the columns present robust standard errors clustered by municipalities in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The relevant coefficient of these models are slightly higher than for the baseline models, though the dynamic versions of the models still give evidence supporting the fulfillment of the parallel trends assumption. Table A3 in the Appendix present the dynamic regressions, while Figure A1 depicts graphically the event study.

Now, the stability of results will be assessed for the largest sample with the majority of municipalities. Table 1.7 show these alternative set of models. Columns (1) and (2) present the models when the year 2015 is excluded from the sample, whereas Columns (3) and (4) exhibit the models when that year is included; the corresponding continuous treatment variables are $Treatment3$ and $Treatment4$. The relevant coefficients remain stable though larger than for the previous specifications: For the models with controls they are 0.136 and 0.126 (see Columns (3) and (4)), being in both cases the respective treatment variables statistically significant at the 1% level.

Yet the dynamic versions of the models still give evidence supporting the fulfillment of the common trends assumption. Table A3 in the Appendix present the corresponding dynamic regressions for this largest sample, whilst Figure A2 show graphically the event study.

Table 1.7: Coca production and suspension of aspersion for the majority of municipalities.

Dependent variable: Share of coca cultivation over 1,000 hectares.

VARIABLES	(1)	(2)	(3)	(4)
Treatment3*Post	0.163***	0.136***		
	(0.050)	(0.046)		
Treatment4*Post			0.148***	0.126***
			(0.041)	(0.039)
Observations	7,770	7,770	8,880	8,880
R-squared	0.690	0.710	0.714	0.732
Municipalities	1,110	1,110	1,110	1,110
Municipality FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	NO	YES	NO	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018

Notes: These models use the largest sample with majority of municipalities and the corresponding treatment variables. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. In Columns (1) and (2) the year 2015 is omitted from the sample, while in Columns (3) and (4) it is included. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. All the columns present robust standard errors clustered by municipalities in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Placebo models

The purpose of this part is to contrast the initial hypothesis and the baseline model's identification with a set of placebo models testing alternative hypotheses about the timing of the impact of the aerial spraying reduction on coca crops. Two questions arise: Is there an impact of the reduction in aerial spraying before 2016? Are there pre-trends originated in the existence of anticipation effects related to the spraying banning?

Columns (1) and (2) of Table 1.8 indicate that there is a negligible and statistically insignificant impact linked to the reduction of aerial spraying since 2014, when 2014 is used as a "fake" ban year. In this case, the treatment variable ($PlaceboTreatment$) corresponds to the intensity of spraying for the period 2011-2013 —i.e., the sum of hectares sprayed during the placebo pre-treatment period for the municipalities with at least one year with positive levels of coca plantations for the period 2011-2013—. Columns (3) and (4) of the same table show that there is also a negligible and statistically insignificant impact linked to the reduction of aerial spraying since 2014, when 2014 and 2015 are used as a "fake" ban years.

Consequently, the analysis corroborates that there is any impact linked to the reduction of aerial spraying before 2016, nor any anticipation effect of the complete suspension of the fumigation program before 2015. Therefore, the relevant effect linked to a reduction of aerial spraying does not correspond to the impact of progressive reductions in it but to a substantial and sudden drop that led to the complete elimination of the policy after its ban (as the result of a constitutional order). This gives additional clues to understand the reason why the impact of the suspension of fumigation is different from the impact it had on coca crops during the years when this policy was allowed and applied —both in qualitative and quantitative terms.

Table 1.8: Placebos.

Dependent variable: Share of coca cultivation over 1,000 hectares.

VARIABLES	(1)	(2)	(3)	(4)
PlaceboTreatment*FakePost	0.009	0.000	0.036	0.020
	(0.016)	(0.014)	(0.025)	(0.021)
Observations	992	992	1,240	1,240
R-squared	0.836	0.858	0.732	0.773
Municipalities	248	248	248	248
Municipality FE	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES
Controls	NO	YES	NO	YES
Years	2011-2014	2011-2014	2011-2015	2011-2015

Notes: Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. In all the regressions the sample was cut in 2014 (Columns (1) and (2)) or in 2015 (Columns (3) and (4)), using as "fake" ban years 2014 or the period 2014-1015, respectively. Hence, in all the regressions the treatment, $PlaceboTreatment$, corresponds to the sum of hectares sprayed during 2011-2013 for the municipalities with at least one year with positive levels of coca plantations for that period. $FakePost$ is the temporal dummy variable: for the first two models it is 0 for the years 2011-2013 and 1 for 2014. For the other two models (columns (3) and (4)) it is 0 for the years 2011-2013 and 1 for 2014-2015. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. All the columns present robust standard errors clustered by municipalities in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

1.5 Mechanisms

This section gives empirical evidence supporting the idea that structural determinants matter for understanding the coca crops' evolution, especially when there are changes in the drug-policy regimes. From the standpoint of different disciplines, some authors have pointed out the relevance of structural factors to explain the growth and persistence of illegal crops in Colombia for more than five decades. See for instance, Rocha-García (2015) for an econometric analysis [20], Molano (1987) for a study of the rural colonization in Colombia in the context of a historical research [21], or OACP (2016) and Mantilla et al. (2021) for a political analysis.

These approaches, though analytically dissimilar, converge in the emphasis on structural factors as one of the leading long-run causes of the development and persistence of illicit crops in Colombia.

In the spirit of this structural approach, I find that two kinds of structural determinants explain to a great extent the mechanisms behind the impact of the spraying banning: 1) The remoteness of wholesale markets to sell agricultural production, and 2) a series of geographical characteristics inherent to the different natural regions that exist in Colombia. While the first determinant will be addressed using a variable that measures the distance to each municipality's principal wholesale food market, the second one will be tackled with a set of regional dummy variables.

1.5.1 The relevance of the remoteness to wholesale markets

The remoteness of wholesale markets to sell agricultural production probably was as key determinant for several Colombian farmers to decide to plant (more) coca. It became more important in the absence of a strong repression

[20] Rocha-García (2015) argues that rural poverty and farmers' vulnerability constitute key factors inducing them to involve in illicit activities. He posits that "the conditions explaining the probability of presence of coca at a municipal scale correspond in its order (of importance) to geographic, socioeconomic, institutional, and microeconomic variables [...]" (Rocha-García, 2015, p. 4) (My own translation.)

[21] Molano (1987) suggests that the crops substitution is a policy alternative to fight against illicit crops, whenever the substitute crops are sufficiently profitable. However, that also means —according to this author— substantial changes in the economic structure, as well as in the social and political structure. Molano concludes that "above all, colonization zones require a program of agrarian reform to limit legally latifundium's or each other monopolist's force aspirations" (Molano, 1987, p. 151) (My own translation).

policy —as had been aerial spraying since the first years of the century— and in a moment when there was a lack of a new consolidated anti-drug policy strategy that would have replaced the fumigation policy and the alternative development policies de-escalated between 2013 and 2015 (Rocha-García, 2019). Although aerial spraying was suspended in October 2015 and the Peace Agreement signed on 24th November 2016, the PNIS was formally approved by the Presidency of the Republic of Colombia through the Decree-law No. 896 of 20th May 2017 and began to be implemented during the same year (Salazar-Valencia et al., 2017). However, many studies have emphasized the lags and shortcomings of its implementation since 2018 until the present day, especially regarding the execution of productive projects for the farmers and investments in public goods and services in the zones of implementation (Garzón et al., 2019; Mantilla et al., 2021; Mejía-Hidalgo, 2021). Therefore, the PNIS "has not consolidated as a transition strategy contributing to the transformation of the Colombian countryside" (Mejía-Hidalgo, 2021, p. 195)

In this conjuncture, the lack of enough profitable legal economic alternatives for the farmers, as well as the limitations in the transportation means to sell legal production may have played a role. Two factors are key for the latter: First, the availability of roads to carry the production[22] and, second, the remoteness of wholesale markets in the coca-producing regions. Both factors are considered in the Peace Agreement as a matter of foment in the context of the RRI and the PNIS: While in Section 4, the need to strengthen the road infrastructure and communications is emphasized, in Section 1, the marketing of alternative agrarian activities —including the finance or co-finance of storage centers and the promotion of urban-market centers– is suggested (OACP, 2016). The following analysis will be focused on the second factor (the remoteness of wholesale markets), leaving the first one for future works.

Table 1.9 presents the estimations of the first set of models of triple differences of Eq. (1.3). The variable of interest corresponds to an interaction

[22] With respect to this point, the investment in the construction of tertiary roads plays a significant role, as they are essential for the coca-producing regions to reduce transport costs, open legal markets, and enhance land value (Rico-Valencia, 2017).

of the treatment of the baseline models, $Treatment * Post$ (see columns (1)-(3)), or the treatment of the alternative models including the year 2015, $Treatment2 {*} Post$ (see columns (4)-(6)), with an index measuring the distance to each municipality's principal wholesale food market, denoted as $MarketDist$. In all the models —except for the regression of Column (2) (see details of the variables and regressions in the Notes of Table 1.9)— the variable of interest is statistically significant and has an economically relevant impact.

The coefficient associated to it for the baseline models with controls (Columns (2) and (3)) gives a value 0.56, which means that a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha), when interacted with the mean value of the index of the distance to the principal wholesale food market, causes an increase of 0.56 hectares coca planted (as a share of municipal area over 1,000 ha) after the fumigation banning. This value represents 14.4% of a standard deviation and 33.9% of the sample mean of coca growing for the pre-treatment year (2014), which corroborates that the impact of the variable of interest is now relevant but still small compared with the huge increase of 144,45% that coca crops exhibited between 2014 and 2018. Considering that the area sprayed decreased by 55,532 ha during this period, this enhanced model predicts an increase of around 31,098 ha in coca plantations, representing only about 30.4% of the total growth of 102,362.92 ha during the same period. Therefore, the impact of the ban on spraying is magnified as a function of the remoteness of the municipality's principal wholesale food market.

The estimations of the regressions including the year 2015 feature similar results, though the relevant coefficient is smaller, giving a value of 0.463 for the models including control variables.

Table 1.9: The influence of the distance to the main wholesale food market.

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MarketDist*Treatment*Post	1.006***	0.560	0.560**			
	(0.348)	(0.356)	(0.227)			
Treatment*Post	-0.226*	-0.095	-0.095			
	(0.115)	(0.120)	(0.075)			
MarketDist*Post	-2.230	-6.883	-6.883***	-2.354	-6.782	-6.782***
	(2.680)	(5.157)	(2.437)	(2.117)	(4.684)	(1.917)
MarketDist*Treatment2*Post				0.809***	0.463*	0.463***
				(0.300)	(0.280)	(0.139)
Treatment2*Post				-0.168	-0.063	-0.063
				(0.105)	(0.102)	(0.046)
Observations	1,736	1,736	1,736	2,032	2,032	2,032
R-squared	0.690	0.734	0.734	0.712	0.751	0.751
Municipalities	248	248	248	254	254	254
Municipality FE	YES	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018	2011-2018

Notes: Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. These models use the baseline sample with 248 municipalities (Columns (1)-(3)) or the baseline extended sample of 254 municipalities when the year 2015 in included (columns (4)-(6)). The potential mechanism is an index of the linear distance to the principal wholesale food market, calculated dividing the original variable by its maximum value, so that it becomes normalized (between zero and one). The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1)-(2) and (4)-(5) present robust standard errors (clustered by municipalities) in parenthesis, while Columns (3) and (6) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6 in the Appendix A presents the same set of triple differences regressions for the models using the larger sample of 327 municipalities. The results are stable, showing that the corresponding variable of interest — $MarketDist{*}Treatment3{*}Post$ when the year 2015 is omitted, or $MarketDist{*}Treatment4{*}Post$ when the same year is included— are statistically significant and economically relevant. The coefficient associated to them are slightly larger than for the baseline models: for the first variable gives 0.595 (columns

(2) and (3)) when including control variables, while it gives 0.502 for the second variable (columns (5) and (6)) including controls too.

Now, Table A7 (see Appendix A) presents the set of triple differences regressions for the models using the largest sample with the majority of municipalities. The variable of interest —$MarketDist * Treatment3 * Post$ when omitting the year 2015, or $MarketDist * Treatment4 * Post$ when it is included— remain being statistically significant, yet show larger associated coefficients: 0.999 for the models omitting the year 2015 (columns (2) and (3)), or 0.82 for the models including it (columns (5) and (6)).

1.5.2 Geographic heterogeneous effects.

Table 1.10 displays the third set of triple differences models of Eq. (1.3). The variables of interest are now a set of dummy variables capturing the different natural regions of Colombia. They capture the presence of heterogeneous effects linked to geographic characteristics of the different natural regions of Colombia[23]. Three different regressions were estimated for the three different samples used, each of them with the corresponding triple-interaction variables using the regional dummy variables: $Treatment*Post$ for the baseline sample with 248 municipalities, $Treatment3 * Post$ for the larger sample with 327 municipalities, as well as for the largest sample with 1,110 municipalities. Figure A3 in the Appendix depicts the natural regions of Colombia.

In the three regressions, the variables of interest interacting with the Amazon Region, the Caribbean Region, and the Andean Region are statistically significant and have positive impacts on the outcome variable. In contrast, the treatment variable interacting with the dummy for the Pacific region is not statistically significant. The dummy for the Orinoco region was chosen as the reference dummy, so that it was omitted from the three regressions.

[23]As I already explained in Section 1.2.1 and Footnote 12, although six natural regions divide the Colombian territory (the Amazon Region, the Andean Region, the Caribbean Region, the Pacific Region, the Orinoco Region, and the Insular region), the latter one is excluded from the present study, since it considers only the continental territory of Colombia.

In the case of the regression for the baseline sample, the variable $gamazonia * Treatment * Post$ is statistically significant at the 1% level, and the associated coefficient is 0,276 (see Column (1)). Hence, a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha) for the municipalities belonging to the Amazon Region, causes a differential increase of 0.276 hectares of coca planted (as a share of municipal area over 1,000 ha) after the spraying banning, relative to the Orinoco Region. Moreover, the variable $gandina * Treatment * Post$ features an associated coefficient of 0.426. This means that a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha) for the municipalities belonging to the Andean Region, causes a differential increase of 0.426 hectares of coca planted (as a share of municipal area over 1,000 ha) after the spraying banning, relative to the Orinoco Region. However, this variable is only statistically significant at the 10% level.

The variable $gcaribe * Treatment * Post$ in the same regression gives a coefficient of 0.196 (see Column (1) again). Thus, a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha) for the municipalities belonging to the Caribbean Region, causes a differential increase of 0.196 hectares of coca planted (as a share of municipal area over 1,000 ha) after the spraying banning, relative to the Orinoco Region. Nonetheless, this variable is only statistically significant at the 10% level.

The regression using the larger sample of 327 municipalities generates similar results, though slightly higher associated coefficients (see Column (2)). Hence, the average mean difference between treated and non-treated turns larger. In this case, the statistical significance of $gandina * Treatment3 * Post$ and $gcaribe * Treatment3 * Post$ improves, reaching the 5% level, while it continues being at the 1% level for the variable $gamazonia * Treatment3 * Post$. The results of the regression for the largest sample of 1,110 municipalities are similar, yet the associated coefficients result larger (see Column (3)).

Table 1.11 presents the estimation regional small-panel regressions of the baseline models with $Treatment * Post$ as the relevant treatment variable. They corroborate the previous results showing that the treatment variable is statistically significant for the Amazon Region, the Caribbean Region, and the Andean Region at the 5% or 10% level; in this case, it is also significant for the regression of the Pacific Region.

In addition, Table A8 in the Appendix A presents the estimation of another set of small-panel regressions with a different partition of the baseline sample: the division by departments. The table includes only the departmental regressions with statistically significant treatments and with a number of municipalities larger than the number of sample years. The results are consistent with Tables 1.10 and 1.11: they reveal that departments of the same natural regions explain the impact of the treatment variables. For the case of the Amazon Region, the regression for Putumayo Department has a statistically significant treatment variable; for the Caribbean Region, the departments of Bolivar and Cordoba exhibit regressions with statistically significant treatment variables. The same happens, yet to a lesser extent, to the Antioquia Department, because a sub-region in it, the Urabá Antioqueño, belongs to the Caribbean Region too.

Moreover, the regressions for the Departments of Antioquia, Nariño, and Valle del Cauca also exhibit statistically significant treatments. Since most of their municipalities belong to the Andean Region, these results corroborate that this region contributes to the impact of the spraying banning. The same occurs for the department of Antioquia, as its regression exhibits a statistically significant coefficient and most of its municipalities belong to this region too. Nonetheless, some municipalities of Nariño and Valle belong to the Pacific Region too, reason why their corresponding regressions also support the results of Table 1.11, showing that this region also contributes to bolstering the "banning effect".

Table 1.10: Geographic heterogeneous effects by regions

Dependent variable: Share of coca cultivation over 1,000 hectares			
VARIABLES	(1)	(2)	(3)
gandina*Treatment*Post	0.426*		
	(0.244)		
gamazonia*Treatment*Post	0.276***		
	(0.096)		
gpacifica*Treatment*Post	-0.021		
	(0.091)		
gcaribe*Treatment*Post	0.196*		
	(0.111)		
Treatment*Post	0.071		
	(0.087)		
gandina*Post	2.419**	1.533**	0.271*
	(1.163)	(0.750)	(0.140)
gamazonia*Post	1.216	1.159	1.046
	(1.750)	(1.657)	(1.463)
gpacifica*Post	3.601***	2.561***	1.286***
	(0.842)	(0.627)	(0.329)
gcaribe*Post	0.717	0.465	0.059
	(0.557)	(0.372)	(0.057)
gandina*Treatment3*Post		0.477**	0.540**
		(0.239)	(0.235)
gamazonia*Treatment3*Post		0.275***	0.269***
		(0.095)	(0.092)
gpacifica*Treatment3*Post		-0.010	-0.001
		(0.090)	(0.088)
gcaribe*Treatment3*Post		0.220**	0.254**
		(0.106)	(0.105)
Treatment3*Post		0.074	0.083
		(0.085)	(0.083)
Observations	1,736	2,289	7,770
R-squared	0.705	0.707	0.716
Municipalities	248	327	1110
Municipality FE	YES	YES	YES
Dept-Year FE	YES	YES	YES
Controls	NO	NO	NO
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)

Notes: These models use the three different types of samples: the baseline sample with 248 municipalities (Column (1)), the larger sample with municipalities producing coca at least for a year during the period 1999-2018, which includes 327 municipalities (Column (2)), and the largest sample with the majority of municipalities, 1,110 municipalities (Column (3)). Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. The year 2015 is omitted from the three regressions. The regional dummy corresponding to the Orinoco Region (gorinoquia) was chosen as the reference category, so that it is omitted from all the regressions. The potential mechanism is the heterogeneity originated by the geographic characteristics of the different regions in Colombia. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. All the columns present robust standard errors clustered by municipalities in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1.11: Regional models.

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)
Treatment*Post	0.267***	0.497**	0.049**	0.071	0.347***
	(0.066)	(0.212)	(0.025)	(0.084)	(0.039)
Observations	196	567	504	133	336
R-squared	0.400	0.167	0.279	0.170	0.307
Municipalities	28	81	72	19	48
Region	Caribbean	Andean	Pacific	Orinoco	Amazon
Municipality FE	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)

Notes: Entries represent the estimated coefficients from regional panel regressions including municipality fixed effects and department-year fixed effects. In all the regressions the year 2015 is omitted and control variables are excluded due to the small size of the regional sub-samples. All the columns present robust standard errors (clustered by municipalities) in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The examination of the heterogeneous effects linked to geographic characteristics reveals that the regions driving the impact of the spraying banning are, in its order of importance, the Amazon region, the Andean Region, the Caribbean Region, and the Pacific region. There is evidence suggesting that the departments of Antioquia, Bolivar, Caquetá, Cordoba, Nariño, Valle del Cauca, and Putumayo explain these results. The reason why these regions may have played a more prominent role in the arising of this effect on coca crops probably lies in the structural problems —as the remoteness of wholesale markets and the lack of enough and good-quality roads— that persist in several small municipalities in the countryside of these regions. Nonetheless, this result is more evident in the case of the Amazon Region, the Caribbean Region and the Pacific Region. Future works should analyze the geographic influence with more amplitude and depth, which goes beyond the purpose and the limits in the extension of this article.

Section A5 of Appendix A analyses the influence of other potential mechanisms and factors explaining the upsurge of coca crops. This complements the results of the present study, as I find that the suspension of spraying is not one of the leading factors explaining the evolution of crops during the post-treatment period, so that the rebound of coca crops during the period of interest may be explained by a confluence of several factors.

1.6 Conclusions

The econometric models show that the ban of aerial spraying had only a statistically significant but modest impact on coca crops: the estimated ATE obtained is around 0.1, which means that a decrease of one hectare of coca sprayed (as a share of municipal area over 1,000 ha) causes only an increase of 0.1 hectares of coca planted (as a share of municipal area over 1,000 ha). This increase is statistically significant at a 0.01% but economically modest as it represents only 2,6% of a standard deviation and 6% of the sample mean of coca growing for the pre-treatment year (2014).

The baseline models predict an increase in the coca plantations around 5,553 ha as a result of the suspension of aerial spraying, which represents only around 5.4% of the total increase in coca crops during the period 2014-2018. Hence, the aerial spraying banning explains only a small percentage of the dramatic increase of 144,45% in the coca crops between 2014 and 2018. These results provide empirical evidence supporting the hypothesis that the ban on aerial spraying led to a statistically significant but modest rise in the coca plantations. Therefore, this factor *ceteris paribus* is not one of the leading causes of the rise of coca crops during the period 2014-2018. Consequently, other factors mentioned in this article, or the conjugation of them may have caused more prominent effects in economic and quantitative terms. This goes in the direction of my initial hypothesis too, which states that the huge increase in coca plantations between 2014 and 2018 may be probably explained by the confluence of various factors —including the interruption of aerial spraying—.

The corresponding event study supports the fulfillment of the parallel trends assumption. The estimated dynamic versions of the baseline model show that the coefficients associated with the dummy variables of the post-treatment period interacted by the treatment variable are all of them statistically significant at the 1% level but economically modest. Instead, the respective coefficients for the pre-treatment years are not statistically significant and very small in economic terms. The latter is also a crucial finding because it gives empirical evidence of the ineffectiveness of aerial spraying during the period 2011-2015. This result goes in the same direction as Mejía et al. (2017), who find that spraying one additional hectare reduces coca crops only by 0.02 to 0.03 hectares.

Hence, there seems to be an asymmetry between the impact of aerial spraying on coca crops and its impact on them after its suspension. This implies that the latter constitutes to a great extent a *rebound effect* linked to structural factors and to the lack of a new consolidated anti-drug policy strategy that would have replaced the eradication and alternative development policies after their de-escalation during the period 2013-2015 (Rocha-García, 2019).

The analysis of potential mechanisms reveals that two kinds of structural determinants explain to a great extent the impact of the spraying banning: First, the remoteness of wholesale markets to sell agricultural products; and second, geographical characteristics inherent to the different natural regions exiting in Colombia. In concrete, I find that a decrease of one hectare of coca sprayed (as a share of municipal area per 1,000 ha), when interacted with the index of the distance to the principal wholesale food market, causes an increase of 0.56 hectares coca planted (as a share of municipal area over 1,000 ha) after the spraying banning, which –as explained in Section 1.5.1— constitutes an economically relevant but still small amount when compared with the huge increase in coca plantations between 2014 and 2018. Regarding geographic heterogeneous effects, I find that the regions pushing the impact of the spraying banning are, in its order of magnitude, the Amazon region, the Andean Region and the Caribbean Region. The reason why these regions may have played a significant role in the arising of the "banning effect" is probably linked to the structural problems —as the remoteness of wholesale markets and the lack of enough and good-quality roads— persisting in several rural municipalities of these regions.

Nonetheless, observing a shortcoming of the implemented empirical strategy is pertinent. The study provides only a short-run analysis focusing on the subsequent years after the interruption of the aerial fumigation program. Future works should study its medium-term impacts, including the years following 2018. By the way, extending the temporal horizon of the model expanding the sample until 2022, would enable us to the develop a more comprehensive analysis if we complement it with an examination of the consequences of the PNIS' implementation on coca crops during the last years.

In terms of public policy, this study implies that drug policy should be more focused on the public investments in infrastructure in the coca-producing municipalities, as was suggested in Section 1 of the Peace Agreement in the context of an "integral rural reform". The analysis of potential mechanisms has shown that structural determinants matter and partly explain the *rebound effect* caused by the suspension of aerial spraying. Furthermore, this study found additional empirical evidence confirming the ineffectiveness of aerial spraying during the 2011-2014 period. In that sense, the present study finds that the shift in drug policy developed during the period 2011-2018, during the government of President Santos, was in the right direction. However, the *rebound effect* was unavoidable after the sudden stop of fumigations due to the difficulty of quickly consolidating the new anti-drug strategy and other factors mentioned in other works (Zuleta, 2017; Santos, 2019; Vargas, 2019; Prem et al., 2021; Rocha-García, 2019). Adding up are the lags and shortcomings facing the PNIS implementation since 2018, particularly concerning the execution of productive projects for the farmers and investments in public goods and services in the zones of implementation (Garzón et al., 2019; Mantilla et al., 2021; Mejía-Hidalgo, 2021). Despite these circumstances, possibly a progressive suspension —not a sudden stop— of aerial spraying might have unleashed a weaker *rebound effect*.

Chapter 2

Weakening law enforcement: bribes and threats in drug trafficking

2.1 Introduction

Despite the enormous amount of effort and resources put by the Colombian government to seize illegal hard drugs like cocaine, bazuco, heroin, and a diverse spectrum of synthetic drugs, the production and sales of these drugs grew dramatically during the last years. Why? Some key factors explain the surge of coca plantations during the period 2014-2018. Recently some works have tackled this question.[1] But another question is the growth of the sales of hard drugs, especially cocaine, bazuco [2] (and other cocaine derivatives), and synthetic drugs in the big and intermediate cities of Colombia and other Latin American Countries. As a result of the stronger efforts to seize and intercept

[1] See Zuleta (2017), Mejía et al. (2019), and Ladino et al. (2019), among others.

[2] The bazuco or basuco is a low cost and extremely impure drug produced from the coca base using diverse kinds of precursors, some of them very dangerous for human health. These include sulfuric acid, kerosene, and methanol, but may include other dangerous inputs used to process and "cut" the drug: gasoline, brick dust, insecticides and even death-human bones. Due to the precursors used to manufacture it, it has a devastating effect on human —physical and mental— health. It has a sweet penetrating smell and produce only short-run affects, the reason why it is very addictive. It is well known as the "drug of the poor people" in Latin American cities, and it is sold in the urban slums (as the so-called "ollas").

drugs going outside the country during the first decades of the century —i.e. to North America, traditionally the bigger consumption market of cocaine—, in the context of the "war against drugs", traffickers began to use new an more diverse trafficking routes (UNODC, 2019, 2020), but at the same time put more efforts to develop the internal markets, specially in the big cities (Raffo and Gómez Calderón, 2017; FIP, 2016; De León and González, 2016; Saborío, 2019).

As a consequence, a new phase of drug trafficking began to consolidate for over two decades of the present century: the micro-trafficking. This kind of drug-business combines two different but intercorrelated processes: On the one hand, the consolidation of a productive and sales model based on the trafficking at relatively small or medium scales of the drugs in the interior of the producer or transit countries, and second, the distribution at retail of the narcotic substances by several dealers in urban zones of these countries. This distribution and commercialization in small doses are what has been called *narcomenudeo*. De León and González (2016) argue that with the development of micro-trafficking and narcomenudeo, the internal markets turned to be an alternative for the operational diversification of criminal bands. The illegal supply tended to be more segmented and with smaller links, so that small bands replaced the big cartels. As a result, countless less visible organizations having a lower production scale (especially in the cities) emerged.

The micro-trafficking is nowadays the most prominent case of drug-trafficking where, due to territorial domain, illegal agents use violence, threats and bribes to condition and co-opt the law enforcement actions to control crime. The result of their actions is the weakening of law enforcement. But —as I will explain in what follows— other cases of these phenomenon have been significant over the last four decades: the performance of the big cartels in Colombia —as the Cali Cartel, the Medellín Cartel, and the Norte del Valle cartel— or the examples of big Mexican Cartels as the Sinaloa Cartel, the Jalisco Cartel or the "Zetas". In all of these historical cases, illegal organizations use both "plata" and "plomo" in different combinations and forms to offset repression policies.

The main result of this illegal performance is the persistence of relatively low interception rates of hard drugs. Although the global interception rate of cocaine has seemed to be growing during last decade, probably partly owing to improved national, regional and international cooperation (UNODC, 2020) it remains at relatively low levels probably between 43% and 68% (UNODC, 2016b). The numbers are also critical in the case of heroin. Although global estimated interception rates of heroine have been growing as a consequence of the upward trend in seizures, (see (UNODC, 2016b, 2019, 2020), historically the interception rate of heroine has been lower than for cocaine (see also the classic work of Farrell (1995)).

For the case of Colombia, according to Yagoub (2016) making adjustments of purity level, the actual interception rate of Colombia should be close to the UNOCD's range between 43% and 68% (UNODC, 2016b). This implies that the interception rate has remained relatively low in the Colombian case.

This paper analyzes the strategies used by drug traffickers to weaken and evade law enforcement in contexts where they have territorial control, so that they own sufficient social, economic and political powers to develop illicit activities co-opting the enforcers actions. In such contexts traffickers tend to act as leaders designing and implementing diverse strategies of coercion and bribery to weaken and neutralize the enforcers' efforts to seize and capture illicit drugs.

Hence, the paper's main goal is to analyze the strategies of coercion and bribery used by traffickers to weaken the interdiction and prosecution efforts of the law enforcement authorities. This implies to explain the functioning of what I call the *coercion and corruption devices* of drug trafficking [3], which

[3]The term *device* can be understood here in a broad Foucauldian philosophical sense: In concrete, as a set of "practices and mechanisms (invariably linguistic and no linguistic, judicial, technical and military) with the purpose of facing an urgency and achieve an effect more or less immediately" (Agamben, 2011, p. 254) A device always plays an strategic function in a power relationship (Posada, 2013) of drug trafficking.

in my model refer to the criminal organizations' capabilities and strategies to encroach and bribe the law enforcement authorities like the police, judges, and even politicians. On one side, the *coercion devices* condition and exert pressure on civil society, officers, and rival groups with the purpose to execute actions for their profits despite the prosecution of control authorities. On the other hand, the *corruption devices* penetrate diverse political structures at a local, regional, or national level to manipulate law and institutions promoting their own interests. In the second section, I will explain both concepts in more detail.

With this purpose, I model the strategic interactions between traffickers and law enforcement authorities in a context where the former use a conjugation of bribes and violence to influence the latter's actions in their favor, preventing the possibility to bargain over the bribe's amount. Therefore the main research question is, how do function these strategies of coercion and bribery?

Other more specific questions surge from here: How do coercion and corruption devices determine the effectiveness of the interdiction policy? What is the optimal rewards system for the law enforcement authorities to potentiate success in interdiction? Does it coincide with the optimal social policy of rewards? What are the rewards system's effects on social welfare?

The starting hypothesis is that these coercion and corruption devices tend to hamper and neutralize the law enforcement authorities' efforts to fight against criminal organizations, even when officers act strategically and have perfect information about the traffickers' actions. Consequently, these apparatuses' functioning flows out in the process of power production that warrants the social domination required for the reproduction of activities outside of the law (Duncan, 2015). As a result, the effectiveness and consequences of the drug-supply repression policies —i.e., if the interdiction policy— depend partly on the efficacy of the coercion and corruption devices of drug trafficking. Does this hypothesis fulfill? I will tackle this question at a theoretical level. Future works could examine it at an empirical level.

Let's consider a couple of examples to illustrate the kind of strategic interactions between illegal agents and enforcers, for which the model is useful to understand the operation's logic of drug-trafficking organizations with territorial control.

Firstly, the most prominent case in the present days is micro-trafficking[4]. An extreme type of this kind of "entrepreneurship" leading by criminal organizations, which try to be kept up invisible to the law, is the so-called "ollas" in the Latin American Cities. The "ollas" are urban territories —corresponding to a neighborhood or a unique block or street of it—, where organized crime imposes its order and laws *de facto* to perform several illegal activities and atrocities: drug trafficking at a small or medium scales, prostitution, torture, kidnapping, white slave trade, and even murder and "pique houses" [5] (Raffo and Segura, 2018). One example of this type of territory was the Bronx, in Colombias' capital city, Bogotá.

The Bronx —also known as the "devil boiler"— was a terrific territory in the capital's historical center, in the epicenter of the high powers of the country, with an extension of 7 blocks (corresponding to a couple of neighborhoods), two of them in the form of an "L" letter. There were micro-trafficking and sales of hard drugs, especially of cocaine, heroin, and bazuco, human dismemberment, child prostitution, enforced disappearances, and kidnappings, everything at only 800 meters of the Presidential House of the Republic (the Casa de Nariño), the Congress of the Republic, the Presidential Batallion and one of the biggest police stations of the city (Raffo

[4]Regarding studies about micro-trafficking in Colombia it is important to mention the works of Escobedo et al. (2017) and De León and González (2016). The first one is a study about micro-trafficking in Bogotá. They posit that the vast efforts to eradicate "hot spots" of crime and drug trafficking in Bogotá, successfully led to the dismantling of big "ollas" as the Bronx and other satellite places such as San Bernardo, Cinco Huecos, el Amparo y María Paz. However, they couldn't prevent the quick reconfigure of the underlying drug-trafficking and distribution networks in other places of the city, resulting in the rise of new sales and "sopladeros" (especial underground places in Colombia, generally houses, where people go to consume diverse kinds of narcotic substances quietly for minutes, hours, or even days) in surrounding areas, which tend to be more sparsely-located and less visible to the authorities.

[5]In Colombia the "casas de pique" correspond to places where the cadavers of murdered persons are cutting up in pieces to wipe out any crime evidence.

and Gómez Calderón, 2017)[6]. It was just behind a recruitment battalion of the Colombian Army, next to the Basilica of the Sacred Heart of Jesus. How could this criminal territory grow there for almost fifteen years? The answer lies partly in the criminal organizations' violent and defense structures — what I have called in another work their *defense apparatus*—[7]. But it also lies in the performance of the *coercion and corruption devices* of drug trafficking.

The drug-trafficking organizations operating there used to bribe officers of different hierarchies permanently, while at the same time they supported strong private security forces headed by groups of gunmen they called "sayayines". This "defense apparatus" was essential to co-opt and condition the corrupt behavior of the local officers.

A second historical example is the case of "the Zetas" in Mexico. They are a criminal organization that emerged from a breakup in the Gulf Cartel in the middle 2000s. They were one of the most violent organizations performing in Mexico, conformed at their beginnings as the armed wing of the Gulf Cartel. In fact, their firsts members were ex-member of the Mexican Army Special Forces, so that hey had especial skills to perform armed actions and military intelligence operations. The key point here, is that they used violent threats based in their highly-skilled capacities to extort in return to offer protection, as well as bribes to the police in the cities, specially in the city of Laredo, in the state of Tamaulipas (Parker, 2018). Therefore, this a prominent example of the joint utilization of "bribes" and "plomo", that is to say of the operation of the *coercion and corruption devices* of drug trafficking.

A third well-known example involves Pablo Escobar. At his beginnings as trafficker, in the seventies, he didn't yet have the social and political powers enough to control a significant fraction of the population in Medellín city nor penetrate governmental institutions, respectively. However, his power depended on the armed wing of his organization (Duncan, 2013). As this author points out, during this period, Escobar "had earned such a dangerous

[6]See also *Revista Semana* 1779, 5-12 de junio de 2016

[7]See Raffo and Segura (2015)

reputation to lead authorities to think twice before rejecting his bribes. Several officials' crimes of the epoch, which passed unnoticed in Medellín's area, had Escobar as prime suspicious (Duncan, 2013, p. 250)." In this case, the key was the combined use of "bribes" and "plomo" to win immunity.

The model I present here is inspired by the works of Dal Bó et al. (2006), Raffo and Gómez Calderón (2017), and Serrano-López (2020), conjugating the approaches of Dal Bó et al. (2006) and Serrano-López (2020). It is a two-stage sequential game in which illegal agents and officers interact and determine the equilibrium seizure probability of drugs.

In the first stage, playing as leaders, the traffickers decide how many efforts they are going to invest in defense and coercion, P, ("el plomo"), and also choose their bribes' offers (what Dal Bó et al. (2006) call "la plata"). In addition, they choose the quantity of drugs sold knowing the inverse demand function they face. In this stage, they know the law enforcement authorities' best response functions to their actions. In the second stage, the law enforcement authorities (LEAs in what follows) choose the amount of efforts to invest in seizing and prosecuting narcotics; they also determine the levels of bribes they will accept. When moving, they have perfect information about the traffickers moves.

The paper is related with four strands in the economics of crime and drug-trafficking theoretical literature: Firstly, a series of classical works on the economics of crime that study the influence of law enforcement on illegal markets. The works of Becker and Stigler (1974), Buchanan (2006), Backhaus (1979) and Sisk (1982) are the point of departure from a conceptual point of view. As I will show, my model supports Becker and Stigler's idea (Becker and Stigler (1974)) that implementing a reward system based on the LEAs' achievements is essential for designing a successful law enforcement system.

A second strand of works studies bribery or influence groups in the context of game theoretical models. The works of Bowles and Garoupa (1997), Kalai et al. (1975) and (Nash, 1950) give the basic framework to understand the equilibrium bribes as a bargain-equilibrium. Nonetheless, my model takes a different analytical path to understand the emergence of a particular bribing equilibrium: Since one of the parts interacting —the traffickers— has territorial and coercive powers, there is no bargaining in the bribes, but they condition the LEAs' strategies. Other works are important references regarding bribery modeling. See, for example, Basu et al. (1992), Bac (2019) and Braun and Gautschi (2006).

Regarding models studying pressure groups, the model of Dal Bó et al. (2006) is also an unavoidable analytical framework to understand the influence exerting pressure groups —i.e., mafias, drug-traffickers, interest groups or illegal armed groups— on officers and politicians employing of bribes ("plata") or the threat of punishment ("plomo"). Their model predicts that using force, i.e., punishments or threats, lowers public officers' returns and high-ability workers' incentives to enter the public offices. Also, lower-cost threats and a larger quantity of resources available to the officers tend to be associated with a greater frequency of corruption and the presence of less competent politicians. Nevertheless, their model doesn't explicitly address the case of drug trafficking organizations as pressure groups. For that reason, they don't introduce any seizure probability —endogenously determined— in their model. The work of Dal Bó (2006) makes a comprehensive review of the literature and models of regulatory capture.

A third strand or works focuses on the more specific theme of drug trafficking and corruption in the context of game theoretical models. Raffo and Gómez Calderón (2017) developed an analytical model in a sequential game-setting with networks to explain illegal agents' decisions related to drug sales in the retail market and the investment in corrupt actions in the context of micro-trafficking and narcomenudeo. Recently, Serrano-López (2020) presented a new model to study de use of violence and corruption as decision variables for traffickers in the coca market. He endogenizes the choice of what he calls *units of private illegal security* and *justice's corruption*, introducing contest success functions in the profits maximizing problem of traffickers. However, these models don't analyze the law enforcement authorities' strategic choices, assuming as exogenous their efforts to prosecute and seize illegal drugs. Also, Serrano focuses the analysis on the study of large or medium-scale traffickers who buy illicit drugs directly to its producer, having monopsonistic power. Hence my model fills a gap in the theoretical literature regarding corruption and seizures.

Lastly, a fourth set of works study corruption and state capture from broader perspectives including political sciences or social network analysis: Duncan (2015), Duncan (2013), Garay Salamanca and Salcedo-Albarán (2012), and Raffo and Segura (2015). As I will show in the following section these works are the touchstone to understand the concepts of *defense apparatus*, *coercion devices* and *corruption devices*.

Summing up, the papers' contribution is threefold: First, I analyze the functioning of the coercion and corruption devices of drug trafficking in the context of the economics of crime, which is a topic not sufficiently studied using game-theoretical models in the field. Second, the model completely endogenizes the interdiction probability as a function of the traffickers and the LEAs strategic choices. As a result, the model solves the equilibrium probability of interdiction as a perfect-subgame Nash equilibrium. Third, The model points out the importance of implementing a reward system based on the LEAs' achievements. Higher premium rates over interdiction achievements are effective for the bribery deterrence. This result goes in the same direction of Becker and Stigler (1974) celebrated study of law enforcement and gives a formal proof of their analysis in a game-theoretic setting.

As a result, I advance in building a political economy of drug-trafficking to explain the equilibrium anti-drug policy as the result of strategic interactions between illegal agents and officials.

The model proves several results. Among them, it gives theoretical support to the starting research hypothesis: Traffickers' strategies hamper and neutralize the law enforcement efforts to seize and prosecute illegal drugs. Despite the conditioning trafficker's moves, the law enforcement effort's fundamental determinant is prosecution and interdiction technology. This unveils the relevance of promoting investments for the development of new and better interdiction and prosecution technologies.

In addition, the model corroborates that the seizure's probability depends positively on the premium received by officers in retribution to their effectiveness, and that higher premium rates strengthen the bribery's deterrence but coming to certain levels may unleash more violence.

Thus, the model shows that rises in the costs of defense and coercion activities reduce the level of resources invested in these activities. Furthermore, it shows that the level of state's capture is increasing in the interdiction and prosecution costs though decreasing in the coercion and defense costs, and in the bribes cost faced by traffickers.

The rest of the chapter follows in this way: In the second section, I introduce the main concepts about the social and political powers of drug trafficking, explaining the coercion and corruption devices operating in it. In the third one, I present the model's assumptions. Then, I give the solution and model's main comparative statics in the fourth and fifth parts, respectively. In the sixth one, I analyze the agency decision problem faced by the anti-narcotics institutions and the problem faced by the government playing as a social planner. In the seventh section I state a brief interpretation of results from the point if view of some historical and empirical facts. Finally, I suggest some conclusions.

2.2 The powers of drug trafficking

Drug trafficking depends on the functioning of a complex productive chain composed of several stages, but it also requires other social and political structures to function and reproduce itself. On one side, it depends on the functioning of a *defense apparatus* that provides the power to guarantee the ownership and defense of properties and resources by force. On the other side, it hinges on the working of a series of *coercion devices* that condition and exerts pressure on civil society, officers, and rival groups to execute actions for their profits despite the prosecution of control authorities. Finally, it also depends on the working of a series of *corruption devices* that take charge of penetrating diverse political structures at a local, regional, or national level to manipulate law and institutions promoting their interests. These three interrelated social and political structures provide criminal organizations with the sufficient power and mechanisms to reproduce themselves and win immunity outside the law.

2.2.1 The defense Apparatus:

The defense drug-trafficking structures have evolved over the decades, depending on the phenomenon's historical phase. During the big cartels' "classical" period of drug trafficking (Tickner et al., 2011) corresponding to the late seventies, the eighties, and the first quinquennium of the nineties, the Cali and Medellín cartels in Colombia conformed strong and highly-armed defense teams composed of bodyguards, private-military convoys, and professional hit-men bands. In contrast, drug-traffickers began to consolidate alliances with big illegal armed groups as the FARC guerrilla and AUC paramilitary groups during the second half of the nineties. After that, the illicit organizations started to work in association with diverse kinds and sizes of criminal bands supporting them (Raffo and Segura, 2015).

Another prominent case, where drug trafficking organizations developed powerful defense structures, was the Mexican Cartels as the Gulf Cartel, the Sinaloa Cartel or the "Zetas", among others. The logic of territorial expansion of Mexican cartels was based on the presence of armed groups controlled by the illegal organizations. At the beginning of the first decade of the XXI century, a bloody narco-war between some of the most influential families of the Sinaloa Cartel began: the family Beltrán-Leyva, the "Chapo" Guzmán family, and the "Mayo" Zambada family. A rupture between the two last families with Beltran-Leyva brothers originated in the control of a trafficking route through Sonora State, flow out into a *vendetta* between the parental networks of both organization's members (Duncan, 2015). The cartels had at their disposal strong private armies endowed with sophisticated weapons.

In the case of the "Zetas", the *defense apparatus* performed co-opting and supporting small criminal organizations in specific territories —in the rural peripheral or in marginal zones in the cities—. These violent structures were based in the offensive attacks committed by groups of gunmen with the purpose to kill the guards of dominant cartels, called "punteros" or "halcones" (Duncan, 2015).

The defense structures respond to the protection and security demands of the members of illegal organizations. In that sense, as they are not under the protection of the law and property right systems, the defense apparatus represents a first primary stage in developing social-subsidiary structures out of the law. In this stage, there does not arise any process of state capture yet. Nonetheless, returning to the case of Colombia, in certain peripheral regions of that country, far away from the central national and urban institutions and without sufficient state presence —i.e., the necessary conditions to erect and preserve the social order—, the sole consolidation of defense apparatuses by big illegal armed groups led to the development of para-states. During more than fifty years of armed conflict, this has been the case in certain rural regions of Colombia, in departments like Putumayo, Caquetá, Guanía, Vichada, Nariño, Cauca, and Choco, among others, with the presence, first of FARC and ELN guerrillas, and decades later, of paramilitary groups like the AUC.

2.2.2 The coercion devices:

These structures co-opt individual citizens, law enforcement authorities, and politicians through diverse forms of intimidation and threat, as *de facto* taxes or "vaccines", extorsion, terrorist acts, "the boleteo" [8], and forced displacement (Raffo and Segura, 2015). They represent a second-more advanced

[8] In Colombian jargon the process of harass through messages with the purpose to extort, intimidate, and threat is called "boleteo".

stage in generating social-subsidiary structures out of the law. In this stage, there is already a process of state capture. However, it occurs on a small scale: the coercion devices operate conditioning and encroaching individuals or small groups without jeopardizing political institutions.

Traffickers co-opt individual players as officers, lawyers, politicians, and other civilian through these kinds of devices with the purpose to achieve immunity in front of the law. One of the most common mechanisms used by them to condition and gain social acceptation is bribery. But, the key fact here is that bribes systems at a small scale don't function alone: their effectiveness to win impunity and social approval depends intimately from the backing of the defense apparatus. Therefore, the operation of coercion devices "the plata" and "the plomo" complement each other. The territorial domain of traffickers may configure strategic interactions where the enforcers can't bargain about the amount of bribes, since they are imposed —explicitly, indirectly or subtly— by illegal agents.

As Duncan (2013) remarks, the analysis of power relationships is more complex when we are dealing with non-individual players as social groups, communities or political parties. In those cases, the performance of coercion devices demands more social approval, and even social domination (Duncan, 2013).

2.2.3 The corruption devices:

These devices constitute a third-more sophisticated stage in generating subsidiary structures to make possible illegal trafficking's social reproduction. This stage is about political structures (more than social structures) that protect illegal activities modifying rules or policies from the inside of political institutions. The illegal agents establish social-strategic links with professional politicians acting as brokers between them and social groups, configuring political networks in which they play strategic roles. For example, they tend to buy votes and perform clientelistic campaigns associated with politicians and candidates during local, regional, or even presidential elections. As a result, illegal agents and their criminal networks —including their productive-chain networks and defense networks— succeed in penetrating political structures through the co-optation of social groups, civil organizations, and democratic institutions. At this stage, the state capture achieves its maximum expression.

Garay Salamanca and Salcedo-Albarán (2012) propose a conceptual framework to understand the corruptions devices' scope. They are more sophisticated than the defense apparatuses and the coercion devices, having their ultimate expression in what they call the State Advanced Capture and the State Co-opted Reconfiguration. According to these authors, the State Co-opted Reconfiguration (RCdE by its Spanish acronym) is the consequence of the state, the governments, and the institutions' penetration that begin with the State Capture (CdE by its Spanish acronym). The RCdE corresponds to "the action of social legal or illegal agents, who through illegal or legal but illegitimate practices, search to modify the regime systematically from its inside, and influence the formulation, modification, interpretation, and applying of the social-game rules and the public policies" (Garay Salamanca and Salcedo-Albarán, 2012, p. 15)[9].

The operation of this third type of structures requires the functioning of the other two —the defense apparatus and the coercion devices— but at a smaller scales. In concrete, the coercion devices operate as connected pieces of a more complex corruption strategy to achieve political power at a local or even national level.

2.2.4 The whole process of state capture:

(Duncan, 2015) gives the conceptual ground to understand the power production processes of drug trafficking, especially in Colombia and Mexico's cases. He explains how the joint functioning of the coercion and corruption apparatuses flow out in a power production process. He argues that in the first instance, drug-trafficking's political power consists of the criminal organization's ability to regulate order in peripheral and marginal societies. In the second instance, it tends to develop the capacity to "accumulate political representation within

[9]My own translation.

democratic institutions to prevent that states with enough coercive media — as the case of the Mexican and Colombian states— repress the basis of its social domination exercise" (*Ibid.*:15) [10].

Traffickers at a large, medium, or small scale carry out state capture processes utilizing coercion and corruption devices. Nonetheless, these two kinds of devices operate under the defense apparatus' shadow in the criminal world: Their effectiveness and threatening capacity are underpinned by this apparatus' presence and actions (actual or probable). Therefore, as a primary stage in developing social-subsidiary structures out of the law, it constitutes the basis and indispensable engine of the criminal structures since they provide the major *de facto* backing to enforce contracts and threats. Besides, it is worth noting that all the defense structures' support plays a role at a tangible-physical level and a symbolical-discursive level: they support even symbolic violence or violence's rhetoric.

In the case of micro-trafficking, for example, the state capture generally occurs at a local-urban level, in the sense that micro-traffickers penetrate specific local political and officer networks to win immunity against the law and the control of the police and even higher law enforcement authorities.

The conceptualization made in this part is useful to advance in developing a political economy of drug trafficking, since it identifies the main structures that enable the social reproduction of illegal activities and the outbreak of a process of state capture that can co-opt governmental institutions from its inside. Nonetheless, a political economy of drug trafficking should also take into account the interactions between the citizens and the state, i.e., the politicians, through electoral processes that may be influenced by cycles of patronage, clientelism, and corruption. The latter analysis can be a matter of study in coming works. The model I will present in what follows focuses on the interactions between enforcers and traffickers, in a context where the latter can co-opt the former's decisions.

[10] My own translation.

2.3 The Model

The model is inspired by the works of Dal Bó et al. (2006), Raffo and Gómez Calderón (2017), and Serrano-López (2020). It conjugates the approach of the former with the one of Serrano-López (2020). It is a two-stage sequential game in which illegal agents and officers interact and determine the equilibrium seizure probability of drugs.

In the first stage, the traffickers choose their efforts on defense and coercion, P,("el plomo") and their offer of bribes, B, ("la plata") knowing the LEA's best response functions to their actions. In this stage, they also choose the quantity of drugs sold, knowing the inverse demand function they face. In the second stage, The LEAs decide the amount of effort, e, they will invest in seizing and prosecuting the narcotics and determine the level of bribes they will accept, having perfect information about previous traffickers' moves.

For simplicity and without loss of generality, I assume that only one officer (the LEA) interacts with a group of traffickers who have already solved their interactions with themselves or their problem of collective action. Therefore, I treat the group of traffickers as a unique illegal agent, T. As a result one officer interacts with a single monopolistic trafficker who has territorial domain in a particular urban zone. That's the reason why traffickers move first: they already have co-opted resources and personnel working for them in a certain territory using their *de facto power* as well as coercion and defense devices. In addition, as monopolistic drug-sellers, they face a captive demand and market power in their territorial domain. Due to the territorial and violent powers exerted by them, bribes are not negotiated with the officers. Instead, they are induced by the traffickers violent moves in the first stage of the game. Thus, there is no Nash bargaining in bribes (e.g. using the Nash (Nash, 1950) or the Kalai-Smorodinsky solution (Kalai et al., 1975)) in the model.

The expected profits of the LEA are given by:

$$
\begin{aligned}
E\left[\Pi_L(e,B,P)\right] = (1-\theta)&\left[w + \varepsilon z p_d q - \frac{1}{2}\gamma e^2 + B - P\right] \\
&+ \theta\left[w + \varepsilon z p_d q - \frac{1}{2}\gamma e^2 + B - P - S - m\right]
\end{aligned}
\tag{2.1}
$$

where θ is the probability of detection of the corrupt officer, z represents the probability of interdiction of the illegal drugs; e is the effort invested by the LEA to control and seize drugs; B are the bribes given by the representative trafficker to the LEA (expressed in units of effort of the LEA); P represents the investment in defense and coercion made by the traffickers to create threats of punishments to the LEA (expressed in units of the traffickers' efforts); q is the quantity of drugs sold by the traffickers in a certain urban territory. p_d is the market equilibrium price of drugs. ε is a premium paid by the government for every unit of drugs seized by the officer; it is a proportion so that $0 \leq \varepsilon \leq 1$. m is a fixed moral cost faced by the LEA for accepting bribes when detected. S is the fine imposed on the corrupt officer when detected, and w represents the wage rate paid to the officer by the public sector. γ is a positive marginal cost parameter that captures the prosecution and interdiction technology.

Simplifying we get:

$$
E\left[\Pi_L(e,B,P)\right] = w + \varepsilon z p_d q - \frac{1}{2}\gamma e^2 + B - P - \theta S - \theta m \tag{2.2}
$$

I assume that $\theta(S+m)$ is relatively small with respect to B so that the LEA will demand and accept positive levels of bribes. Hence, in this model we deal with corrupt-type officers. Furthermore, it is important to note that following Dal Bó et al. (2006) I assume that P constitutes a credible threat of death, but in any case it may not affect the official survival. Therefore the officer's expected profits will never be zero or negative due to the possibility to die.

The LEA is supervised by the governmental anti-narcotics agencies. In the sixth section I reconsider the model's solution, including another stage of the game preceding the other two, in which the governmental antinarcotics agency solves their agency problem dealing with the LEA's incentives.

The expected profits of the trafficker (T) are given by:

$$E\left[\Pi_T(B,P,e)\right] = (1-z)\left[p_d q - cq - \beta B - \rho P\right] + z\left[-cq - \beta B - \rho P\right]$$

Simplifying this expression gives:

$$E\left[\Pi_T(B,P,e)\right] = (1-z)p_d q - cq - \beta B - \rho P \tag{2.3}$$

where $1-z$ represents the probability of drugs not seized by the officer, or what is the same, the proportion of drugs effectively sold by the traffickers; $\rho \geq 1$ is a positive parameter related to the cost of every unit invested in defense by the traffickers, i.e.,the marginal cost of investment in defense and coercion. Analogously, $\beta \geq 1$ is the marginal cost of investment one unit of effort in bribes by the group of traffickers. I assume that both cost parameters are larger or equal than one for two reasons: First, investing one unit of efforts in bribes or defense is relatively costly for traffickers, since both activities are developed outside the law and their performance involves a complex operation with many agents and logistic processes in reality. In terms of the model's framework, these parameters' domains constitute two relevant stability conditions: 1) The cost of investing one unit of efforts in bribes for the group of traffickers is higher than the benefit of receiving a unit of them for the LEA. 2) The cost of investing one unit of efforts in defense and coercion for the group of traffickers is higher than the cost of facing a unit of them (in the form of violent threats) for the LEA. Second, as it will be shown ahead in Corollaries 2.1 and 2.2 (see also the proof of the Contest Equilibrium Theorem in the Appendix), assuming $\beta \geq 1$ and $\rho \geq 1$ is a sufficient condition for the z's equilibrium-range to be well bounded in terms of the valid ε's domain, both of which must be between zero and one. These parameters, ρ and β, are an important part of traffickers' technologies of coercion and corruption, respectively.

c corresponds to the constant marginal cost of selling drugs. In what follows, and without loss of generality, I assume that the sales' marginal cost is zero. If it were positive, the solution would be equivalent but less tractable. Nonetheless, assuming very small marginal costs of sales makes sense as they are insignificant compared with the marginal costs of defense and bribes (ρ and β, respectively).

B enters linearly as a cost in trafficker's expected profits because following the classic work of Buchanan (2006) and Sisk (1982) I consider that the "bribe system is, thus, similar to a tax system in which revenues are earmarked for a particular expense item; bribes impose costs just as do taxes and are earmarked for the payment of police salaries"(Sisk, 1982, p. 395). Hence, from the point of view of Buchanan (2006) and Sisk (1982), the police efforts can work to the traffickers as an input that gives them the "right to operate in a given police jurisdiction" (Sisk, 1982, p. 395).

In addition, by simplicity I assume that as a cost P enters linearly in trafficker's profits [11]. This is a common assumption in conflict models (Hirshleifer (1995, 2000), Skaperdas and Syropoulos (2001, 1995, 1996)).

Following Serrano-López (2020), Grossman and Mejía (2008), Mejía and Restrepo (2016), among other works modeling the interactions between control authorities and the traffickers, or more generally, between officers or politicians (or the government) and the criminals, I assume that the probability of interdiction is determined in a contest framework by the LEA and the group of traffickers. In concrete, following Serrano-López (2020), I choose a standard simple contest success function (CSF) in the *ratio form*[12] as:

$$z = \frac{(e - B)}{(e - B + P)}, \tag{2.4}$$

where it can be easily checked that z is a concave-increasing function of e,

[11] As we will see in what follows $(1 - z)$ and z depend on B, P and e too.

[12] In this simple form of function used, the scale-parameter equals to one. For a comprehensive analysis of different kinds of CSF see Hirshleifer (1995, 2000).

and a convex-decreasing function of P and B. This means that, as expected, the probability of interdiction grows in the own LEA's efforts, but decreases in the traffickers' efforts in bribes ("la plata") and coercion and defense ("el plomo"). Exactly the opposite occurs for the probability of drugs not seized —the traffickers' success probability—, which is given by:

$$1 - z = \frac{P}{(e - B + P)}, \tag{2.5}$$

where $1 - z$ is a concave increasing function of P and B and a convex-decreasing function of e.

It is worth noting that in this model as well as in Serrano-López's paper, the bribes play an interdiction-neutralizing role, different from the P's logic. This manner to enter in the success functions can be conceived as a *reactive scheme* of traffickers, different to their use of the defense apparatus, which can be understood as an *offensive scheme*. This can be seen by the fact that if P equals zero, the success probability for traffickers will be zero too, while the probability of interdiction will be 1. Instead, when B is zero, $z = \frac{e}{(e+P)}$ while $1 - z = \frac{P}{(e+P)}$ [13].

[13]In a more general setting the CSF may include the presence of an "offensive" component of bribes by which they exert and additional "offensive" impact on the CSF. In this general setting, the traffickers' success probability would be

$$1 - z = \frac{P + \alpha\phi B}{(e - \phi B(1-\alpha) + P)},$$

where $\alpha \in [0, 1]$ is a parameter capturing the strength of the "offensive" component of bribes; $\phi \in [0, 1]$ is another parameter capturing the level of LEA's honesty, being zero for completely honest officers, and one for officers in principle accepting every amount of bribes. While the interdiction probability would be

$$z = \frac{(e - \phi B)}{(e - \phi B(1-\alpha) + P)}$$

Notice that if $\alpha = 0$ and $\phi = 1$, we have the present model's case, in which bribes don't play any "offensive" role but a "reactive" one. Whilst in another extreme case when $\alpha = 1$ and $\phi = 1$, bribes would only play an "offensive" role, but not a "reactive" one. In that other case we will have $z = \frac{(P+B)}{(e+P)}$, and $1 - z = \frac{e-B}{(e+P)}$. In this article, I focus on the case where $\alpha = 0$ and $\phi = 1$. In a future paper, I will examine the model in this general setting, emphasizing in the opposite case to the treated here: the case where bribes only

Finally, I assume that the inverse demand function facing the monopolistic trafficker is linear and given by

$$p_d = \alpha - q, \tag{2.6}$$

where $\alpha > 0$ is the drug-market size.

2.4 Solution

In what follows, I express B in units of LEA's efforts as be, where b represents the fraction of the LEA's efforts co-opted in the form of bribes[14]. The sequential model can be solved by backward induction, beginning with the LEA's decision problem in the second stage.

2.4.1 Second stage:

The problem to solve by the LEA in the second stage is:

$$\max_{e,b} \quad E\left[\Pi_L(e,b,P)\right] = w + \varepsilon p_d q \frac{e(1-b)}{(e(1-b)+P)} - \frac{1}{2}\gamma\ e^2 + eb - P - \theta S - \theta m \tag{2.7}$$

The first order conditions are:

$[b]$:

$$-\varepsilon p_d q \frac{eP}{(e(1-b)+P)^2} + e = 0 \tag{2.8}$$

$[e]$:

$$\varepsilon p_d q \frac{(1-b)P}{(e(1-b)+P)^2} - \gamma e + b = 0 \tag{2.9}$$

Eq.(2.8) represents the first order condition with respect to b. It establishes that, in the optimum, the marginal disutility of the bribes demanded, $-\varepsilon p_d q \frac{eP}{(e(1-b)+P)^2}$,

play an "offensive" role, in which $\alpha = 1$.

[14] Exactly the same results will be obtained if the model is solved with B in levels. But I preferred to express this variable as a proportion for tractability.

is equal to their positive marginal impact on expected profits, e, measured in levels of LEA's efforts. It corresponds to a maximum of LEA's expected profits in b, as the second derivative is negative.

Meanwhile, Eq.(2.9) corresponds to the LEA's first order condition with respect to e. It shows that, in the optimum, the marginal utility of interdiction efforts, $\varepsilon p_d q \frac{(1-b)P}{(e(1-b)+P)^2}$, summed to its positive marginal impact on the total quantity of bribes demanded, b, is equal to their marginal costs, γe.

The second derivative of the expected profits with respect to e is negative too. The objective function is strictly concave in b and e. It can be proved that the sufficient conditions for a global maximum in terms of the minors of the Hessian matrix hold as $|H_1] = -\frac{2\varepsilon p_d q e^2 P}{(e(1-b)+P)^3} < 0$ and $|H_2] = \frac{2\varepsilon p_d q e P(\gamma e + 2(1-b))}{(e(1-b)+P)^3} > 1$.

Combining the first order conditions we get:

$$\frac{1}{1-b} = \frac{1}{\gamma e - b}, \tag{2.10}$$

which is a condition that states the relationship that must hold in equilibrium between the marginal rate of substitution of b for efforts and their relative costs. Clearing up e from this equation we get:

$$e^* = \frac{1}{\gamma} \tag{2.11}$$

This result represents the second stage Nash equilibrium for e and indicates that the LEA's equilibrium efforts depend on the interdiction technology, i.e., on the interdiction and prosecution costs' parameter, γ. As the marginal rate of substitution between b and e is independent of P and the drug's sales, e does not depend on these variables in equilibrium. In addition, when e changes, the impact of b on the interdiction probability and its impact on the revenues cancel out.

The following proposition formalizes this finding:

Proposition 2.1. *The perfect-subgame Nash equilibrium value for e^* depends on the costs' side of the technology of interdiction and prosecution, expressed by the parameter γ. It is a convex decreasing function in γ.*

Proof. Straightforwardly from the previous equation. ■

Now, replacing the previous result in the first order condition for b we obtain the subgame equilibrium level of bribes per unity of efforts demanded by the LEA:

$$b \equiv f(P) = 1 + \gamma P - \gamma\sqrt{\varepsilon p_d q P} \tag{2.12}$$

Eq.(2.12) represents the reaction function of b with respect to P. Also, we can define the reaction function of B with respect to P

$$B \equiv be \equiv F(P) = \frac{1}{\gamma} + P - \sqrt{\varepsilon p_d q P} \tag{2.13}$$

Both curves are parabolic functions of P, decreasing for relatively small levels of P and increasing for relatively large levels of it. Figure 2.1 depicts this result.

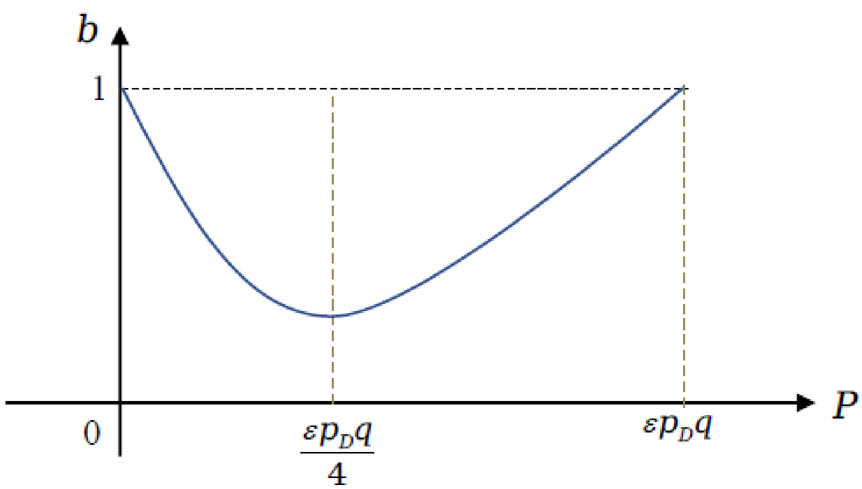


Figure 2.1: LEA's reaction function

The following proposition formalizes this result:

Proposition 2.2. $\forall P \in [0, \varepsilon p_d q]$, *$F(P)$ and $f(P)$ are parabolic functions of P, convex-decreasing for $P < \frac{\varepsilon p_d q}{4}$ but increasing for $P > \frac{\varepsilon p_d q}{4}$.*

Proof. See Appendix. ■

The intuition behind these results are the following: The quantity of bribes demanded by the LEA, both in absolute levels and per efforts, are induced by the level of violence's threats, P, created by the traffickers in the first stage. This means that the trafficker's moves in the first stage condition the quantity of bribes accepted by the LEA, which is the same as to say that they co-opt a fraction of the LEA's efforts in the form of bribes acting as illicit taxes (Buchanan, 2006; Sisk, 1982). To be concrete, for P levels smaller than a quarter of the potential premium revenues he would obtained with a marginal increase in z, $\frac{\varepsilon p_d q}{4}$, he will lower his bribe's demand when P increases. The contrary will occur for P larger than $\frac{\varepsilon p_d q}{4}$. While in the first (decreasing) segment of the curve P and b behave as strategic substitutes, in the second (increasing) one they behave as strategic complements.

This strategic reaction of the LEA captures the functioning of a coercion strategy of traffickers, which is possible by the territorial domain exhibited by the illegal agents giving them the power to move first. This strategy is one of the functioning mechanisms of the *coercion and corruption devices*, and that's why there is no bargaining on bribes in the model, since the credible threats of violence condition them. It clearly shows that in this type of criminal performance, characterized by the exhibitions of territorial and violent powers, "the plata" and "the plomo" complement each other configuring diverse kinds of coercion and corruption mechanisms.

2.4.2 First stage:

In the first stage, traffickers maximize their expected profits with respect to P and q knowing the LEA's best-response function of b with respect to their P choices. They also know the equilibrium level in efforts $e^* = \frac{1}{\gamma}$ that the LEA will choose given the technology of interdiction and capture, expressed by γ, and the inverse demand function of drugs they face. Hence their problem is:

$$\max_{P,q} \quad E\left[\Pi_T(P, f(P), e^*, q)\right] = \frac{P}{((\frac{1}{\gamma})(1-f(P)+P)}(\alpha-q)q - \beta(\frac{1}{\gamma})f(P) - \rho P \tag{2.14}$$

The fist order conditions are (FOCs):

$[P]$:

$$\frac{1}{2}\left[\frac{\sqrt{(\alpha-q)q}}{\sqrt{\varepsilon}} + \beta\sqrt{\varepsilon(\alpha-q)q}\right]P^{\frac{1}{2}} - (\rho+\beta) = 0 \tag{2.15}$$

$[q]$:

$$(\alpha-2q)\left(\beta\sqrt{\varepsilon} + \frac{1}{\sqrt{\varepsilon}}\right) = 0 \tag{2.16}$$

Eq.(2.15) corresponds to the T's first order condition with respect to P. It shows that, in the optimum, the marginal utility of defense and coercion's efforts (the first term on the left side), is equal to their marginal (direct and indirect) costs, ρ and β, respectively. The interpretation of this condition is similar to the one corresponding to a typical model of conflict (see Hirshleifer (1995, 2000), Skaperdas and Syropoulos (2001, 1995, 1996), and Raffo (2007)). It can be checked that this point corresponds to a maximum in trafficker's expected profits, as they are a concave function of P.

Meanwhile, Eq.(2.16) represents the first order conditions with respect to q. It is a consequence of price policy of the typical monopolist facing risk: the expected marginal revenue must be equal to the marginal cost (here the marginal cost of sales is zero by assumption). It can be checked that it corresponds to a maximum of trafficker's expected profits in q.

Clearing up q from Eq.(2.16) we obtain the equilibrium sales of drugs:

$$q^* = \frac{\alpha}{2} \tag{2.17}$$

As expected it depends positively on the market size. As a consequence $p_d^* = \frac{\alpha}{2}$ and $p_d^* q^* = \frac{\alpha^2}{4}$.

Now, using these results and clearing up P from Eq.(2.17), we get the perfect-subgame Nash equilibrium of P, P^*.

$$P^* = \frac{\alpha^2\left(\frac{1}{\varepsilon} + 2\beta + \beta^2\varepsilon\right)}{16(\beta+\rho)^2} \tag{2.18}$$

As expected, in equilibrium P depends inversely from ρ —the marginal cost of P—(See Figure 2.2). Also, P is a convex-increasing function of the market size of drugs. It is a logical result as the investments in defense and violence depend positively on the size of the illegal rents, which depend directly on the expected value of the sales, $(1-z)\cdot p_d q$ (Figure 2.3). Furthermore, it is a parabolic function of to the premium rate won by the LEA, ε. For relative low levels of it (i.e, for $\varepsilon < \dfrac{1}{\beta}$), when this parameter increases, traffickers react investing less resources in violent threats, whereas when ε is relatively large ($\varepsilon > \dfrac{1}{\beta}$) the opposite occurs (see Figure 2.4). As I will show in the next section, the explanation relies on the impacts of changes in ε over the bribes for every segment of his values.

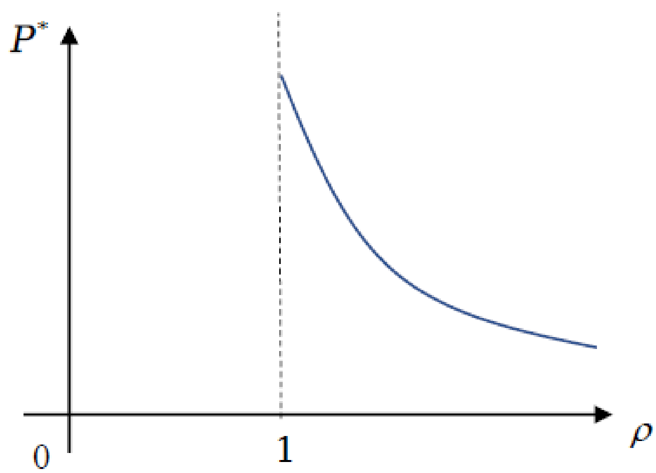


Figure 2.2: Investment in defense as a function of its marginal cost

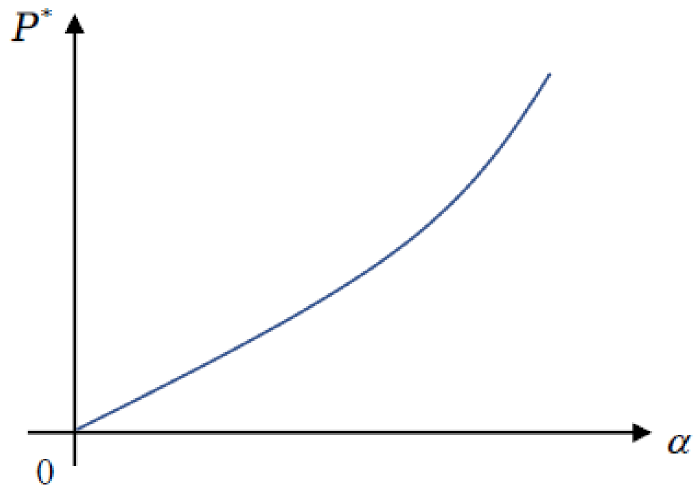


Figure 2.3: Investment in defense as a function of the drug market size

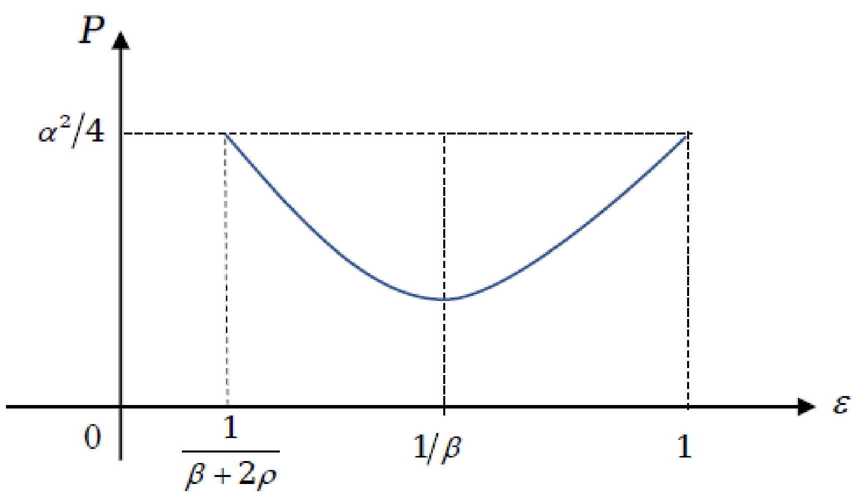


Figure 2.4: Investment in defense as a function of the premium rate

In addition, an increase in β can lead to a rise or a fall traffickers' investments in "plomo" depending on the relative value of ε with respect to $\frac{1}{\rho}$. For $\varepsilon > \frac{1}{\rho}$ $\left(\varepsilon < \frac{1}{\rho}\right)$, P increases (decreases) when there is a rise (fall) in β. While in the first case traffickers will have more incentives to substitute bribes for "plomo" due to the relative costs of both alternatives —ρ relatively large— and the lower propensity of the LEA to accept them —which depends on the value of ε as I will show—, in the second one $\left(\varepsilon < \frac{1}{\rho}\right)$ will occur the contrary: traffickers will have fewer incentives to substitute bribes for "plomo" and the LEA will have a higher propensity to accept them as long as $\varepsilon\rho < 1$.

The following result formalizes these results:

Proposition 2.3. *In the perfect-subgame Nash equilibrium, i) P is a convex-increasing function in α, ii) and a convex-decreasing function in ρ. iii) $\forall \varepsilon \in \left[\frac{1}{\beta+2\rho}, 1\right]$, it is a parabolic function of ε, convex-decreasing for $\varepsilon < \dfrac{1}{\beta}$ but convex-increasing for $\varepsilon > \dfrac{1}{\beta}$. iv) It increases (decreases) when there is a rise in β for $\varepsilon > \frac{1}{\rho}$ $\left(\varepsilon < \frac{1}{\rho}\right)$.*

Proof. See Appendix. ■

2.4.3 Closing the Model and main equilibrium relationships:

Replacing P^* and q^* in $f(P^*)$ we can close the model.

$$b^* = 1 - \frac{\alpha^2\gamma}{16(\beta+\rho)^2}\left(2\rho - \frac{1}{\varepsilon} + \beta^2\varepsilon + 2\rho\beta\varepsilon\right) \tag{2.19}$$

This equation shows the b^* perfect-subgame Nash equilibrium level, which for the paramaters' values of the model and in particular $\varepsilon \in \left[\dfrac{1}{2\rho+\beta}, 1\right]$ is between zero and one.

Eq. (2.19) shows that the amount of bribes per unit of efforts is a concave decreasing function of the market size (see Figure 2.5) This means that *ceteris paribus* the larger the market of drugs, the larger is the amount of resources invested by traffickers in "plomo" but the smaller the amount invested in "plata".

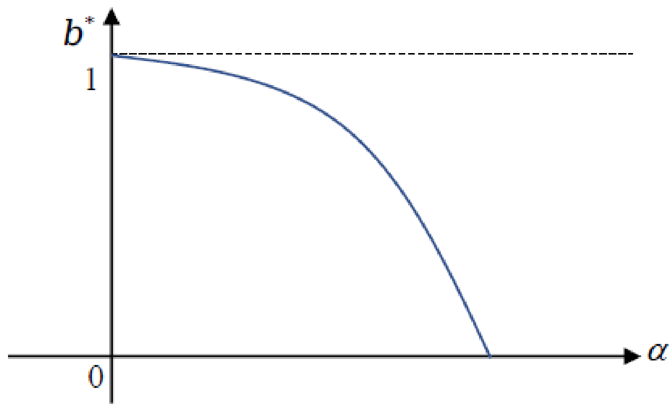


Figure 2.5: Bribes per LEA's efforts as a function of the drug market-size

In addition, it can be checked that the bribes (per unit of efforts) decrease with γ. This means that the higher the costs of LEAs efforts, the lower the level of bribes (per unit of efforts) (see Figure 6). As $e^* = \frac{1}{\gamma}$, this implies that in equilibrium *ceteris paribus* there is positive relationship between the level of b^* and e^*.

Furthermore, b^* is a parabolic function of ρ; this relationship is shaped by the form of the reaction curve of b with respect to P and its impact on b^* (see Figure 2.7).

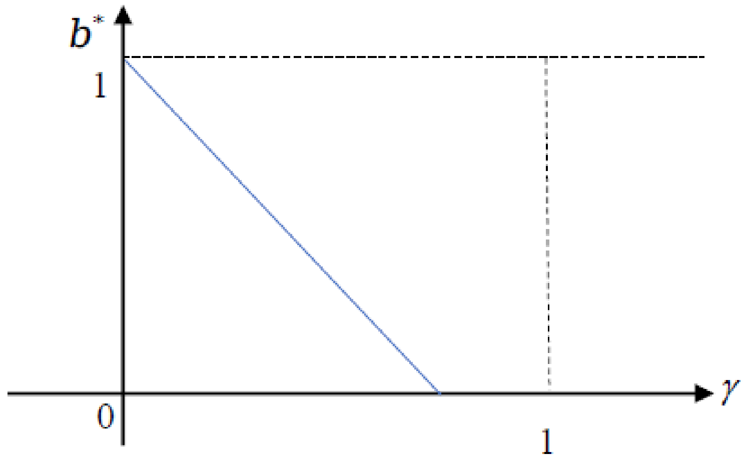


Figure 2.6: Bribes per LEA's efforts as a function of the cost parameter of interdiction and prosecution technology

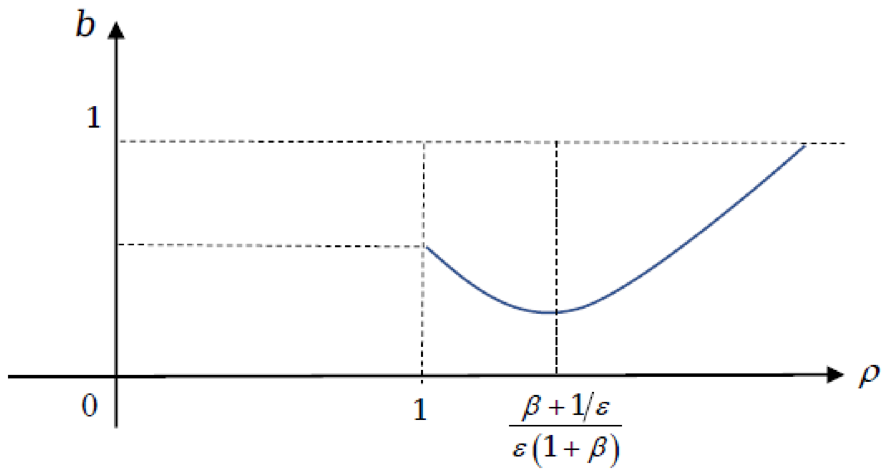


Figure 2.7: Bribes per LEA's efforts as a function of the marginal cost of investments in defense

Apart from this, b^* decreases as ε grows. Since with the growth of this parameter a more successful activity of the LEA in terms of the seizures turns more profitable, his propensity to accept bribes declines. The decrease tends to be steeper for relative lower values of the parameter —i.e. for $\varepsilon < \frac{1}{\beta}$— because for this configuration the investment in P^* by the traffickers decreases with ε too. Figure 2.8 depicts this function.

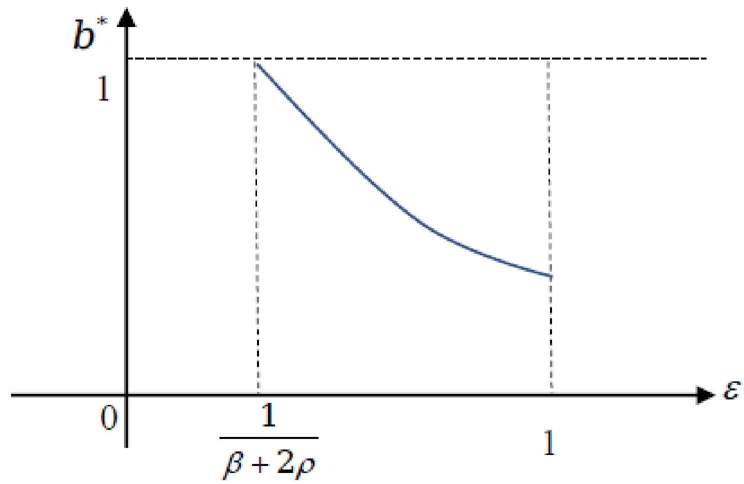


Figure 2.8: Bribes per LEA's efforts as a function of the premium rate

The following proposition formalizes these results:

Proposition 2.4. *In the perfect-subgame Nash equilibrium, i) b is a concave-decreasing function in* α*, ii) and a linear-decreasing function in* γ*. iii)* $\forall \varepsilon \in \left[\frac{1}{\beta+2\rho}, 1\right]$*, it is a convex decreasing function of* ε*. iv) It increases (decreases) when there is a rise in* β *for* $\varepsilon < \frac{1}{\rho}$ $\left(\varepsilon > \frac{1}{\rho}\right)$*. v) it is a parabolic function of* ρ*.*

Proof. See Appendix. ∎

It can be checked that the same results hold for bribes in absolute terms, B.

Replacing e^*, P^*, b^*, and q^* in the contest success functions we obtain the equilibrium interdiction probability, z^*, and the traffickers' success probability, $(1 - z^*)$

$$z^* = \frac{\beta - \frac{1}{\varepsilon} + 2\rho}{2(\beta + \rho)}, \tag{2.20}$$

$$(1 - z^*) = \frac{\frac{1}{\varepsilon} + \beta}{2(\beta + \rho)}. \tag{2.21}$$

The following theorem summarizes these results and establishes the perfect-subgme equilibrium outcomes of the contest between the LEA and the traffickers determining the seizure probability of equilibrium. It also ensures the closing of the model in terms of the parameters' domain. For these reasons it constitutes one of the main results of the model.

Contest Equilibrium Theorem. *In the perfect-subgame Nash equilibrium: i) z^* is a concave-increasing function of ρ, ii) and a convex-decreasing (convex-increasing) function of β for $\varepsilon > \dfrac{1}{\beta}$ $(\varepsilon < \dfrac{1}{\beta})$. iii) Also, $\forall \varepsilon \in \left[\frac{1}{\beta+2\rho}, 1\right]$ it is an increasing function of ε. The analogous opposite effects occur for $(1-z^*)$.*

Proof. See Appendix. ■

Corollary 2.1. $\left[\varepsilon \in \left[\frac{1}{(\beta+2\rho)}, 1\right]\right] \Rightarrow \left[\left(z^* \in \left[0, \frac{\beta+2\rho-1}{2(\beta+\rho)}\right]\right) \wedge \left((1-z^*) \in \left[\frac{1+\beta}{2(\beta+\rho)}, 1\right]\right)\right].$ *These domains and ranges imply that $(\beta + 2\rho) > 1$ (see proof of the Contest Equilibrium Theorem in the Appendix).*

Corollary 2.2. *A sufficient condition for $(\beta + 2\rho) > 1$ is that $(\beta \geq 1) \wedge (\rho \geq 1)$.*

That's the logical reason, as I already stated in the third section, why I assume that $(\beta \geq 1) \wedge (\rho \geq 1)$, apart from the first intuitive reason I mentioned there.

As I will explain in more detail in the next section, when ρ —the marginal cost to invest in defense and coercion— increases, traffickers tend to allocate lower resources, i.e., fewer efforts, to this kind of violent activities in equilibrium (P^*). But, at the same time, they decrease or increase bribes' offers (depending on the costs' parameters relative levels), all of this resulting in a higher probability of interdiction, as well as in a lower success' probability for them. What explains these results is that, in every case, the effect on P^* is stronger. Meanwhile, when β grows the effect on both P^* and b^* depend on the relative values of ε and $\frac{1}{\rho}$: For $\varepsilon > \frac{1}{\rho}$, z^* falls since P increases and at the same time

b decreases. This means that in this case bribes has been substituted for "plomo", being e^* at a constant level; this happens because for this parameter configuration, while the traffickers tend to prefer more "plomo" over bribes, the LEA is less prone to accept bribes since he is receiving a relative high premium rate. The contrary occurs for $\varepsilon < \frac{1}{\rho}$. In the special case where $\varepsilon = \frac{1}{\rho}$, z^* remains the same as β go up.

One increase in the premium rate received by the LEA flows out to a rise in the seizure probability insofar as it strengthens deterrence to bribery, whilst the investment in coercion and defense can grow or fall depending on its relative level. Figures 2.9 and 2.10 show these relationships:

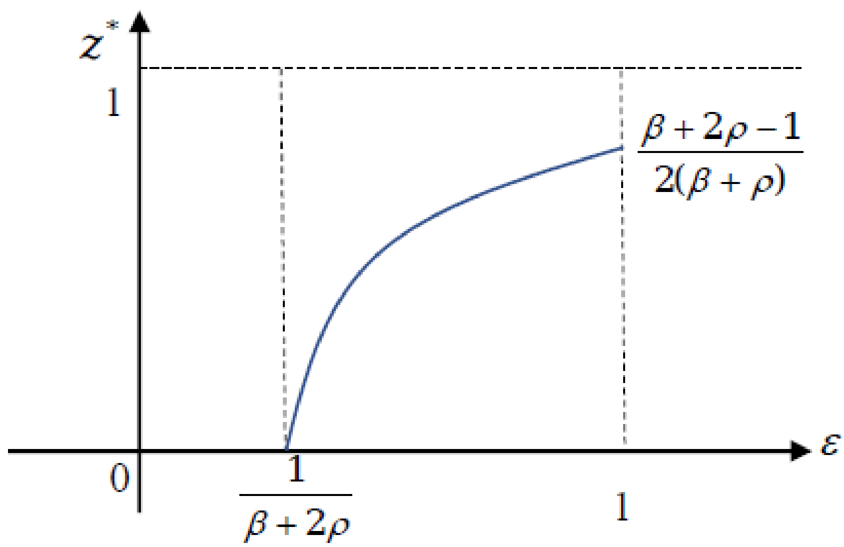


Figure 2.9: Seizure probability as a function of the premium rate

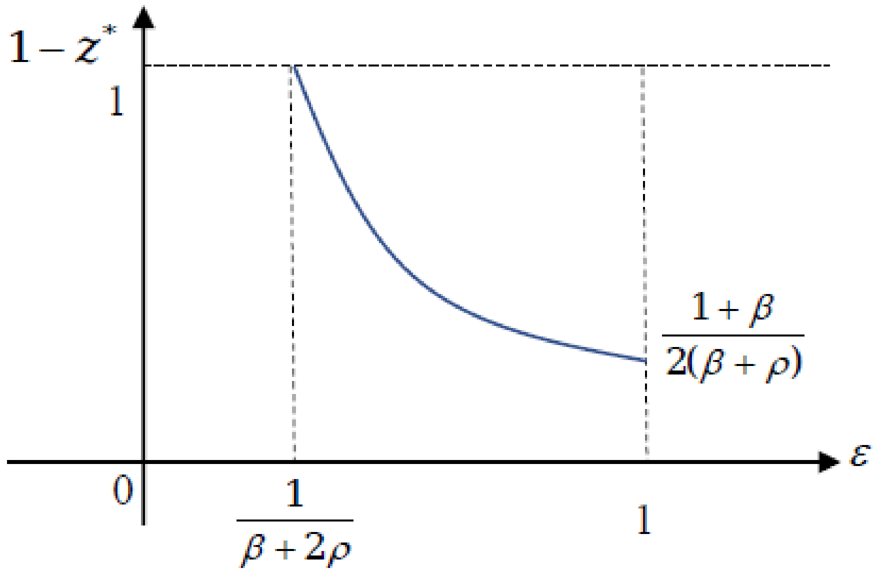


Figure 2.10: Traffickers' success probability as a function of the premium rate

Now, replacing e^*, P^*, b^*, q^*, z^*, and $(1-z^*)$ in the expected profit functions and simplifying we get the equilibrium expected profit-functions:

$$E\left[\Pi_L{}^*\right] = w + \frac{1}{2\gamma} + \frac{\alpha^2}{4(\beta+\rho)}\left[\rho\varepsilon - 1\right] - \theta(m+S) \tag{2.22}$$

$$E\left[\Pi_T{}^*\right] = \frac{\alpha^2}{16(\beta+\rho)}\left[\varepsilon\beta^2 + 2\beta + \frac{1}{\varepsilon}\right] - \frac{\beta}{\gamma} \tag{2.23}$$

Three key findings result on expected profits: Firstly, relatively high values of the premium rate and of w with respect to $\theta(m+S)$ are a necessary condition for the LEA equilibrium expected profits to be positive. This finding is in the flavor of Becker and Stigler (1974) analysis of corruption deterrence: they adduce that the key action to discourage corrupt enforcement when detection is uncertain is "to *raise* [15] the salaries of enforcers above what they could get elsewhere, by an amount that is inversely related to the probability of detection, and directly related to the size of bribes and other benefits from malfeasance" (Becker and Stigler, 1974, p. 6).

[15] Italics from the cited authors.

Indeed LEA's expected profits are always linear-increasing in the premium rate, ε (see Figure 2.11). This means that high wage rates and seizure-premiums are relevant for the performance of the officers: The "carrots" given for a successful performance should be big enough to compensate for the expected "sticks" received in case of detection for bribery.

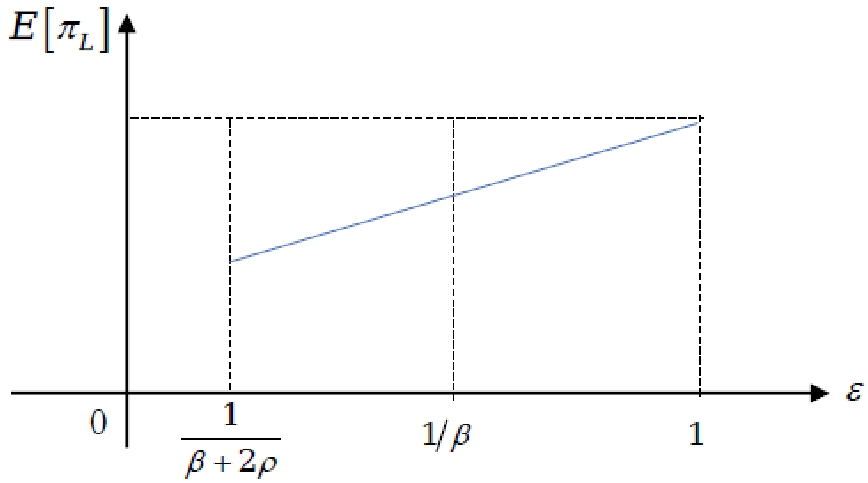


Figure 2.11: LEA's expected profits as a function of the premium rate

Second, paradoxically when the premium rate ε is higher than the productivity to invest one unit in coercion and defense $\frac{1}{\rho}$ the LEA's expected profits depend positively from the market size, α, too. Figure 14 depicts this case. The opposite will happen for $\varepsilon < \frac{1}{\rho}$. This is a somewhat perverse but not unusual result of a policy of law enforcement incentives based in seizure premiums. In fact, the correlation between the returns to enforcers and the returns to violators —when law violation is successful— tend to be positive (Becker and Stigler, 1974). Although higher premium rates lead to increases in the seizure probability and the LEA's expected profits, the incentives it induces are linked to the drug-market size.

Figures 2.12 and 2.13 show, respectively, that the LEA's expected profits are a convex decreasing function in β and a convex increasing function in

ρ. The first relationship is explained by the impact that increases in β have on the equilibrium amount of bribes. The second one is explained by the influence of ρ on z and P.

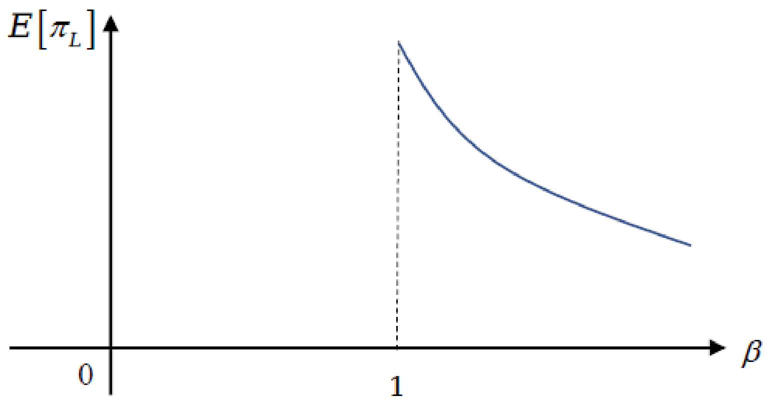


Figure 2.12: LEA's expected profits as a function of the marginal cost of investments in defense

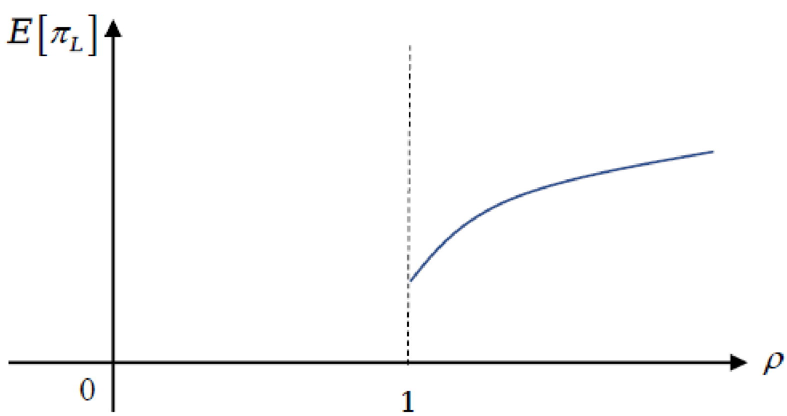


Figure 2.13: LEA's expected profits as a function of the marginal cost of investments in bribes

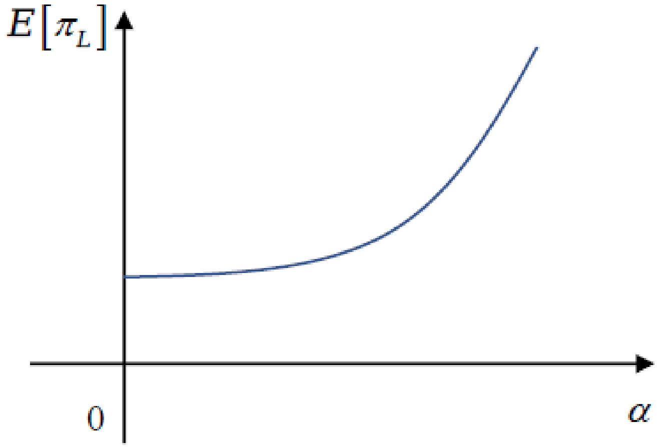


Figure 2.14: LEA's expected profits as a function of the drug market size when $\varepsilon > \frac{1}{\rho}$

Third, for relatively large values of the drugs market's size, the expected profits of traffickers tend to be positive. They are an increasing-convex function of this variable (see Figure 2.18). This is a logical result as the market size is the essential fuel for the illegal business. This emphasizes the relevance of consumption prevention policies for fighting against drug trafficking.

The following propositions summarize the main results for the expected equilibrium profits of the LEA:

Proposition 2.5. *In the perfect-subgame Nash equilibrium, i)* $E\left[\Pi_L{}^*\right]$ *is a concave-increasing function of* ρ*, ii) and a convex-increasing function of* α *when* $\varepsilon > \frac{1}{\rho}$*. iii) It is also a convex-decreasing function of* γ*, iv) and a convex-decreasing function of* β*. iv) Furthermore,* $\forall \varepsilon \in \left[\frac{1}{\beta+2\rho}\right]$*, it increases linearly in* ε*.*

Proof. See Appendix. ■

Proposition 2.6. *In the perfect-subgame Nash equilibrium, i)* $E\left[\Pi_T{}^*\right]$ *is a convex-decreasing function of* ρ*, ii) and a convex-increasing function of* α*.*

iii) It is also a concave-increasing function of γ*, iv) and* $\forall \varepsilon \in \left[\frac{1}{\beta+2\rho}\right]$*, it is a parabolic function of* ε*, decreasing for* $\varepsilon < \dfrac{1}{\beta}$ *but increasing for* $\varepsilon > \dfrac{1}{\beta}$*.*

Proof. See Appendix. ■

Figures 2.15, 2.16, and 2.17 show, respectively, the trafficker's expected profit as a function of ε, γ, and ρ.

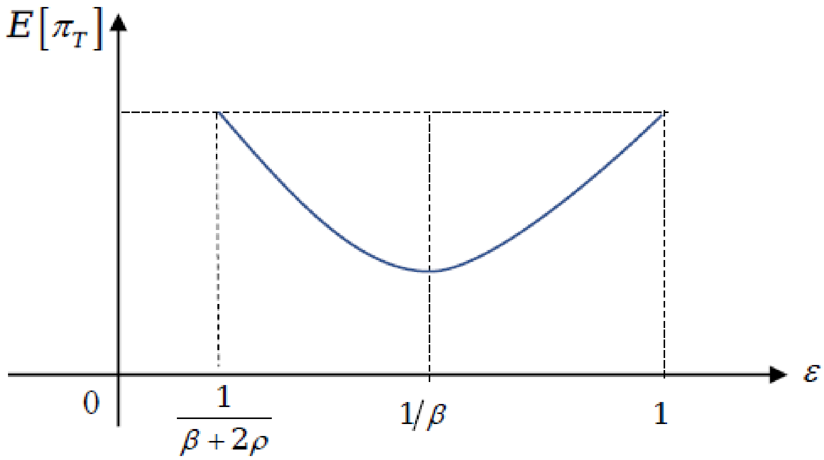


Figure 2.15: Trafficker's expected profits as a function of the premium rate

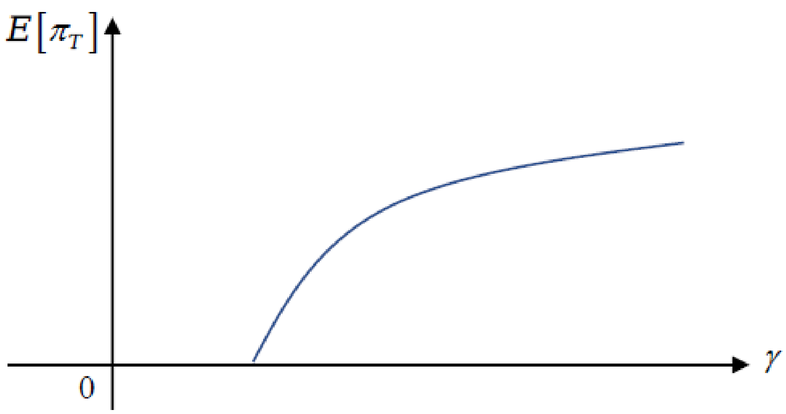


Figure 2.16: Trafficker's expected profits as a function of the cost parameter of interdiction and prosecution technology

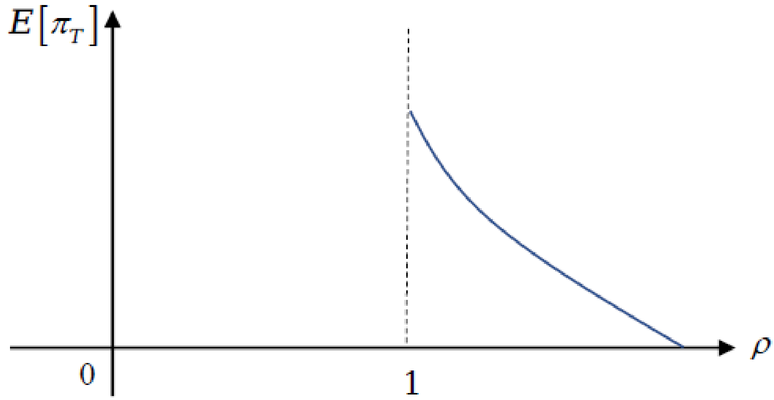


Figure 2.17: Trafficker's expected profits as a function of the marginal cost of investments in defense

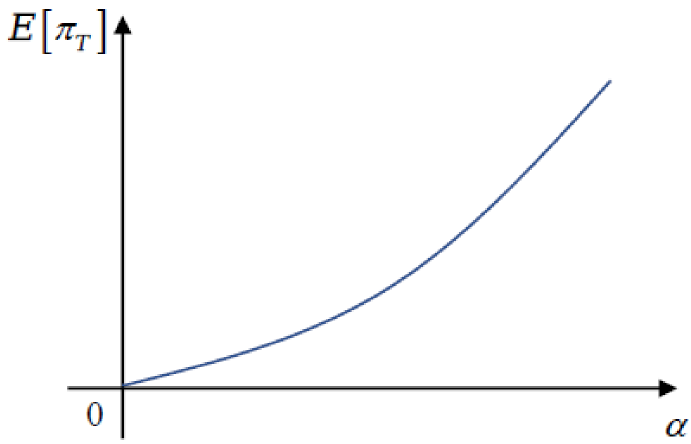


Figure 2.18: Trafficker's expected profits as a function of the drug market size

2.5 Comparative Statics: A recapitulation

Changes in the premium rate

This variable plays a key role in the model as it captures the influence of rewards policy on officer's interdiction and capture effectiveness. An alteration in the premium rate has several effects that will alter the agents' incentives to invest in "plomo" and "plata". When the government or the law enforcement institutions —in the head of the anti-narcotics agency, the department of police, or the Defense Ministry— increases the premium rate, ε, the incentives to accept bribes by the LEA weaken. On the one hand, an increase in ε can induce increases or decreases in the investments of "plomo" by traffickers depending on the level of this parameter with respect to the inverse of the bribes-cost parameter $\frac{1}{\beta}$, —or what is the same, the marginal productivity to investments in bribes—. In concrete, for $\varepsilon < \frac{1}{\beta}$, P^* decreases when ε rises, but it begins to increase when $\varepsilon > \frac{1}{\beta}$ (see Proposition 3). This implies that P^* has its minimum level with respect to the premium rate precisely in the point where $\varepsilon = \frac{1}{\beta}$. To understand this relationship, it is important to note that increases in ε have two types of effects on traffickers' expected profits: On one side, negative *rent effects*, as *ceteris paribus* they tend to lower the success probability of traffickers, $(1 - z)$, due to the direct impact they have on the LEA's bribes demand. This effect negatively impacts the investment on "plomo" as it reduces its marginal utility. On the other side, *ceteris paribus* they provoke falls in b, which tend to lower traffickers' costs, inducing higher marginal utility from investing one additional unit of P. Both effects arise from the fact that traffickers know the LEA's reaction function. The net effect on P will depend on the strength of both effects.

On the other hand, bribes both per unity of efforts (b^*), and in absolute levels (B^*) are convex decreasing in ε (See Proposition 2.4). These changes arise due to the fact that this policy adjustment strengths the incentives to get better results in interdiction as it enhances the effectiveness of rewards, taking into account that an additional unit of bribes —or in other words, an additional unit of efforts co-opted by the traffickers in the form of bribes— has a negative marginal effect on the interdiction in probability. In this case, the policy adjustment has two different kinds of effects on the bribes' demand: Firstly, a negative effect, since increases in the premium rate lead to falls in it for constant levels of P. Second, an induced effect unleashed by the impact on P^* —through the reaction function $f(P)$—, which can be positive when P^* increases for relative large levels of it (i.e. $P^* > (\frac{\varepsilon p_d q}{4})$), or negative for relative small levels of P^* ($P^* < (\frac{\varepsilon p_d q}{4})$). In every case, the first kind of effect is stronger and the net result of an increase in ε is a downfall in bribes.

As I already remarked, one increase in ε, leads to a rise in z^* —this variable is concave-increasing in it (see Eq.(2.20) and Contest Equilibrium Theorem)— but to a decrease in $1 - z^*$ —which is convex-decreasing in it (see Eq.(21) and Contest Equilibrium Theorem)—. Moreover, due to all the effects explained before, the LEA profits are a linear increasing function of the premium rate (see Eq. 2.22 and Proposition 2.6), and a parabolic function for the traffickers' expected profits. The latter function replicates the impact of ε's changes on P^*. Indeed the traffickers' expected profits can be written as:

$$E\left[\Pi_T{}^*\right] = \frac{(\beta+\rho)}{4}P^* - \frac{\beta}{\gamma}$$

The influence of the premium rate on the officer's choices is crucial to understand the relevance of compensation on performance to the bribery deterrence, more than wage rate increases. As Becker and Stigler (1974) argue this system of incentives is essential to enhance the trust in officers. In their own words: "Trust calls for a salary premium not necessarily because better quality persons are thereby attracted, but because higher salaries impose a cost on violations of trust" (Becker and Stigler, 1974, p. 12).

Changes in defense costs

When there is an increase in traffickers' defense costs, the efforts they invest in violent activities tend to decrease (see Eq. (2.18)). This a result of the negative *rent effect* and the *substitution effect* driven by the increase in ρ, which is *a direct cost effect*. However, when ρ increases, the bribes don't increase in any case: when ($\rho \leq \dfrac{\beta+\frac{1}{\varepsilon}}{\varepsilon(1+\beta)}$) they tend to go down or remain equal, but when ($\rho > \dfrac{\beta+\frac{1}{\varepsilon}}{\varepsilon(1+\beta)}$) they tend to go up (See Proposition 2.4 and its proof). In the first parameter configuration the substitution effect with respect to P is weaker, we are in the increasing segment of $f(P)$ (see Eq.(2.12)) and P^* and B^* —or b^*— are strategic complements; thus, in the second one, the substitution effect is stronger, and we are in the decreasing segment of $f(P)$ where P and B are strategic substitutes.

Due two the conjunction of the latter effects, the probability of interdiction rises (see the Contest Equilibrium Theorem), whereas the traffickers' probability of success sinks; Something similar happens with the expected profits of the LEA and traffickers, respectively (see Propositions 2.5 and 2.6, and their proofs).

Changes in bribes costs

If β increases, b^* can go down while P^* go up, or it can be that b^* can go up while P^* go down. Hence in both cases b^* and P^* behave as strategic substitutes, so that they are in the decreasing segment of $f(P)$. In concrete, when $\varepsilon > \frac{1}{\rho}$, P rises, whereas b drops. Conversely, when $\varepsilon < \frac{1}{\rho}$, P fall, whereas b strengthens (see Propositions 2.3 and 2.4). In the special case when ($\varepsilon = \frac{1}{\rho}$) neither of them changes when β increases. The key fact to understand the variables' movements under these different parameters configurations lies in the influence of relative large o small values of the premium rate over bribery deterrence: For relative large levels of it ($\varepsilon > \frac{1}{\rho}$) the LEA is less prone to accept more bribes when P go up; the opposite happens for relative small levels of the premium rate ($\varepsilon < \frac{1}{\rho}$); the LEA is more prone to accept more bribes when P goes down. Furthermore, for $\varepsilon > \frac{1}{\rho}$ traffickers tend to invest more resources in P as their success probability tend to be smaller for $\varepsilon\rho > 1$. The converse occurs for ($\varepsilon\rho < 1$, so that they invest fewer resources in P^* although β had increased. Hence, from the traffickers' point of view, the substitution effect between the offers of b and P is stronger in the first parameter configuration, ($\varepsilon\rho > 1$).

In addition, one increase in the bribes' costs leads to a fall in the seizure probability but to an increase in the success probability on the trafficker's side for ($\varepsilon > \frac{1}{\rho}$) (see Contest Equilibrium Theorem). But, the opposite occurs for ($\varepsilon < \frac{1}{\rho}$). Also when there is an increase in β the LEA's profits decrease (see Proposition 2.5). Nonetheless the impact on traffickers' profits is ambiguous.

Changes in the drug-market size

When α rises the quantity of drugs sold increases. Because of the monopolistic nature of drug sales, their equilibrium prices rises, so that the sales' value increases more than proportionally. As a result, the traffickers' expected profits rise more than proportional than it (see Eq. (2.23)). Since the LEA's expected profits depend positively on the premium rate (over the value of the drug sales) when $\varepsilon > \frac{1}{\rho}$, his expected profits may increase with α too (see Eq. (2.22)). At the same time, the amount of resources invested in defense and coercion, P^*, increases (see proposition 2.3). In contrast, the quantity of bribes decreases —both as absolute levels and as a proportion of efforts (see Eq. (2.19))—. What explain this effect on bribes is that, when the value of sales rises, the incentives for bribes weaken, whereas they strengthen for "plomo".

Changes in interdiction-efforts costs

Increases in γ lead to proportional decreases in b^* (see Eq.(2.19) and Proposition 2.4). Since the LEA's efforts decrease when their cost's parameter grows, he tends to accept lower level of bribes. Instead, P doesn't change, as it is independent of γ (see Eq.(2.18)). Consequently, the LEA's expected profits decrease, while traffickers' expected profits increase.

Drug trafficking and state capture

$\alpha = 4\sqrt{\dfrac{(\frac{\beta}{\gamma})(\beta+\rho)}{\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right]}}$ can be understood as a threshold of the drug-market size beyond from which traffickers have incentives to be active as a *pressure group* Dal Bó et al. (2006).

Definition 2.1. *Let* $\alpha \equiv \widehat{\alpha} = 4\sqrt{\dfrac{(\frac{\beta}{\gamma})(\beta+\rho)}{\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right]}}$ *be a threshold beyond traffickers use the coercion and corruption devices.*

The reciprocal of $\widehat{\alpha}$ can be understood as an index of state capture SCI, because the higher it is, the easier for traffickers to activate their coercion and corruption apparatuses. The following definition states it formally:

Definition 2.2. *$SCI \equiv \frac{1}{4}\sqrt{\frac{[\varepsilon\beta^2 + 2\beta + \frac{1}{\varepsilon}]}{(\frac{\beta}{\gamma})(\beta+\rho)}}$ is a index of state capture.*

The analysis of the state capture index allows us to obtain the following results:

Firstly, it can be checked that SCI is a parabolic function of the premium rate, decreasing for $\varepsilon < \frac{1}{\beta}$ but increasing for $\varepsilon > \frac{1}{\beta}$. This is a consequence of the relationship between this parameter and P^*, which I already explained in the preceding sections. As a result, the level of ε minimizing state capture is $\varepsilon = \frac{1}{\beta}$

Secondly, increases in the defense costs, always lead to decreases in the level of state capture, because –as I already proved– they lead to lower levels of "plomo", which means a less intensive activity of the coercion devices, and in the aftermath, lower violence.

Thirdly, it can be proved that an increase in β induces a decrease in SCI, because higher costs of bribes lead to lower level of bribe's offers. This happens despite, for low levels the premium —i.e. $\varepsilon < \frac{1}{\beta}$—, b^* increases with β (see Proposition 2.4). A political consequence of this finding is that the law enforcement authorities should configure the institutional and legal conditions that make bribes substantially costly.

Lastly, increases in the costs parameter of LEA's efforts tend to bolster the level of state capture. The explanation is simple: Worse technological and institutional conditions for interdiction and traffickers prosecution, lead to lower levels of LEA's efforts, which facilitates the performing of corruption and coercion devices and the defense apparatus. Again this reveals the importance of the progress in the technology of interdiction and control. The government should increase the investments in $I + D$ for this sector.

2.6 Social welfare and the optimal premium rate

In this section I analyze the agency problem solved by the law enforcement institutions or the anti-narcotics department. Thus, I compare its results with the solution of the government's problem as a social planner when its unique goal is maximizing social welfare.

2.6.1 The anti-narcotics department agency problem

Let's consider now that the sequential game has three stages. In the first stage, the anti-narcotics department (AND) chooses the incentives system maximizing the LEA's expected output, giving the observed value of the drugs interdicted. The other stages of the game correspond to the basic model's first and the second stages (see previous sections), which remain as before. The AND acts as *a principal* behaving as an incorruptible agent: His role can be conceived as a superior, "which is itself incorruptible by other criminals or by the police officers suspected of corruption" (Bowles and Garoupa, 1997, p. 78). Following standard Holmstrom and Milgrom (1987) model, I assume that the incentives system chosen by the principal is a linear one given by:

$$I(\widetilde{x}) = w - \theta S + \varepsilon \widetilde{x}, \tag{2.24}$$

where w represents the wage rate paid to the LEA, θS the expected fine imposed to the corrupt officer, and ε the premium rate as before. $\widetilde{x}$ corresponds to the observed LEA's output level. The AND doesn't know the actual level of efforts invested by the LEA to seize drugs but the observed level of the value of drugs seized:

$$\widetilde{x} = zp_d q + \mu; \tag{2.25}$$

Where μ is a random variable with normal density, zero mean, and constant variance: $\mu \sim N(0, \sigma^2)$.

As the AND is risk-neutral, his expected utility is:

$$E\left[U_{An}\right] = E[\widetilde{x} - I(\widetilde{x})]. \tag{2.26}$$

This extended game can be solved as an agency problem, being its third and second stages equilibria the solution of the basic model. Hence, *the agent's problem* corresponds to the problem solved by the LEA in the third stage knowing trafficker's choices in the second stage. The AND also knows traffickers P choices in the second stage of the new game. The problem of the principal is then to choose the optimum level of the premium rate subject to the *incentive compatibility constraints* and the *participation constraint*. The *incentive compatibility constraints* (ICC) are expressed by the first order conditions solving the basic game and its sequential structure; that is to say, the fulfillment of them lead to the solution of the basic game discussed in the previous sections. On its part, *the participation constraint* (PC) requires that the expected profits of the LEA be greater or equal than an opportunity salary he might earn in an alternative legal job; let w_A this salary. w_A can be understood as a level of reservation utility for the AND. Thus, the principal's decision problem is:

$$\begin{array}{ll} \max\limits_{\varepsilon} & E[\widetilde{x} - I(\widetilde{x})] \\ \text{subject to} & \text{FOCs of the LEA and trafficker (ICC),} \\ & E\left[\Pi_L\right] \geq w_A. \text{ (PC)} \end{array}$$

Replacing Eqs. (2.24) and (2.25) in Eq.(2.26) and evaluating this equation in traffickers and LEA FOCs (Eqs. (2.8), (2.9), (2.15) and (2.16)), the problem can be written as:

$$\begin{array}{ll} \max\limits_{\varepsilon} & E[z^* p_d^* q^* + \mu - w + \theta S - \varepsilon(z^* p_d^* q^* + \mu)] \\ \text{subject to} & E\left[\Pi_L^*\right] \geq w_A. \text{ (PC)} \end{array} \tag{2.27}$$

This problem is equivalent to maximize the AND expected utility evaluated at the basic model's solution, subject to the participation constraint. The solution of this agency problem gives:

$$\varepsilon^* = \frac{1}{\sqrt{\beta}}, \tag{2.28}$$

which lies between zero and one as long as $\beta \geq 1$. This result reveals that the optimum premium rate equals the inverse of the root square of the marginal productivity of investing in bribes, $\frac{1}{\beta}$. Again as $\beta \geq 1$, this implies that $\varepsilon^* > \frac{1}{\beta}$. This means that for the expected value of seizures (net of LEA's rewards) and the whole system of incentives to be optimal, the rate of retribution for the enforcement effectiveness should be higher than the marginal productivity of investments in bribing and equal to $\frac{1}{\sqrt{\beta}}$. This marginal retribution difference between the LEA and traffickers will strengthen incentives to deter the former from accepting all the bribe's offers of the latter.

Now, replacing this result in the perfect-subgame equilibrium *participation constraint* —when binding— we can obtain the optimal wage rate payed to the LEA:

$$w^*(\varepsilon^*) = w_A + \theta(m+S) - \frac{\alpha^2}{4(\beta+\rho)}\left[\frac{\rho}{\sqrt{\beta}} - 1\right] - \frac{1}{2}\gamma. \tag{2.29}$$

The optimal LEA's wage rate depends positively on the fine and moral costs incurred in case of detected; It also depends positively on γ. However, it depends negatively on the drug-market size, and on ρ.

Replacing the optimal premium rate in the equilibrium levels of defense and coercion investments, P, and bribes b we get:

$$P^*(\varepsilon^*) = \frac{\alpha^2\left(\sqrt{\beta} + 2\beta + \beta^{\frac{3}{2}}\right)}{16(\beta+\rho)^2}$$

$$b^*(\varepsilon^*) = 1 - \frac{\alpha^2\gamma}{16(\beta+\rho)^2}\left(2\rho - \sqrt{\beta} + \beta^{\frac{3}{2}} + 2\rho\sqrt{\beta}\right)$$

The *agency-optimal* levels of the interdiction probability and the trafficker's success probability give the following results:

$$z^*(\varepsilon^*) = \frac{\beta - \sqrt{\beta} + 2\rho}{2(\beta + \rho)},$$

$$(1 - z^*(\varepsilon^*)) = \frac{\sqrt{\beta} + \beta}{2(\beta + \rho)}.$$

Replacing these results in the equilibrium expected profits we obtain:

$$E\left[\Pi_L{}^*(\varepsilon^*)\right] = w^* + \frac{1}{2}\gamma + \frac{\alpha^2}{4(\beta + \rho)}\left[\frac{\rho}{\sqrt{\beta}} - 1\right] - \theta(m + S) = w_A, \quad (2.30)$$

$$E\left[\Pi_T{}^*(\varepsilon^*)\right] = \frac{\alpha^2}{16(\beta + \rho)}\left[\beta^{\frac{3}{2}} + 2\beta + \sqrt{\beta}\right] - \frac{\beta}{\gamma} \quad (2.31)$$

2.6.2 The social planner solution

Now, consider the government acts as a social planner looking forward to maximize social welfare. The government can't directly control traffickers agents as they are outside the of law. Nor can it influence directly the LEA's best-responses to illegal agent's strategies. But it can control the premium rate level, so that the social cost associated to illegal activities are at least as possible. In addition, the government knows the perfect-subagme equilibrium solution of the basic model, since it knows the strategic interactions between the LEA and the traffickers. Hence, the government's decision problem will be to minimize traffickers' equilibrium expected profits subject to the LEA's expected profits being larger or equal than his opportunity salary, w_A:

$$\begin{aligned} \min_{\varepsilon} \quad & E\left[\Pi_T{}^*\right] = \frac{\alpha^2}{16(\beta + \rho)}\left[\varepsilon\beta^2 + 2\beta + \frac{1}{\varepsilon}\right] - \frac{\beta}{\gamma} \\ \text{subject to} \quad & E\left[\Pi_L^*\right] \geq w_A. \end{aligned} \quad (2.32)$$

Solving with a binding constraint we get:

$$\varepsilon^s = \frac{1}{\beta}, \quad (2.33)$$

Thus, the social optimal level of the premium rate is just the reciprocal of the marginal costs of bribes, that is to say, the marginal productivity of investing in bribes. Therefore, in the social optimum, the rate of retribution for the enforcement effectiveness equals the marginal productivity of investments in bribing. The intuition behind this result is that when $\varepsilon^s = \frac{1}{\beta}$ the investments in defense and coercion P reach their minimal level with respect to the premium rate. This can be checked using Eq. (2.18) and minimizing with respect to the premium rate. In addition, the social planer decision problem is equivalent to minimizing the SCI with respect to ε. This can be checked using Definition 2.2. As a result, the social planner solution enables us to minimize the process of state capture. Replacing Eq. (2.33) and using the constraint over the LEA's expected profits we can solve for the social optimal wage rate:

$$w^s(\varepsilon^s) = w_A + \theta(m+S) - \frac{\alpha^2}{4(\beta+\rho)}\left[\frac{\rho}{\beta} - 1\right] - \frac{1}{2}\gamma. \tag{2.34}$$

As, $\frac{1}{\sqrt{\beta}} > \frac{1}{\beta}$ it is easy to check that $w^s > w^*$. Substituting the social optimal premium rate in P and b we get:

$$P^s(\varepsilon^s) = \frac{\alpha^2\beta}{4(\beta+\rho)^2}$$

$$b^s(\varepsilon^s) = 1 - \frac{\alpha^2\gamma\rho}{4(\beta+\rho)^2}$$

The social optimal levels of the equilibrium levels of the interdiction probability and the trafficker's success probability can also be calculated:

$$z^s(\varepsilon^s) = \frac{\rho}{(\beta+\rho)},$$

$$(1 - z^s(\varepsilon^s)) = \frac{\beta}{(\beta+\rho)}.$$

It is easy to check that $P^s(\varepsilon^s) < P^*(\varepsilon^*)$ and that $b^s(\varepsilon^s) > b^*(\varepsilon^*)$. In the same way, it can be checked the same measuring the bribes in absolute levels: $B^s(\varepsilon^s) > B^*(\varepsilon^*)$. Furthermore, $z^s(\varepsilon^s) < z^*(\varepsilon^*)$ and, as result $(1 - z^s(\varepsilon^s)) > (1 - z^*(\varepsilon^*))$. This reveals that, although in the social optimum the level of "plomo" achieves its minimum, the bribes level and the interdiction probability are greater than in the *agency-solution* for the AND. Consequently, for higher than $\frac{1}{\beta}$ levels of the premium rate, the opportunity cost to increase the interdiction effectiveness and lower the bribes is the unleashing of more violence.

Lastly, replacing the social optimal premium rate in the expected profits we obtain:

$$E\left[\Pi_L{}^s(\varepsilon^s)\right] = w^s + \frac{1}{2}\gamma + \frac{\alpha^2}{4(\beta+\rho)}\left[\frac{\rho}{\beta} - 1\right] - \theta(m+S) = w_A, \tag{2.35}$$

$$E\left[\Pi_T{}^s(\varepsilon^s)\right] = \frac{\alpha^2\beta}{4(\beta+\rho)} - \frac{\beta}{\gamma} \tag{2.36}$$

Comparing results it is easy to check that $E\left[\Pi_T{}^s(\varepsilon^s)\right] < E\left[\Pi_T{}^*(\varepsilon^*)\right]$.

The comparison between the *social-planner solution* and the AND's *agency-solution* has two significant implications for the analysis: 1) In the social optimal solution —with the minimum possible level of "plomo"— the government will have to tolerate positive levels of bribes and, consequently, the presence of a certain degree of corruption. 2) A society where the coercion and corruption devices of drug trafficking operate —with the resultant arising of a state's capture process—, in which the government establish a very high level of the premium rate —close to one— will produce perverse incentives, as it would trigger violence and possibly the unleashing of *narco-wars*.

2.7 Some key facts: A brief interpretation of results

Recent global trends in the quantities of cocaine seized reveal a tendency towards stabilization in seizure levels (UNODC, 2020). Although global seizures have grown, their rate of change has been diminishing in the last years. In 2018, the total global quantity of cocaine seized increased by 2.7 percent, to 1,311 tons (before to purity adjustments), over the preceding year. However, the annual rate of increase fell from a 41 percent increase in 2015 to a 23 per cent increase in 2016 and 13 per cent in 2017, and to a less than 3 percent increase in 2018. (UNODC, 2020, p. 78). Probably, this means the global seizures are tending to a long-run equilibrium.

What is more surprising is that in Latin America, cocaine seizures have decreased during last years; Between 2017 and 2018 they decrease 4% to 721 tons. In Colombia the drop was more substantial: 7% coming to a lower level 457 tons seized in 2018 (UNODC, 2020). At the same time, Perú and Bolivia reported a decline in cocaine seizures of 4%. What explain this result? The stabilization of coca bush during 2018 could explain these trends partly, but is is not clear the reason why seizures went down in Latin America between 2017 and 2018.

However, the key point here is that, although the global interception rate[16] of cocaine has seemed to be growing during last decade, probably partly owing to improved national, regional and international cooperation (UNODC, 2020) it remains at relatively low levels probably between 43% and 68% (UNODC, 2016b). For the case of Colombia, for example, the Colombian government celebrated the high increase in cocaine seizures reported for 2016 —a record of 300 metric tons of cocaine— claiming this would mean an interception rate of nearly 75% of al the cocaine produced that year (Yagoub, 2016). But this author shows, that considering the differences in purity between seizures and the potential production of cocaine, and the presence of measurement error both in the registered coca crops an the estimated coca-crops yields, it seems there is an over-estimation in the interception rate of cocaine.

According to Yagoub (2016) "[if] cocaine production estimates are adjusted

[16] The interception rate of a drug estimates the percentage of it that becomes seized with respect to the total level of its production. The seizures statistics are not directly comparable with production's estimations, because seizures tend to have different purity levels and the potential production for cocaine an heroin are estimated from the coca and poppy crops, respectively. Therefore, it is not an easy task to obtain tight estimations of them. For the purpose or our analysis the level of the interception rate is significant, since it represents an empirical estimation of the interdiction rate, which is endogenous in my model.

to account for an 85 percent average purity level, authorities would still have seized between a third (per UNODC figures) and a half (per US government figures) of last year's production. If adjusted to low-end estimate of 65 percent purity, authorities would have seized between 25 and 40 percent of total cocaine production" (Yagoub, 2016, p. 3). Thus, Yagoub argues that, by making this adjustment, the actual interception rate should be closer to the UNOCD's range between 43% and 68% (UNODC, 2016b). In a nutshell, this implies that the interception rate has remained relatively low in the Colombian case.

The figures are not different in that sense for the case of heroin. Although global estimated interception rates of heroine have been growing as a consequence of the upward trend in seizures, (see (UNODC, 2016b, 2019, 2020), historically the interception rate of heroine have been lower than the same rate for cocaine (see also the classic work of Farrell (1995)).

The model developed in the preceding sections makes an attempt to explain why the drugs interceptions rates —captured in the model by the interdiction probability— tend to be relatively low, as long as the interdiction efforts tend to be counterbalanced by the trafficker's strategies. Or course, coming works should study these trends empirically, attempting to corroborate some causality relationships.

Moreover, the model is also relevant to explain another crucial stylized fact: the expansions or contractions in the value of cocaine markets affect the levels of violence in countries that are part of the global cocaine trafficking network. Recently, the work of Aziani (2020) found empirical evidence supporting this relation. In his own words: "The study provides empirical support for the argument that specific economic dynamics of cocaine markets are important determinants of violence. Indeed, this study shows that fluctuations in the value of cocaine markets serve as a plausible explanation for the increase in lethal violence at country level" (Aziani, 2020, p. 247).

Regarding the different parameter configurations of the model —i.e. with respect to the level of the premium rate— it is possible to identify different *typical situations* (Popper et al., 1997) in the diverse drug trafficking scenarios.

The Colombian case historically corresponds to a *typical situation* characterized by the used of both higher levels of violence and bribes by traffickers. As a result, the seizure probability —expressed empirically by the interception rate— has been relatively low. Theoretically, this is consistent with relatively low levels of the premium rates and officers' wage rates —$\varepsilon < \frac{1}{\beta}$—. Indeed, the wage rates of enforcers and police officers in Colombia are relatively low, and there is no a well-established system of rewards tied to the success in interdiction tasks.

The case of Mexico tends to be similar to the Colombian one: it is closer to a *typical situation* characterized by high levels of violence —triggered by the big cartels in the context of narco-wars— and high levels of bribery and corruption. However, the wage rates of enforcers and police officers tend to be higher than in Colombia (Duncan, 2015).

In contrast, the case of the U.S. corresponds to a *typical situation* where traffickers tend to use lower levels of "plomo", and in addition the levels of bribes are moderate. As a result, the rates of interception of hard drugs in this country tend to be relatively high (UNODC, 2019, 2020), and this is partly a result of a well-established system of rewards tied to the success in interdiction tasks. In addition, police officer's and enforcers' salaries tend to be relatively high. Therefore, probably this is a case where the premium rate is closer to its optimum level or the optimum-agency level discussed above, so that $\frac{1}{\beta} \leq \varepsilon \leq \frac{1}{\sqrt{\beta}}$. The result of this pattern is that the level of state capture by the illegal agents is very low (Duncan, 2015).

Finally, the European case is different to the others, because drug trafficking is being characterized during the last decade by an unprecedented growth in drug sales –specially of cocaine sales– coming from Colombia, Perú and Bolivia (UNODC, 2019, 2020). in this context, traffickers tend to use very high levels of "plata" but very low levels of "plomo" (den Held, 2021).

And, though enforcers and police officer's rewards are relatively low, the seizures and interception rates remain comparatively high (UNODC, 2019, 2020). The model developed in this chapter is not useful to explain this case. Nevertheless, the third chapter linked to this research will address this interesting case.

2.8 Conclusions

The model analyzes the strategic interactions between the traffickers and law enforcement authorities in a context where the former acts as leaders, moving first, as they own territorial domain. It gives them sufficient conditions to deploy *de facto* power and also market power to develop illicit activities, i.e., drug trafficking. As a consequence, they perform within the functioning of a series of *coercion and corruption devices*, which gives them the possibility to use "plomo" and "plata" —in diverse combinations and levels— to weaken and avoid law enforcement. Through violent threats and bribes, the traffickers design and implement diverse strategies to weaken and neutralize the enforcers' efforts to seize and capture illicit drugs.

This analytical framework is useful two explain the performance of drug trafficking in cases where violence and corruption play a joint role and are nested up. The cases of micro-trafficking —and in particular of the so called "ollas" in urban Latin American cities— is the most prominent case nowadays. But the model is also useful to explain strategic interactions in the cases of big illegal organizations as the Mexican Cartels —i.e. the Sinaloa Cartel, the Jalisco Cartel or the "Zetas"— or the Colombian cartels as the Cali Cartel, the Medellín Cartel, or the Norte del Valle Cartel, which operated in the past decades.

From the point of view of the strategic interactions at play, the key fact of the model is that moving first, traffickers have the coercion capabilities to condition the officer's demand of bribes. Hence in this model there is no bargaining —the Nash (Nash, 1950) or the Kalai-Smorodinsky solutions (Kalai et al., 1975)) are not relevant here— , since traffickers co-opt a fraction of the LEA's efforts in the form of bribes.

Under these assumptions, trafficker's bribes-offers hamper and neutralize the law enforcement efforts to seize and prosecute illegal drugs. Hence the model gives theoretical evidence supporting the starting hypothesis. As a result, the LEAs' perfect-subagame equilibrium level of efforts will depend only on the costs involved in interdiction and prosecution activities. This result shows the relevance of encouraging investments to improve the interdiction and prosecution technologies, even in a world where officers can be bribed. This finding goes in the same direction as Raffo et al. (2021), who emphasize the importance of technological improvement in interdiction and prosecution policies.

Despite the conditioned acceptance of bribes by the LEAs, higher wages rates for them are relevant to the effectiveness in interdiction and enforcement, as their profits tend to be positive. In addition, higher wage rates tend to attract higher-skilled and more competitive officers (Dal Bó et al., 2006). Another model considering the possibility that a certain proportion of officers won't accept bribes —-following Dalbó et al.'s framework—- would be more appropriate to analyze the consequences of the wage rate level and the coercion and corruption apparatuses' activity on the workers' skills and abilities when entering into the official sector —i.e., to the law enforcement activities—.

However, the most important result of the model is to show the relevance to fund a rewards system based in the LEAs' achievements: it shows that higher premium rates are effective to deter the acceptance of bribes by the officers, as it tends to rise the interdiction probability. This result goes in the same direction of Becker and Stigler (1974) analysis of law enforcement. As a result, increases in the premium rate have a positive impact on the expected LEA profits.

Nonetheless, the welfare analysis unveils the possible negative consequences of a law enforcement policy based on a system of salary premium tied to the seizure effectiveness: high levels of premium rates can unleash subsequent increases in violence by the part of illegal agents, as a way to offset the bribery deterrence. Consequently, the social optimum level of the premium rate should be lower than one and close to the actual productivity of the bribing investments. The solution of the agency problem for the law enforcement institutions corresponds to an equilibrium premium rate higher than this value.

Besides, it is vital to warn about the possible adverse effects of this kind of reward system when dealing with "crimes with victims". The system based in enforcement awards only functions when we are dealing with "victimless crimes" as drug-trafficking, prostitution or smuggling. Furthermore, the model also shows that increases in the defense and coercion costs will always discourage them, although the same will not occur with bribes for certain configurations of the relevant parameters.

Furthermore, the model shows that higher levels in the value of drugs sold trigger a larger level of "plomo". This result goes in the same direction of recent empirical examination of Aziani (2020), who corroborates that expansions or contractions in the value of cocaine markets affect the levels of violence in countries that are part of the global cocaine trafficking network.

On the other hand, increases in the bribes' costs lead to more defense and coercion efforts for sufficiently high values of the premium rate. In contrast, they lead to decreases in the level of bribes for sufficiently low levels of the same parameter.

The model also shows that the level of state's capture depends positively on the interdiction and prosecution costs but negatively on both the coercion and defense costs and the bribes' costs faced by traffickers. It also depends on the premium rate in the same way as this parameter affects the traffickers' expected profits and the quantity of "plomo".

Although the model is useful to analyze the strategic interactions between illegal agents and enforcers determining interdiction probability, it is important to mention it has a few shortcomings, as any model: First, the model treats traffickers as a single unit of choice —as if they had solved their collective action problem—. This means the model focus on analyzing the case of one monopolistic trafficker. Further investigation, should develop the analysis under different market structures: the case of perfect competition, the case of oligopoly, or the monopolistic competition structure. This would enable us to understand better the effect of market structure on the traffickers and the law enforcement authorities' interactions.

Second and consequence of the latter, the model disregards the cooperative and not cooperative interrelations that influence criminal activities, which produce different kinds of network externalities between agents involved in crime. Other strand of work have tackled this network-effects (see Ballester et al. (2010) or Calvó-Armengol and Zenou (2004), Ballester et al. (2006), inter alia).

Third, a dynamic-game setting with many periods will be more appropriate to study stable and medium-term agreements between illegal agents and officers about bribes, based in continuing relationships. In this sense, the model gives a simplified picture of the dynamics at stake and the medium or long-term implicit contracts between criminals and enforcers. Although, strictly speaking it is not a model of "casual corruption" in the sense of Bowles and Garoupa (1997), because the point of departure is that traffickers have *ex ante* territorial control, that is, before playing they already have established domination relationships between other agents (the inhabitants in that territory including the law enforcement authorities). Consequently, we are not dealing with a "casual relationship" but a simplified picture of a –if not continuing at least— frequent relationship.

Lastly, it is worth noting that this work points out promising avenues of future research: Taking into account the mentioned shortcomings of the model, developing a more general analytical framework in terms of the drug-market structure would be a contribution. On the other side, building a dynamic game with many periods, would shed light on the medium or long-term relationships shaping the performance of illegal organizations. Thirdly, modeling the bribing strategies of traffickers in contexts without violent threats —i.e. without the operation of permanent violent or defense actions, or what is same, without activating their *defense apparatus* or their *coercion devices*— would be relevant to explain the recent-years boom of the European cocaine market. This will be addressed in the following chapter.

Chapter 3

A corruption model of drug trafficking

3.1 Introduction

During the last few decades, corruption has been gaining importance with respect to violence as a criminal strategy to weaken law enforcement at the drug-trafficking wholesale market. Traffickers' strategies to bribe and corrupt the law enforcement authorities (i.e., port and custom officers, anti-drug agents and other authorities (EMCDDA, 2021)) have allowed the recent boom of cocaine shipments from Latin America to Europe, for which hidden or camouflaged transport in containers has evolved as the principal method to smuggle drugs trans-nationally (Ramírez, 2021). In such a context[1], corruption has turned more important than violence, leading to a scenario where —in the words of den Held (2021)— "a cancer of corruption" has been developed.

During the last thirteen years drug supply in Europe has reached historical levels. There has been a general increase in the quantity of drugs seized: except for cannabis resin, the quantities of them have risen during the period 2009-2019 and more markedly since the middle of that decade (EMCDDA,

[1]Different contexts face illicit organizations at other stages of the whole illegal productive chain, e.g. in its downstream links where drugs are produced, or in its upstream links where they are distributed and sold at a retail level.

2021). As the European Drug Report for 2021 (EMCDDA (2021)) claims, methamphetamine, MDMA [2] and cocaine have been the drugs with the highest increments in quantities seized during the period 2009-2019, with increases of 931%, 456% and 256%, respectively. The same inform posits that such a high increase may be attributed to the behavior of psychotropic consumers in Europe, but also to the greater role played by the Old Continent as a territory of transit, export, or even production of the drugs [3].

Furthermore, the purity of hard drugs as cocaine and heroin seized in E.U. has been growing in the last years, while their prices have remained stable (EMCDDA, 2019, 2021). Those are clear signals of the recent boom in these psychoactive substances in the region. In the case of cocaine, its purity grew during the past decade reaching a level 57% higher than in 2009, while in the case of heroin it increased 23% between 2009 and 2019 (EMCDDA, 2021).

But more remarkable is how illegal business quickly adapted to the restrictions originated by the COVID-19 pandemic: there is little evidence of supply disruptions, but an acceleration in the arising of digital trading and drug crypto markets (EMCDDA, 2021). Indeed, recent reports adduce that the surge of drug consumption i.e., of cocaine in Europe is linked to the pandemic, since lockdowns provoked several personal reactions including drug taken (Forthomme, 2022). Supported in a recent inform of BSI (BSI, 2021), this author adds that the pandemic, apart from increasing unemployment, produced deviations and breaks in global supply chains that “provide a perfect opportunity for criminal gangs to insert themselves in the international trading system —and the coincidental rise of encrypted

[2] Most commonly known as Ecstasy or Molly, the MDMA (3,4-methylenedioxy-methamphetamine) is a synthetic drug belonging to the chemical family of phenethylamines with both stimulant and hallucinogenic effects (NIDA, 2021).

[3] For many years, Cannabis and synthetic drugs —e.g. amphetamines, methamphetamines and MDMA— have been produced in Europe (EMCDDA, 2019). However, there is evidence of a growing importance of EU in the global market of these substances (EMCDDA, 2019). In the meanwhile, it is also troubling the recent surge of heroin and cocaine-producing laboratories in the region. In the latter case, they have been used not only as ‘secondary extraction facilities’ to recover cocaine from materials in which it has been mixed to camouflage it during transport, but also to manufacture crack (EMCDDA, 2021).

communication channels and cryptocurrencies would have made it all the easier to engage in illegal operations and escape detection" (Forthomme, 2022, p. 4). Therefore, in the present context, technological advances in trafficking and distribution methods as well as the development of diverse kind of corruption strategies —mainly directed to port and custom authorities— have played a prominent role.

This article analyzes theoretically the influence of corruption in drug trafficking at the midstream stages of the illegal productive chain, wherein drugs are trafficked (i.e., transported, distributed and sold) at a medium or large scale. Traffickers interact with the law enforcement authorities (the LEAs in what follows) offering them bribes to evade the control and interdiction policies. Each LEA may accept (or not) the offers, depending on the moral costs she is expecting to face for accepting bribes if detected. In case of acceptance they will bargain with traffickers the amount of money to receive in exchange for allowing them trafficking and selling drugs. The key point is that corruption constitutes an essential mechanism to the performance and growth of illegal activities: the higher the probability of successful bribery, the greater the prospect gains of traffickers. Therefore, corruption is a decisive mechanism determining the possible entry of illegal agents to drug trafficking as well as the quantity of drugs sold, given other relevant parameters as the costs they face.

Moreover, some factors as the drugs market size, the traffickers' weight in the bribes' bargaining process, and technological progress regarding either traffickers' costs or transport and trafficking systems, are relevant to fuel illegal activities, as they encourage corruption and the entry to illegal markets. As a consequence, they weaken the deterrence effects of the different anti-drug policies at hand.

Hence, the article's main goal is to analyze the influence of corruption in the performance of drug trafficking at the midstream stages of the illegal productive chain, as well as the factors encouraging it. This implies to analyze the strategic interactions between the traffickers and the LEAs determining the process of bargaining on bribes and the equilibrium level of them to be traded, and what is more relevant here, the way in which these corruption processes determine the equilibrium level of drug sales, as well as the proportion of traffickers actually entering to illegal markets. Moreover, it is essential to examine and compare the effectiveness of the different anti-drug policies to deter corruption and the performance of illegal agents.

Other more specific questions are also relevant here: Which are the main forces fueling corruption and drug trafficking at this level? How effective are the traditional criminal policy instruments (i.e., fines imposed to traffickers or to officers, and the probability of detection of corrupted officers) to deter corruption and drug-trafficking? ¿Are there any other alternative anti-drug policy instruments?

The starting hypothesis is that, although traditional criminal policy instruments in general tend to be effective to deter corruption and crime —i.e. drug trafficking in this context—, as predicted by the seminal works in the economics of crime (Becker (1968) and Bowles and Garoupa (1997)), there is another effective alternative: a premium rate given to the LEAs in retribution to their achievements in interdiction activities. This idea was indeed suggested earlier by Becker and Stigler (1974) in their classic study of law enforcement.

The analytical framework proposed constitutes a three-stage sequential game in which traffickers and officers interact determining the probability of successful bribery, the equilibrium levels of bribes, as well as the equilibrium quantity of drugs sold and the proportion of traffickers actually entering to illegal markets. The model is based in Bowles and Garoupa's analysis of casual police corruption (Bowles and Garoupa (1997)) and in more recent works modeling drug-trafficking markets.

The article is related with at least three strands in the literature on the economics of crime and illegal markets: First of all, theoretically the model is based in some of the seminal papers in the economics of crime, which contributed to the development of the *Beckerian canonical model* and gave the conceptual basis for studying law enforcement in the context of illegal markets. In fact, as I will explained in the following section, the analytical framework is based in the models of Becker (1968), Ehrlich (1973), Polinsky and Shavell (1979) and Bowles and Garoupa (1997), but other classical works studying law enforcement in the general context of criminal or illegal activities give fundamental insights to the conceptual analysis of law enforcement (Becker and Stigler (1974), Buchanan (2006), Backhaus (1979) and Sisk (1982)). In particular, Becker and Stigler (1974) remark the relevance that would have a reward system based on enforcers' achievements for designing a successful law enforcement system. They also point out the importance of an appropriate salaries' policy to improve law enforcement systems.

A second strand of relevant works focus on the study of drug trafficking and drug markets. They constitute an already vast and broad literature — most of it recent—, that study drug markets in the context of the *economic theory of illegal goods and markets* (Becker et al., 2006)[4]. Numerous works, which can be included in this field, study drug trafficking in its different stages and dimensions. For instance, the works of Poret and Téjédo (2006), Raffo and Segura (2018, 2015), and Raffo (2015) study the upper stages of the productive chain assuming an oligopoly market structure and — in the latter three cases— using social networks to understand criminal interactions, between traffickers or dealers. In the meanwhile, Costa Storti and De Grauwe (2012) use a monopolistic competition market structure to explain the downward trend in drug's retail prices due to globalization during the period 1990-2006. Other works focus on the bottom stages of the illicit productive chain (see Serrano-López (2020) and Grossman and Mejía (2008)), or assume vertical integration of the industry (see Raffo (2010), Ortiz (2009)), or develop a comprehensive analysis of the whole productive chain (Chumacero (2008), Mejía and Restrepo (2016))[5].

[4]Becker et al. (2006) was the first work clearly using this denomination for referring to the economic analysis of illegal markets in the broader context of the economics of crime.

[5]Most of the literature on the *economic theory of illegal goods and markets* until 2011 is surveyed in Raffo (2011).

All these works give insights to the modeling of drug trafficking in the present work. But none of them focus on the analysis of drug trafficking at the midstream stages of the illicit productive chain, wherein the examination of illegal agents' attempts to corrupt law enforcement authorities and bargain with them plays a significant role, which is what this chapter, roughly speaking, pretends. For this reason, models studying corruption and bribery are also pertinent here; they constitute a third strand of relevant literature. Apart from the model of Bowles and Garoupa (1997), the works of Basu et al. (1992), Bac (2019) and Braun and Gautschi (2006) are important references for the analytical comprehension of bribery. Furthermore, the works of Kalai et al. (1975) and Nash (1950) offer the seminal theoretical schemes to understand bribes as Nash-equilibria resulting from bargaining processes.

It is worth adding that some works have tackled the analysis of corruption in drug trafficking, but in contexts different from the one analyzed in the present paper. For instance, Serrano-López (2020) uses Contest Functions to analyze the success probability of traffickers as a function of variables of violence and corruption, in the context of large or medium scale traffickers who buy drugs to their producers; but there is no bargaining in his model since corruption enters as an input of the traffickers' Contest Success Function. Besides that, Raffo and Gómez Calderón (2017) examine the corrupt actions of traffickers at the retail level in the context of micro-trafficking and "narcomenudeo"[6]. With that purpose they propose a model in a sequential game-framework with criminal networks. However, there is no bargaining in their model neither.

Consequently, the model proposed in this article can be embedded in the *Beckerian economics of crime research program* (Becker and Landes,

[6] The micro-trafficking refers to a particular model of production and sales of illegal drugs, characterized by the traffic of psychoactive substances at relatively small or medium scales, to sell them at a retail level through the working of large teams of dealers in the urban zones of big cities across Latin America. This kind of distribution model has been called "narcomenudeo". The micro-trafficking arose prominently in the cocaine-producer countries as Colombia, Peru and Bolivia since the first decade of the current century, as a strategy to develop domestic markets (Cawley, 2013).

1974; Fuchs, 1994; Lakatos, 1970)[7], as it connects the Becker-Polinsky-Shavell formulation (Becker, 1968; Polinsky and Shavell, 1979), on which Bowles and Garoupa (1997) are also based, to the analysis of bribing and corruption in drug markets. In that sense, it contributes to the current developing of this research program in three different ways: First, it analyses bribing and corruption in a similar framework to Bowles and Garoupa's model, but in a more specific and market-structured context corresponding to drug-trafficking at a wholesale scale. Therefore, it gives more market-structure to the Bowles and Garoupa's framework, providing analytical foundations to develop other possible extensions of the model in the near future.

Second, it makes a contribution in the more specific fields of *illegal goods and markets* and *drug policy*, by which a detailed and comparative examination of the different anti-drug policy alternatives to fight against drug-trafficking and corruption has been made. Here, following Becker and Stigler (1974) analysis of law enforcement, another less commonly used criminal-policy is recommended as a key instrument to improve the enforcement reward-system: a premium rate on officers' interdiction achievements.

Third, within the same context, the article contributes to a comprehensive analysis and modeling of the midstream stages of drug trafficking, for which there is still a gap in the literature on illegal goods and markets.

The model proves several results. First of all, the model points out that the drug-market size is the most powerful force encouraging the performance of illicit organizations and weakening corruption deterrence. Secondly, if traffickers have more weight than the LEAs in bribery bargaining, more traffickers are encouraged to enter to the market.

With respect to anti-drug policy, according to seminal papers in the field (Becker, 1968; Bowles and Garoupa, 1997), this model corroborates that traditional criminal policy instruments are effective to deter the entry of more

[7]In its beginnings, Becker and Landes (1974) called this research program "a program of basic research in law and economics" (Becker and Landes, 1974, p. 16).

traffickers to illicit markets in the presence of corrupt agents. Nonetheless, it proves that fines on traffickers are less effective since they generate perverse incentives encouraging corruption. Consequently, fines to corrupted LEAs or the development of better police technologies and strategies to detect and capture corrupt officers represent more effective alternatives.

In addition, the model shows that, though higher salaries may not have a direct impact on corruption deterrence neither on trafficking discouragement, they encourage officers interdiction-activities, as they breed higher expected profits. Higher salaries constitute an alternative anti-drug policy instrument (Becker and Stigler, 1974).

But a more remarkable result is that a premium rate given to the officers in retribution to their achievements in interdiction, provides another alternative and effective policy instrument to combat drug trafficking at the wholesale level. This alternative policy tend to be a powerful instrument for low levels of the premium rate. This is demonstrated in Section V.

The document proceeds as follows. Section 3.2 presents the model's assumptions. Section 3.3 develops and solves the model using backward induction. Section 3.4, formulates and analyzes the perfect-subgame equilibrium results. The final section concludes and remarks avenues for future research.

3.2 The Model

The present model is based in Bowles and Garoupa's model of casual police corruption (Bowles and Garoupa (1997)) and in previous works modeling drug-trafficking markets and pressure groups (Raffo and Gómez Calderón (2017) and Dal Bó et al. (2006)). It integrates the Becker-Polinsky-Shavell formulation (Becker, 1968; Polinsky and Shavell, 1979), on which Bowles and Garoupa (1997) are also based, to the analysis of bribing and corruption in drug trafficking.

The model focus on the midstream links of the illegal productive chain, wherein drugs are trafficked i.e., transported, distributed and sold at a medium or large scale. I assume there is vertical integration between these links, so that each trafficker is trafficking and selling illicit drugs at the wholesale market to other retailers located in consumption centers.

In a three-stage game setting similar to Bowles and Garoupa (1997)'s framework I model the strategic interactions between traffickers and the LEAs, in which the first decide to enter (or not) to the illegal activities and attempt to traffic and sell drugs having market power in specific segments of illegal markets. With that purpose illegal agents offer bribes to evade the control and interdiction policies of the LEAs. For their part, the latter decide if they will accept (or not) the bribes's offers and, in case of accepting corruption, they will bargain with traffickers the amount of money to receive in exchange for allowing them trafficking and selling drugs.

The timing of the game is the following: In the first stage traffickers revise their prospective decisions regarding entering (or not) to the illegal activities (long-run choice), and the amount of drugs to sale as well as the wholesale price to charge in the case of entry (short-run choice). In deciding to enter to the illegal market, traffickers compare the returns and costs from drug trafficking. A key fact in this stage is that the fixed costs of trafficking and selling drugs are heterogeneous, differing between traffickers. In the second stage, the LEAs select the level of efforts (e) they will invest in interdiction activities to seize drugs. Although it does not affect the value of the seizure probability, it determines the salary payments received by the LEA, and thus their equilibrium expected profits. When choosing e each LEA knows her attitude towards corruption, i.e., if she will accept bribes or not. In the third stage, both agents bargain over the amount of bribes to be exchanged. Following Bowles and Garoupa (1997), I assume that the bargaining solution is guided by the approach of Cadot (1987), by which corruption is modeled as a game. Solving for the bargaining solution enables us to find the probability of successful bribery.

I assume there is a continuum of traffickers, $i \in [0, I]$ who maximize their expected profits as a function of the quantity of drugs sold, q, and the amount of bribes bargained, B. Their expected profits also depend on the seizure probability of drugs z, a fine $F > 0$ imposed in case of being convicted, and the costs function of trafficking and selling drugs, $C(q)$, which in principle is assumed to be of the linear type: $C_i(q) = cq_i + \mu_i$, where c is the marginal cost of trafficking and selling drugs, being this parameter homogeneous between traffickers. The variable costs, cq_i, capture all the labor and input payments involved in the trafficking and selling of drugs at the wholesale level. $\mu_i \in \mathbb{R}_{++}$ represents the fixed costs faced by each trafficker for trafficking and selling drugs, which is heterogeneous between them. It includes all the technology, infrastructure, logistics, and capital traffickers need to transport, distribute and sell drugs at the wholesale level independently of their amount; For example, this is the case of the technology and logistics of the drugs' transportation from the producer to the consumer countries, or the physical capital, e.g., the facilities needed to storing the narcotic substances, either at the departure port or the arrival port, or the basic means of transportation used for their transport —e.g, fast boats, small vessels, or even semi-submersible craft—. All the components of the *defense apparatus* needed the ensure protection and security *by the force* of all the resources and properties used by the illegal organizations enter here too.

However, as marginal costs are insignificant in comparison with fixed costs and for the sake of simplicity, I will assume in what follows that they tend to zero[8]. Therefore, the costs of trafficking and selling drugs may be stated simply as:

$$C_i = \mu_i, \tag{3.1}$$

The expected profits of trafficker i are given by:

$$E\left[\Pi_i^T(q_i, B_i)\right] = (1-z)\left[p_{di}q_i - \mu_i - \phi B_i - \theta F\right] + z\left[-\mu_i - \phi B_i - F\right]$$

[8]It can be checked that by letting $c > 0$ similar results are obtained, although the model's solution turns to be trickier

where z is the seizure probability faced by the illegal drugs at the wholesale stage, while $1 - z$ corresponds to the success probability of trafficking and selling drugs. As I will show, both are homogeneous between traffickers; p_{di} is the wholesale price of drugs fixed by the monopolistic seller i; B_i is the amount of bribes payed by traffickers in case of successful bribery; ϕ denotes the probability of successful bribery (such that $0 \leq \phi \leq 1$), which is also the same for every trafficker. Notice that either in case of success or in case of failure every trafficker faces a fine. In the first state of the world, he still receives a fine, θF, which corresponds to F multiplied by the probability that the (potentially) corrupted LEA be detected.

As I will show in the following sections, because all the parameters with the exception of μ_i are homogeneous between traffickers, $q_i = q, \forall i \in [0, I]$. For this reason, $p_{di} = p_d$ and $B_i = B, \forall i \in [0, I]$[9]. Hence, in what follows I will omit the i-sub-indices, without forgetting that μ_i is heterogeneous within the continuum of traffickers. Simplifying one gets:

$$E\left[\Pi_i^T(q, B)\right] = (1 - z)\left[p_d q - \theta F\right] - \mu - \phi B - zF$$

One of the main hypothesis of the model involves the probability of interdiction. I assume that it depends on two fundamental factors. First, it depends on a technological factor, ψ, such that $0 < \psi < 1$, capturing all the technologies and methods used to transport and traffic illegal drugs camouflaged or hidden from the enforcement authorities or the anti-narcotic police. In most of the cases these technologies and methods are very effective. In the case of coca trafficking to Europe during the last years, for which container shipping is the main form of transnational transport (Ramírez, 2021), the seizure probability tends to be very low. "Every year, 750 million containers are shipped around the globe, but less than two percent of these are inspected. This has provided traffickers with the perfect opportunity to reach global markets. The challenge is camouflaging large consignments of

[9] If there is symmetry in the sales' levels in equilibrium, the same will happen for prices fixed by traffickers when facing similar inverse-demand functions. In consequence, the amount of bribes bargained for every pair of traffickers and officers will the same, since —as we will see in the next section— the equilibrium amounts of bribes are a function of q and p_d.

cocaine to minimize the risk of seizure while maximizing profits"(Ramírez, 2021, p. 2). Indeed, the interception rate of the alkaloid tend to be low, probably between 10 and 20 percent (McDermott, 2021; Bargent, 2021). That's the reason why I assume that ψ is close to one, $\psi \to 1^-$.

Second, it depends on the probability of successful bribery, ϕ, which will be analyzed in the following section. This is the case of illegal shipments to Europe too, where corruption has gained importance during the last decade as an indispensable input and process for successfully trafficking. This has led to a scenario wherein "the plata" has risen over "the plomo" (den Held, 2021). The key point from the point of view of trafficker's success probability is that without corruption the drug shipments can't be transported.

Taking into account both seizure determinants at the wholesale stage, I assume that

$$z = 1 - \phi\psi, \tag{3.2}$$

equation by which the seizure probability decreases linearly with the probability of successful bribery, ϕ, and the technological factor, ψ. Notice that if the probability of successful bribery were 0, then the seizure probability would be at its maximum level, 1. On the other extreme, if $\phi = 1$, as $\psi \to 1^-$, z will be close to 0. On the other side, the success probability of a trafficker is given by:

$$1 - z = \phi\psi, \tag{3.3}$$

so that the traffickers' seizure probability is directly proportional to the probability of successful bribery and the technological factor. If the first were zero, then $1 - z$ would be zero. On the contrary, if it were one, $1 - z$ would be close to one (as $\psi \to 1^-$). Replacing $1 - z$ in the trafficker's expected profits one gets:

$$E\left[\Pi_i^T(q, B)\right] = \phi\psi\left[p_d q - \theta F\right] - \mu - \phi B - (1 - \phi\psi)F \tag{3.4}$$

On the other side, there is a continuum of officers (LEA's), $j \in [0, J]$ who maximize their expected profits as a function of the level of efforts (e) they invest in interdiction activities, and the level of bribes B they would accept from traffickers in case they were corrupted by them and accept bargaining. I assume that every LEA is risk-neutral. If corrupted, each officer faces two possible states of the world:

1. She is detected committing corruption acts by a superior or the anti-narcotics agency with probability θ, in which case her expected profits are:

$$we + \varepsilon(1 - \phi\psi)p_d q - \frac{1}{2}\gamma e_j^2 + B - S - m_j,$$

2. She is not detected with probability $1 - \theta$, in which case she does not face neither fine nor any moral cost.

$$we + \varepsilon(1 - \phi\psi)p_d q - \frac{1}{2}\gamma e_j^2 + B,$$

where ε corresponds to a premium paid by the government —i.e. the anti-narcotics agency[10]— for every unit of drugs seized by a LEA. As it is a proportion, $0 \leq \varepsilon \leq 1$. As a result, $\varepsilon(1 - \phi\psi)p_d q$ is the fraction of the value of seized drugs —at market wholesale prices— the officers receive as a reward for their achievements in interdiction activities. The term $m \in \mathbb{R}_+$ represents a moral cost faced by the LEAs for accepting bribes when detected. This parameter is subjective and heterogeneous between the LEAs and will capture the attitudes towards corruption. $S \in \mathbb{R}_{++}$ denotes the fine imposed on the corrupt officer when detected, w represents the wage rate paid to her by the public sector, and we are then the wage incomes earned by them. $\gamma > 0$ is a parameter related to the costs of the LEAs' efforts, which captures the prosecution and interdiction technology; it is homogeneous between all the officers.

Since there is also symmetry in the efforts equilibrium levels, $e_j = e, \forall j$. Furthermore, although, parameter m will vary between traffickers, I will omit

[10]Following other works I assume that officer's superiors are incorruptible (Bowles and Garoupa, 1997; Basu et al., 1992).

its sub-indices in what follows for the simplicity of notation. The expected profits of the LEA are then given by:

$$
\begin{aligned}
E\left[\Pi_j^L(e,q,B)\right] = (1-\theta)\left[we + \varepsilon(1-\phi\psi)p_d q - \frac{1}{2}\gamma e^2 + B\right] \\
+ \theta\left[we + \varepsilon(1-\phi\psi)p_d q - \frac{1}{2}\gamma e^2 + B - S - m\right]
\end{aligned}
$$

Simplifying one gets:

$$
E\left[\Pi_j^L(e,q,B)\right] = we + \varepsilon(1-\phi\psi)p_d q - \frac{1}{2}\gamma e^2 + B - \theta(S+m) \tag{3.5}
$$

The bribe system can be conceived similar to a tax system, where revenues are allocated for specific expense items (Buchanan, 2006). Bribes give traffickers the right to operate in particular police jurisdictions (Buchanan, 2006; Sisk, 1982). That's why B enters linearly in both agents' expected profits.

Lastly, it is assumed that the inverse demand function facing each monopolistic trafficker is linear and given by

$$
p_d = a - q, \tag{3.6}
$$

wherein $a > 0$ is the drug-market size.

3.3 Solution

The model can be solved by backward induction, beginning with the bribes' bargaining in the third stage.

3.3.1 Third stage: bargaining

Every pair of traffickers and officers bargain about the amount of bribes. Both agents compare their expected payoffs with bribes and without them when deciding to bribe. This means they evaluate the net expected payoffs of bribery when bargaining. If there is successful bribery, by definition $\phi = 1$; if not, then $\phi = 0$. Let's consider first the traffickers decisions. It can be seen from Eq. (3.4) that when there is successful bargaining, trafficker's expected payoffs are given by:

$$E\left[\Pi_i^{ST}(q,B)\right] = \psi p_d q - B - \mu + \psi(1-\theta)F - F; \tag{3.7}$$

In contrast, if bargaining is not successful their expected payoffs are:

$$E\left[\Pi_i^{NST}(q)\right] = -\mu - F. \tag{3.8}$$

Consequently, their net payoffs from bribes are then:

$$NE\left[\Pi_i^{T}(q,B)\right] = \psi p_d q - B + \psi(1-\theta)F. \tag{3.9}$$

Now, consider the officers payoffs: Using Eq. (3.5) it can observed that when successful bargaining their expected profits will be:

$$E\left[\Pi_j^{SL}(e,q,B)\right] = we + \varepsilon(1-\psi)p_d q - \frac{1}{2}\gamma e^2 + B - \theta(S+m); \tag{3.10}$$

In the other case when bargaining is unsuccessful their expected profits correspond to:

$$E\left[\Pi_j^{NSL}(e,q)\right] = we + \varepsilon p_d q - \frac{1}{2}\gamma e^2. \tag{3.11}$$

Therefore, their net payoffs from bribes are:

$$NE\left[\Pi_j^{L}(e,q,B)\right] = B - \varepsilon\psi p_d q - \theta(S+m); \tag{3.12}$$

It is worth noting that the terms we for both situations —with successful bribery (Eq. 3.10) and without it (Eq. 3.11)— cancel each other out, since the equilibrium level of efforts with successful bribery —that will be denoted as e^{S*}— is equivalent to its level with unsuccessful bribery –soon to be denoted as e^{NS*}— . I will prove it when analyzing the second-stage equilibrium of the game.

Following Cadot (1987) and Bowles and Garoupa (1997) the asymmetric Nash Product of the net payoffs are:

$$\mathcal{P} \equiv [\psi p_d q - B + \psi(1-\theta)F]^{\alpha} [B - \varepsilon\psi p_d q - \theta(S+m)]^{1-\alpha}, \tag{3.13}$$

where $\alpha \in (0,1)$ denotes the weight of traffickers in bargaining, whereas $1-\alpha$ denotes the weight of the LEAs.The bargain problem is then to maximize the asymmetric Nash Product with respect to B:

$$\max_{B} \quad [\psi p_d q - B + \psi(1-\theta)F]^{\alpha} [B - \varepsilon\psi p_d q - \theta(S+m)]^{1-\alpha}, \tag{3.14}$$

Solving for B gives the amount of bribes bargained B^* :

$$B^* = (1-\alpha)[\psi(1-\theta)F + \psi p_d q] + \alpha [\varepsilon\psi p_d q + \theta(S+m)]. \tag{3.15}$$

It can be checked that this third-stage equilibrium level of bribes corresponds to a global maximum as $\alpha \in (0,1) \Rightarrow \dfrac{\mathrm{d}^2\mathcal{P}}{\mathrm{d}B^2} < 0$. In the special case when $\alpha = 1/2$ we would get the symmetric Nash bargaining solution (Nash, 1950), which corresponds to the Kalai-Smorodinsky solution too (Kalai et al., 1975).

To be a feasible bribe, B^* must be such that the net expected payoffs from the bribes for traffickers and LEAs be positive, so that both are better off when successfully bargaining. Replacing B^* in the respective net expected payoffs it can be proved that for relatively small levels of the detection probability of corrupted LEAs, θ, these conditions are satisfied. In concrete:

i) $NE\left[\Pi_i^T(q,B)\right] = \psi p_d q - B^* + \psi(1-\theta)F \geq 0 \iff \theta \leq \dfrac{\psi[F + (1-\varepsilon)p_d q]}{(S+m)}$,

ii) $NE\left[\Pi_j^L(e,q,B)\right] = B^* - \varepsilon\psi p_d q - \theta(S+m) \geq 0 \iff \theta \leq \dfrac{\psi[F + (1-\varepsilon)p_d q]}{(S+m)}$

Eq. (3.15) indicates several interesting results for the third-stage equilibrium: i) The equilibrium level of bribes is increasing in the fine charged to the traffickers, F. This make sense as, the higher is F, the more is willing to pay a trafficker to avoid the fine. In fact, the term $\psi p_d q + \psi(1-\theta)F$ in $NE\left[\Pi_i^T(q,B)\right]$ corresponds to the trafficker's willingness to pay for the bribe. ii) An analogous effect occurs with the sanction applied for the LEA in case of detection, S: one increase in it leads to a rise in B^*. As S increases, the LEAs' expected loss caused by the bribe —which corresponds to $\varepsilon\psi p_d q + \theta(S+m)$— goes up, so that they will be expecting a higher compensation in terms of bribes. iii) The impact of one increase in the LEAs probability of detection, θ, depends on the weight of the two types of agents in bargaining: if the weight of traffickers is large, it increases; the contrary occurs if it is small. iv) By the same reason B^* also increases with m. This means that, if corrupted, higher m-type officers —that is to say agents facing higher moral costs— will demand higher compensations in terms of bribes.

Moreover, v) one increase in the value of drugs trafficked and sold, $p_d q$, results in a higher level of B^*. This is explained by the fact that with a higher $p_d q$ the trafficker's willingness to pay for the bribes increases, while the LEAs' expected loss for them also increases [11]. vi) The amount of bribes increases with the premium rate, ε. This is due to the positive impact of it on the LEAs' expected loss for the bribe, by which they tend to demand a higher compensation in terms of bribes. vii) An increase in the technological factor, ψ, leads to a rise in B^*. The explanation is similar to the preceding effects. viii) It can be checked that an increase in the traffickers' weight in bargaining will cause a decrease in B^*. This results holds as $\theta \leq \dfrac{\psi\left[F+(1-\varepsilon)p_d q\right]}{(S+m)}$.

Probability of successful bribery

Replacing B^* in the LEAs' expected profits it is possible to determine the LEAs who will accept bribes (or not) depending on their attitudes toward corruption —captured by their parameter m—, and thus the probability of successful bribery. Hence, replacing Eq. (3.15) in Eq. (3.12) and simplifying it can be seen that her third-stage net expected profits are given by:

[11] Nonetheless, the effect of a change in $p_d q$ on B^* is only a third-stage partial effect, because —as I will show when solving for the first stage of game— both p_d and q are endogenous.

$$NE\left[\Pi_j^L(e,q)\right] = (1-\alpha)\left[\psi F - \psi(1-\varepsilon)p_d q - \theta(S+m+\psi F)\right]. \qquad (3.16)$$

As a result, the agent j will be corrupt if

$$(1-\alpha)\left[\psi F - \psi(1-\varepsilon)p_d q - \theta(S+m+\psi F)\right] \geq 0 \iff \theta \leq \frac{\psi\left[F+(1-\varepsilon)p_d q\right]}{(S+m+\psi F)}.$$

Then, following Bowles and Garoupa (1997) it is possible to define a threshold of beyond for which a LEA won't be corrupted:

$$\widetilde{m} = \begin{cases} \psi\left[\dfrac{F(1-\theta)}{\theta} + \dfrac{(1-\varepsilon)p_d q}{\theta}\right] - S & \text{if } 0 \leq \theta \leq \dfrac{\psi\left[F+(1-\varepsilon)p_d q\right]}{(S+\psi F)} \\ 0 & \text{otherwise} \end{cases} \qquad (3.17)$$

Therefore, all the js such that $m \leq \widetilde{m}$ will be corrupted, while the rest of them won't be corrupted. Thus, for the first $B = B^*$, whereas for the latter $B = 0$. The probability of an officer to be corrupted is then given by:

$$L(m < \widetilde{m}) = \int_0^{\widetilde{m}} l(m)\, dm \qquad (3.18)$$

As a result, the probability of successful bribery can be endogenized as $\phi = L(\widetilde{m})$.

Several results can be pointed out with respect to the critical value $\widetilde{m}$ and the probability of corruption: 1) One increase in F leads to a rise in it, which means that a higher fine imposed to traffickers will encourage corruption, leading to an increase in the probability of successful bribery. Notice that $\dfrac{\mathrm{d}\phi}{\mathrm{d}F} = \dfrac{\mathrm{d}L(\widetilde{m})}{\mathrm{d}\widetilde{m}} \cdot \dfrac{\mathrm{d}\widetilde{m}}{\mathrm{d}F} = l(\widetilde{m}) \cdot \dfrac{\phi(1-\theta)}{\theta} > 0$. This result is consistent with F's impact on B^*, already explained. 2) On the contrary, one increase in the sanction applied for the LEAs in case of detection, S, will cause a fall in $\widetilde{m}$, discouraging corruption: $\dfrac{\mathrm{d}\phi}{\mathrm{d}S} = \dfrac{\mathrm{d}L(\widetilde{m})}{\mathrm{d}\widetilde{m}} \cdot \dfrac{\mathrm{d}\widetilde{m}}{\mathrm{d}S} = -l(\widetilde{m}) < 0$. 3) A similar effect will occur when there is an increase in the LEAs' detection probability,

θ, since $\dfrac{\mathrm{d}\widetilde{m}}{\mathrm{d}\theta} = -\psi\left[\dfrac{F}{\theta^2} + \dfrac{(1-\varepsilon)p_d q}{\theta^2}\right] < 0$. These results go in the same direction of Bowles and Garoupa (1997)'s findings for their (more general) crime model.

Furthermore, 4) the larger is the value of drugs trafficked and sold, $p_d q$, the higher is $\widetilde{m}$. Therefore, an increase in this variable encourages corruption [12]. 5) On the other hand, an increase in the premium rate, ε has the opposite effect on $\widetilde{m}$. That's the reason why the premium rate constitutes an important policy instrument to increase corruption deterrence. Its analysis —as I already remarked— is one of the contributions of the present model. 6) It can also be checked that one increase in the technological factor, ψ, will cause a rise in $\widetilde{m}$, encouraging corruption and leading to an increase in the probability of successful bribery. 7) From Eq. (3.17) it gets clear that the weight in bargaining of each kind of agent does not affect $\widetilde{m}$, nor the probability of successfully bargaining, as a consequence. The same result was found by Bowles and Garoupa (1997).

3.3.2 Second stage: LEAs' choices on e

In this stage the LEAs choose their optimal level of efforts, e. Each one knows her own level of m —that is to say her attitude toward corruption— . Hence the problem solved by the subset of officers for which $m \leq \widetilde{m}$ is different from the one solved by the rest of them. Let's begin with the latter: The LEAs with $m > \widetilde{m}$ know they are not corruptible, so that their decision problem corresponds to[13]:

$$\max_{e} \quad E\left[\Pi_j^{NSL}(e,q)\right] = we + \varepsilon p_d q - \frac{1}{2}\gamma e^2 \tag{3.19}$$

The first order conditions is:

$$w - \gamma e = 0 \tag{3.20}$$

[12] It is important to observe that the effect of a change in $p_d q$ on $\widetilde{m}$ is only a third-stage partial effect too, since p_d and q are endogenous.

[13] For incorruptible officers the term $\theta(S+m)$ disappears in the expected profits as θ is zero for them.

This condition states that on her optimum an incorruptible LEA chooses the effort level for which the wage rate equals the marginal costs of efforts. It can be checked that it corresponds to a maximum as $\dfrac{\mathrm{d}^2 E\left[\Pi_j^{NSL}(e,q)\right]}{\mathrm{d}e^2} = -\gamma < 0$. From Eq. (3.19) we can obtain the equilibrium level of efforts for an incorruptible LEA, e_J^{NS*}.

$$e^{NS*} = \frac{w}{\gamma}, \tag{3.21}$$

equation which shows that the level of efforts depends positively and in a proportional way on w, and inversely on the interdiction cost parameter, γ. Replacing in the respective expected profits, one gets the second-stage equilibrium expected profits for incorruptible officers.

$$E\left[\Pi_j^{NSL}(e^*,q)\right] = \frac{w^2}{2\gamma} + \varepsilon p_d q, \tag{3.22}$$

which increases with the wage rate and the premium-rate payments, $\varepsilon p_d q$, but decreases with γ.

Now, consider the decision problem for the corruptible officers, for which $m \leq \widetilde{m}$. Their choice problem is:

$$\max_e \quad E\left[\Pi_j^{SL}(e,q,B^*)\right] = we + \varepsilon(1-\psi)p_d q - \frac{1}{2}\gamma e^2 + B^* - \theta(S+m), \tag{3.23}$$

The first order conditions is then:

$$w - \gamma e = 0, \tag{3.24}$$

the same we got for incorruptible officers. As a result, the second-stage equilibrium level of e for incorruptible officers equals its level for corruptible officers:

$$e^{S*} = \frac{w}{\gamma}, \tag{3.25}$$

Replacing in their respective expected profits, also using Eq. (3.15) and rearranging terms, one gets the second-stage equilibrium expected profits for corruptible officers:

$$E\left[\Pi_j^{SL}(e^*, q, B^*)\right] = \frac{w^2}{2\gamma} + \varepsilon p_d q + (1-\alpha)\theta(\widetilde{m} - m), \tag{3.26}$$

which is increasing in the wage rate and in the premium-rate payments, though decreasing in γ. In addition, it depends positively on the term $(1-\alpha)\theta(\widetilde{m}-m)$, which captures the revenues coming from successful bribery. Notice that this term increases with the LEAs' weight in bargaining $(1-\alpha)$, the detection probability, θ, and the difference between $\widetilde{m}$ and m.

Therefore, comparing the two previous equations, it can be easily checked that
$\forall (j,j') \in \left\{(j,j')/j \in [0,\widetilde{J}] \wedge j' \in (\widetilde{J}, J]\right\}, [E\left[\Pi_j^{SL}(e^*, q, B^*)\right] \geq E\left[\Pi_{j'}^{NSL}(e^*, q)\right]],$
where $[0,\widetilde{J}]$ is the ordered subset of officers for which $m \leq \widetilde{m}$, being its inferior limit $j = 0$, the LEA for which $m = 0$, and its upper limit, $j = \widetilde{J}$, the LEA for which $m = \widetilde{m}$. The complement subset, $(\widetilde{J}, J]$ corresponds to the set of incorruptible officers, wherein $j = J$ represents the officer with the maximum level of moral costs, $m = m_{max}$. I will prove formally this result further on when solving the perfect-subgame equilibrium for the whole game.

3.3.3 First stage: traffickers' sales and entry decisions

In the first stage traffickers decide the amount of drugs to be trafficked and sold, which is a short-run decision. They also revise their prospective choices regarding to enter (or not) to illegal activities, which is a long-run decision. They take these decisions knowing what will be the bargained-equilibrium level of bribes (given by Eq. (3.15)) and the probability of successful bribery (given by Eq. (3.18)) (Bowles and Garoupa, 1997). However, also following Bowles and Garoupa (1997) I assume each trafficker does not know the specific LEA-type (corruptible or incorruptible) with which he will bargain.

Replacing Eq. (3.18) in Eq. (3.15) each trafficker's expected bribes level can be calculated:

$$B^* = (1-\alpha)\left[\psi(1-\theta)F + \psi p_d q\right] + \alpha\left[\varepsilon\psi p_d q + \theta S + \theta E\left[m/m < \widetilde{m}\right]\right]; \quad (3.27)$$

Now replacing this equation in the traffickers' expected profits (given by Eq. (3.4)) and making some algebra one gets:

$$E\left[\Pi_i^T(q, B^*)\right] = \alpha\theta\left[L(\widetilde{m})\widetilde{m} - \int_0^{\widetilde{m}} ml(m)\,dm\right] - F - \mu. \tag{3.28}$$

Short-run decisions

With atomistic monopolistic competition the short-run decision problem for each trafficker (taking into account equations for the inverse demand function (Eq. (3.6)) and $\widetilde{m}$ (Eq.(3.17)) will be:

$$\max_q \quad E\left[\Pi_i^T(q, B^*)\right] = \alpha\theta\left[L(\widetilde{m}(q))\widetilde{m}(q) - \int_0^{\widetilde{m}(q)} ml(m)\,dm\right] - F - \mu. \tag{3.29}$$

Simplifying, the first order condition gives:

$$L(\widetilde{m}(q))\alpha\psi(1-\varepsilon)\left[a - 2q\right] = 0; \tag{3.30}$$

equation from which the equilibrium level of q for every trafficker i can be obtained:

$$q^* = a/2, \tag{3.31}$$

Eq. (3.31) corresponds to the perfect-subgame Nash equilibrium level of q[14]. It shows that —as expected— q^* is equal for every trafficker (remember that marginal costs tend to zero for all of them) and depends positively on the market size, a[15]. Replacing in the inverse demand function (Eq. (3.6))

[14]Notice that as $\alpha\psi(1-\varepsilon) \geq 0$, and $L(\widetilde{m}(q)) \in [0, 1]$ as well as increasing in q, the unique solution to this problem corresponds to $q^* = a/2$

[15]This is a standard result for a monopolistic firm facing a linear demand function and zero marginal costs.

the equilibrium wholesale price of drugs can be calculated:

$$p_d{}^* = a/2; \tag{3.32}$$

As a consequence, the perfect-subgame Nash equilibrium level of the drugs' wholesale price depends positively on the market size[16].

Using Eqs. (3.31) and (3.32) the equilibrium level of the value of drugs trafficked and sold by every i can be calculated;

$$p_d{}^* q^* = a^2/4; \tag{3.33}$$

This equation shows that in equilibrium the value of drugs trafficked and sold by each trafficker in the wholesale market increases with a (the market size). In fact, it can be easily proved that $p_d{}^* q^*$ is a strict convex-increasing function of this parameter. This result is explained by the impact of parameters' changes both in q^* and $p_d{}^*$. They reveal that the market size —as expected— is the essential and most powerful force fueling this kind of illegal activities. Figure 3.1 depicts this relationship.

[16] This is also a standard result for a monopolistic firm with linear demand function and null marginal costs.

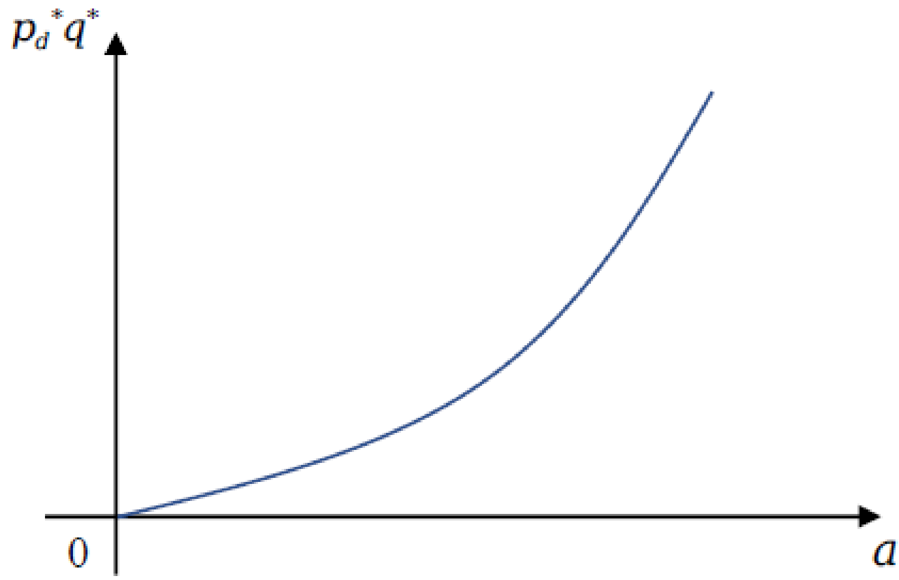


Figure 3.1: Value of drugs sold as a function of the market size.

Long-run decisions

In the long-run traffickers decide to enter (or not) to the illegal business. Replacing Eqs. (3.31) and (3.33) in their expected profits one gets:

$$L(\widetilde{m}^*)\alpha\left[\psi(1-\varepsilon)(a^2/4)+\psi(1-\theta)F-\theta S-\theta E\left[m/m<\widetilde{m}^*\right]\right]-F-\mu, \tag{3.34}$$

where $\widetilde{m}^*$ corresponds to the critical value of the parameter of attitude towards corruption, m, evaluated in subgame-perfect Nash equilibrium:

$$\widetilde{m}^* = \begin{cases} \psi\left[\dfrac{F(1-\theta)}{\theta}+\dfrac{(1-\varepsilon)(a^2/4)}{\theta}\right]-S & \text{if } 0\leq\theta\leq\widetilde{\theta} \\ 0 & \text{otherwise;} \end{cases} \tag{3.35}$$

where $\widetilde{\theta}\equiv\dfrac{\psi\left[F+(1-\varepsilon)(a^2/4)\right]}{(S+\psi F)}$.

Using Eq. (3.28) traffickers' expected profits can be written simply as:

$$E\left[\Pi_i^{T*}(q^*,B^*)\right] = \alpha\theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right] - F - \mu. \qquad (3.36)$$

The decision to entry (or not) will depend on $E\left[\Pi_i^T(q^*,B^*)\right]$ (Bowles and Garoupa, 1997). Traffickers will entry if $E\left[\Pi_i^T(q^*,B^*)\right] \geq 0$. In other case they won't do it. As μ is heterogeneous between traffickers, this parameter will be the key decision factor for the traffickers long-run choice: A trafficker will decide to enter to the market and traffic drugs if and only if:

$$\mu \leq \alpha\theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right] - F. \qquad (3.37)$$

Therefore, the threshold of fixed costs, μ, beyond for which traffickers won't entry to illegal business will be:

$$\widetilde{\mu} = \alpha\theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right] - F. \qquad (3.38)$$

It can be proved that $\widetilde{\mu}$ is a convex-decreasing function of θ, so that $\widetilde{\mu} \geq 0$ only if $\theta \leq \dfrac{L(\widetilde{m}^*)\psi(F+(1-\varepsilon)(a^2/4)) - F/\alpha}{L(\widetilde{m}^*)(\psi F + S) + \int_0^{\widetilde{m}^*} ml(m)\,dm} < \widetilde{\theta}$ (see below Long-run Equilibrium Theorem). Furthermore, it can be proved that $\widetilde{\mu}$ is a convex-increasing function of ψ, reason why $\widetilde{\mu} \geq 0$ only if $\psi \geq \left[\dfrac{F(1-\theta)}{\theta} + \dfrac{(1-\varepsilon)(a^2/4)}{\theta}\right]^{-1}\left\{S + \dfrac{F}{\alpha\theta L(\widetilde{m}^*)} + \dfrac{\int_0^{\widetilde{m}^*} ml(m)\,dm}{L(\widetilde{m}^*)}\right\}$ (see Long-run Equilibrium Theorem too). In addition, it can be proved that $\widetilde{\mu}$ is a linear increasing function of α, for which $\widetilde{\mu} \geq 0$ only if $\alpha \geq \dfrac{F}{\theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right]}$ (see also Long-run Equilibrium Theorem).
Let
$\hat{\theta} \equiv \dfrac{L(\widetilde{m}^*)\psi(F+(1-\varepsilon)(a^2/4)) - F/\alpha}{L(\widetilde{m}^*)(\psi F + S) + \int_0^{\widetilde{m}^*} ml(m)\,dm}$,
$\hat{\psi} \equiv \left[\dfrac{F(1-\theta)}{\theta} + \dfrac{(1-\varepsilon)(a^2/4)}{\theta}\right]^{-1}\left\{S + \dfrac{F}{\alpha\theta L(\widetilde{m}^*)} + \dfrac{\int_0^{\widetilde{m}^*} ml(m)\,dm}{L(\widetilde{m}^*)}\right\}$, and
$\hat{\alpha} \equiv \dfrac{F}{\theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right]}$. The following theorem formalizes the

existence of a perfect-subgame equilibrium level of $\widetilde{\mu}$ as a function of the model's parameters, which determines the long-run equilibrium:

Long-run Equilibrium Theorem. *In the perfect-subgame Nash equilibrium,* $(\forall\alpha \in [\hat{\alpha}, 1])(\forall\psi \in [\hat{\psi}, 1])(\forall\theta \in [0, \hat{\theta}])(\exists\widetilde{\mu}(\widetilde{m}^*) \geq 0)$*, such that* $\widetilde{\mu}(\widetilde{m}^*)$*: i) is a strict convex-increasing function of* a*, ii) increases linearly with* α*, iii) is a strict convex-increasing function of* ψ*, iv) a strict convex-decreasing function of* F*, v) a strict convex-decreasing function of* S*, vi) a strict convex-decreasing function of* θ*, and vii) and a strict convex-decreasing function of* ε*.*

Proof. See appendix. ■

In Eq. (3.37), the second term $-F$ captures the impact of the traffickers' sanction on deterrence (Becker, 1968; Bowles and Garoupa, 1997): The higher it is, the lower is the critical value μ, and hence, the stronger is trafficking deterrence. On the other hand, the term $\alpha\theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right]$, which is positive by construction, weakens deterrence: the larger it is, the higher is the critical value μ. This term captures the impact of corruption on deterrence, and reveals that corruption weakens deterrence. This goes in the same direction of the findings of Bowles and Garoupa (1997)'s model.[17]

As a result, the proportion of traffickers actually selling drugs is given by:

$$\Upsilon(\mu < \widetilde{\mu}) = \int_0^{\widetilde{\mu}} \upsilon(\mu)\,d\mu \tag{3.39}$$

3.3.4 Closing the model

The seizure probability and the traffickers equilibrium-success probability can be written in equilibrium respectively as:

$$z^* = 1 - L(\widetilde{m}^*)\psi, \tag{3.40}$$

[17] In the following section the possible deterrence instruments will be analyzed with more detail.

$$(1 - z^*) = L(\widetilde{m}^*)\psi, \tag{3.41}$$

Eqs. (3.40) and (3.41) show that in equilibrium both the seizure probability and traffickers' success probability are functions of ψ and the other parameters determining the probability of successful bribery (through $\widetilde{m}^*$). Using Eqs. (3.18) and (3.35) it can be checked that while z^* increases with S, θ, and ε, it decreases with, F, a and ψ. As expected, they have the opposite effects on $(1-z^*)$. In addition, α does not affect neither of them as it doesn't determine $\widetilde{m}^*$. Proposition 3.1 formalizes results regarding z^*. An analogous analysis can be done for $(1 - z^*)$.

Proposition 3.1. *In the perfect-subgame Nash equilibrium, $\forall\psi \in [\hat{\psi}, 1]$ and $\forall\theta \in [0, \hat{\theta}]$, i) z^* is a monotonic decreasing function of a, ii) a monotonic decreasing function of ψ, iii) a monotonic decreasing function of F, iv) a monotonic increasing function of S, v) a monotonic increasing function of θ, and vi) a monotonic increasing function of ε.*

Proof. i) It can be checked that $\forall a \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}z^*}{\mathrm{d}a} = -l(\widetilde{m}^*)\psi^2 \dfrac{(1-\varepsilon)(a/2)}{\theta} < 0$, which ensures that z^* is a monotonic decreasing function of a. ii) $\forall\psi \in [\hat{\psi}, 1]$, $\dfrac{\mathrm{d}z^*}{\mathrm{d}\psi} = -l(\widetilde{m}^*)\psi \left[\dfrac{F(1-\theta)}{\theta} + \dfrac{(1-\varepsilon)(a^2/4)}{\theta}\right] - L(\widetilde{m}^*) < 0$, which ensures that z^* is a monotonic decreasing function of ψ. iii) $\forall F \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}z^*}{\mathrm{d}F} = -l(\widetilde{m}^*)\psi^2 \dfrac{(1-\theta)}{\theta} < 0$, so that z^* always decreases with F. iv) z^* is a monotonic increasing function of S, since $\forall S \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}z^*}{\mathrm{d}S} = l(\widetilde{m}^*)\psi > 0$. v) It can be checked that, $\forall\theta \in [0, \hat{\theta}]$, $\dfrac{\mathrm{d}z^*}{\mathrm{d}\theta} = l(\widetilde{m}^*)\dfrac{\psi^2}{\theta^2}\left[F + (1-\varepsilon)(a^2/4)\right] > 0$, reason why z^* is a monotonic increasing function of θ. vi) $\forall\varepsilon \in [0, 1]$, $\dfrac{\mathrm{d}z^*}{\mathrm{d}\varepsilon} = l(\widetilde{m}^*)\psi^2 \dfrac{(a^2/4)}{\theta} > 0$. This assures that z^* is always an increasing function of ε. ■

To close the model only finding LEAs equilibrium expected profits is missing. Replacing Eq. (3.33) in the second-stage equilibrium expected profits of incorruptible LEAs one gets:

$$E\left[\Pi_j^{NSL*}(e^*, q^*)\right] = \frac{w^2}{2\gamma} + \varepsilon(a^2/4). \tag{3.42}$$

Now, replacing Eqs. (3.33) and (3.35) in the second-stage equilibrium expected profits of corruptible LEAs one gets:

$$E\left[\Pi_j^{SL*}(e^*, q^*, B^*)\right] = \frac{w^2}{2\gamma} + \varepsilon(a^2/4) + (1-\alpha)\theta(\widetilde{m}^* - m). \tag{3.43}$$

With the latter equations it can be proved that expected profits will be greater for corruptible LEAs than for incorruptible ones in equilibrium. The following proposition states it formally:

Proposition 3.2. *Let* $\mathcal{J} = \left\{(j, j')/j \in [0, \widetilde{J}] \wedge j' \in (\widetilde{J}, J]\right\}$. *In the perfect-subgame Nash equilibrium,* $\forall (j, j') \in \mathcal{J}, [E\left[\Pi_j^{SL*}(e^*, q^*, B^*)\right] \geq E\left[\Pi_{j'}^{NSL*}(e^*, q^*)\right]]$.

Proof. Using Eqs. (3.31) and (3.33) it was already proved that $\forall i \in [0, I], q^* = a/2$, and that $p_d{}^* q^* = a^2/4$.Then,
$\forall (j, j') \in \mathcal{J}, E\left[\Pi_j^{SL*}\right] \geq E\left[\Pi_{j'}^{NSL*}\right] \iff (\forall j \in [0, \widetilde{J}]) \left[(1-\alpha)\theta(\widetilde{m}^* - m) \geq 0\right]$.
The right hand of the equivalence holds since $(\forall j \in (0, \widetilde{J}))(m < \widetilde{m}^*)$; also, for $j = 0, m = 0$, so that $((1-\alpha)\theta(\widetilde{m}^*)) > 0$ too; Lastly, for $j = \widetilde{J}, m = \widetilde{m}^*$, so that $((1-\alpha)\theta(\widetilde{m}^* - \widetilde{m}^*) = 0$ ■

3.4 Perfect-subgame equilibrium results

3.4.1 Factors fueling trafficking

Increases in the market size

The drug-market size, a, is the most powerful force behind the illicit organizations' performance. One increase in it leads to a rise in the value of drugs (see Eq. 3.33). As a result, B^* and LEAs' $\widetilde{m}^*$ –which are convex-increasing functions of this parameter— increase too (see Proposition 3.3 in the Appendix C). Therefore, it weakens corruption deterrence leading to a boost in the probability of successful bribery. In addition, one increase in a provokes a raise in the critical value of fixed costs, since $\widetilde{\mu}^*$ is convex-increasing in a (see Long-run Equilibrium Theorem), so that the equilibrium number of traffickers selling drugs grows. What explains this result is that one increase in a entails a rise in traffickers' expected profits (see Proposition 3.4 in the Appendix C) due to its impact on traffickers' revenues. Their success probability goes up when there is an increase in a too, while the seizure probability falls (see Eqs. (3.40)-(3.41) and proposition 3.1).

On the LEAs side, one increase in the market size results in an increment in the expected profits for incorruptible officers as well as for corruptible ones (see Propositions 3.5 and 3.6 in the appendix). This effect arises from the fact that for both type of officers, expected profits depend positively on the value of drug sales, due to the premium payments received by them as a function of interdiction achievements and also to the bribery revenues (only in the case of the latter (see Eq. 3.15)).

More traffickers' weight in the bargaining process

Changes in the traffickers' weight in bargaining (α) don't have any impact on the critical value of parameter m ($\widetilde{m}$) (see Eqs. (3.17) and (3.35)), so that they don't affect the successful probability of bribery (see Eq. (3.18)) neither corruption deterrence. Nonetheless, one increase in α leads to an upturn in the critical value of fixed costs, $\widetilde{\mu}$ (see Long-run Equilibrium Theorem), generating increases in expected profits for traffickers (see Proposition 3.4). That's the reason why the larger is α, the higher is the number and proportion of traffickers selling drugs; indeed their expected profits tend to grow, since traffickers' revenues go up (see Proposition 3.4). However, their success probability does not depend on this parameter as $\widetilde{m}^*$ remains independent of it. The same happens with the LEAs' seizure probability

On the LEAs' side, a larger level of α, does no alter the expected profits for incorruptible officers (see Eq. (3.42)), but have a negative impact on expected profits for corruptible officers (see Eq. (3.43) and Proposition 3.6), as their bribery revenues go down.

Technological progress

Increases in parameter ψ due to technological progress in drug transportation and trafficking weaken the interdiction effectiveness (see Proposition 3.1). Although I have assumed that ψ is close to one, with the aim to capture the actual low rates of interception of drugs with $z^* = 1 - L(\widetilde{m}^*)\psi$ —between 10 and 20 percent in the case of cocaine (McDermott, 2021; Bargent, 2021)—, there can still be improvements in transportation and trafficking technology leading to even higher levels of ψ. This can be the case of using more sophisticated methods of drugs transportation —e.g. faster and noiseless semi-submersible craft—, or better methods to camouflage the illegal commodities in containers.

Any of these improvements straightforwardly flows out in an increase of the traffickers' success probability as well as a decrease in the seizure probability (see Eqs. (3.40)-(3.41) and Proposition 3.1). Due to its effect on the equilibrium level of bribes (see Eq.(3.15)), one increase in the technological factor provokes a growth in the LEAs' critical value $\widetilde{m}^*$ (see Proposition 3.3). That's the reason why technological improvements encourage corruption, inducing higher equilibrium levels of the probability of successful bribery (see Eq. (3.18)).

Moreover, one increase in ψ boosts a rise in the critical value of traffickers' fixed costs too: it can be checked that $\widetilde{\mu}^*$ is a convex-increasing function of ψ (see Long-run Equilibrium Theorem). Its impact on traffickers' expected profits explains this effect (see Proposition 3.4). For this reason, technological improvements promote the entry of more traffickers to the illicit activities and, consequently, (by Eq. (3.39)) the proportion of them actually selling drugs.

The LEAs expected profits for incorruptible officers do not depend on ψ as long as they are not fueled by bribery revenues (see Eq. (3.42)). In contrast, expected profits for corruptible agents increase linearly with it (see Proposition 3.6). This paradoxical result emerges from the impact ψ has on $\widetilde{m}^*$, which is a determinant of their expected profits (see Eq. (3.43)).

3.4.2 Anti-drug policy

The criminal policy used to repress and prosecute drug-trafficking organizations in the midstream links of the illegal productive chain include diverse instruments designed to seize drugs and deter the criminal performance. One of them is interdiction policy, focused on efforts of law enforcement authorities to seize drugs at the departure port, during transportation, or at the arrival port of illicit shipments. Although the model does not capture the direct effect of these efforts on interdiction probability, it allows us to analyze their indirect impact on officers' expected profits through salary payments, and also the indirect impact of other policy instruments —i.e. F, S, θ, and ε, on the probability of successful bribery, $L(\widetilde{m}^*)$, which captures the efforts or complicity of law enforcement authorities to deter or foster bribery, respectively, depending on their types —incorruptible or corruptible, respectively—. The importance of corruption deterrence lies in the fact that —as I already explained— corruption is an essential input for successful drug-smuggling and transportation. Remember that $L(\widetilde{m}^*)$ is endogenous in the model, being it an essential determinant of the equilibrium probability of interdiction $(z^* = 1 - L(\widetilde{m}^*)\psi)$.

Another instrument is the anti-narcotics agencies and officers' effort invested to capture drug-smugglers and wholesale traffickers. The present model does not analyze directly but indirectly this instrument through the seizure probability and the impact of officers' efforts on expected profits through salary payments. A third policy-instrument is related with the laws and actions implemented by the judicial system and the government to capture, prosecute, and convict corrupt officers. The parameter θ indicates their resulting performance dealing with the capture and prosecution of corrupt officers. Other two instruments constitute the basic judicial tools to deter crime: First, the fine faced by traffickers when drugs are seized (F), or even when not, depending on the probability of corrupted officers to be detected, in which case the expected fine is θF. Second, the sanction imposed to corrupted officers (S) when detected by a superior or the anti-narcotic agency directly. These three latter tools —F, S, and θ— are the standard criminal-policy instruments in Becker-type models (Becker, 1968; Ehrlich, 1973; Polinsky and Shavell, 1979; Bowles and Garoupa, 1997).

In the present work, I am proposing the analysis of another criminal-policy instrument: the premium payments received by officers as a function of their interdiction achievements, $\varepsilon z^* {p_d}^* q^*$ and, i.e., of the premium rate, ε. The model allows us to analyze the effects of this policy instrument on corruption, drug-trafficking deterrence and the endogenous variables. In the following lines, I will analyze the effects of w, F, S, θ, and ε on them.

Increases in the officers' salaries

If the government approves one increase in the officers' salaries, w, their equilibrium level of efforts —both for incorruptible and corruptible officers—, will go up (see Eqs. (3.21) and (3.22)). As a consequence, their equilibrium salary payments ($\frac{w^2}{2\gamma}$) will grow more that proportionally, resulting in higher expected profits for both type of officers (see Eqs. (3.22) and (3.26)); it can be checked that in both cases expected profits are convex-increasing functions of w (see Propositions 3.5 and 3.6).

Nonetheless, changes in w don't affect neither the drug-sales levels nor their value (see Eqs. (3.31) and (3.33)). They don't have any influence on traffickers expected profits neither (see Proposition 3.5). That's the reason why changes in this parameter don't affect traffickers decisions. Furthermore, changes in the officers' wage rate don't have any effect neither on B^* nor on the critical value $\widetilde{m}^*$. As a result, salary adjustments do not have any direct impact on corruption deterrence, nor on trafficking discouragement. Nevertheless, this kind of policy will be useful to encourage officers' public service, as it promotes a better policy reward, with higher expected profits for them.

However, as I will show, a rewards policy considering a retribution linked to officers' interdiction achievements will be more effective to deter corruption and drug trafficking. Both alternatives to improve enforcement through an appropriate rewards policy —throughout the wage policy or the implementation of a premium rate on achievements— go in the same direction of Becker and

Stigler (1974) analysis of law enforcement. These authors point out that a key policy to discourage corruption in cases when detection is uncertain is "to *raise* [18] the salaries of enforcers above what they could get elsewhere, by an amount that is inversely related to the probability of detection, and directly related to the size of bribes and other benefits from malfeasance" (Becker and Stigler, 1974, p. 6). But they add that a better policy choice would be the "compensation of enforcers on performance, or by a "piece-rate" or a "bounty", instead of a straight salary (Becker and Stigler, 1974, p. 14), that is to say, they consider a rewards policy based on a system of retribution over enforcement achievements a more effective alternative[19].

Increases in the fine imposed to traffickers

F affects corruption and drug-trafficking deterrence in opposite directions: On the one hand, increases in it, induce rises in the equilibrium level of bribes, B^*, and in the critical value $\widetilde{m}^*$ (see Proposition 3.3), leading to higher levels of the probability of successful bribery. As a consequence, they weaken corruption deterrence [20].

On the other hand, increases in F imply lower equilibrium levels of the critical value of traffickers' fixed costs, $\widetilde{\mu}$: it can be checked that $\frac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}F} = \frac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}\widetilde{m}^*} \cdot \frac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}F} = \alpha\theta L(\widetilde{m}^*)\psi^{\frac{(1-\theta)}{\theta}} - 1 < 0$. As a result, increases in F strengthen drug-trafficking deterrence, discouraging the entry of a certain number of traffickers to illegal markets. It is worth noting that, the first term of

[18] Italics from the cited authors.

[19] Becker and Stigler (1974) posit that such kind of enforcement rewarding would be even more efficient if private agents provide enforcement services. In their own words: "Why not then generalize this system, and let *anyone* enforce statutes and receive as compensation for performance the fines levied against convicted violators? Specialist enforcement firms would develop and would either compensate victims *en masse* (by appropriate division of penalties with, e.g., the motor vehicle fund), or retain all awards for themselves [italics from the cited authors]" (Becker and Stigler, 1974, p. 14). However, in the case of a victimless crime like drug trafficking, where a system of rewards on achievements will depend on the quantity of drugs seized, it does not seem to be feasible to develop a private enforcement system, since it will promote perverse incentives for them to grab (illegally) at least part of the drugs seized. The huge value of illegal drugs would be the perfect breeding ground for private enforcers to grab part of the drugs interdicted.

[20] I already explained these effects at the end of section 3.1 when analyzing the third-stage results.

$\frac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}F}$, $\alpha\theta L(\widetilde{m}^{*})\psi\frac{(1-\theta)}{\theta}$ —which is lower than one—, is always positive (see Long-run Equilibrium Theorem), capturing the impact of F's increase on the proportion of officers who become corrupted. Nonetheless, the second negative effect, -1, dominates the first one, and thus the net effect is a deterrence increase. This second term captures the direct effect of the fine on traffickers' expected profits. Indeed, its impact on them is exactly the same (see Proposition 3.4).

Furthermore, the expected profits of incorruptible officers do not depend on the traffickers' fine (see Eq. 3.42). In the meanwhile, the expected profits of corrupt agents are linear-increasing in it: $\frac{\mathrm{d}E\left[\Pi_{j}^{SL^{*}}(e^{*},q^{*},B^{*})\right]}{\mathrm{d}F} = (1-\alpha)(1-\theta)\psi > 0$ (see Proposition 3.6). This effect captures the influence of this parameter on the corruption-revenues received by this type of officers; Note that it would be nonexistent if the probability of detection, θ, were one, or if the weight of traffickers in bargaining, α, were one.

Furthermore, increases in F lead to decreases in the seizure probability and to increases in the traffickers' success probability owing to its effect on $\widetilde{m}^{*}$ (see Proposition 3.1). Therefore, yet paradoxical, higher levels of F weaken law enforcement as they boost corruption.

Increases in the fine imposed to officers

When analyzing the third-stage results, I already proved that increases in S provoke rises in B^{*} but reductions in $\widetilde{m}^{*}$. Therefore, tighter fines on traffickers, discourage corruption: it can be checked that $\frac{\mathrm{d}\widetilde{m}^{*}}{\mathrm{d}S} = -1 < 0$ (see Proposition 3.3). As a result, $\frac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}S} = \frac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}\widetilde{m}^{*}} \cdot \frac{\mathrm{d}\widetilde{m}^{*}}{\mathrm{d}S} = -\alpha\theta L(\widetilde{m}^{*}) < 0$ (see Eq. (38) and Long-run Equilibrium Theorem). Hence, increases in S flow out in an enhancement of drug-trafficking deterrence, because the proportion of traffickers actually selling drugs goes down (see Eq. (3.39)). The reason why the critical value of fixed costs ($\widetilde{\mu}$) falls, is that traffickers expected profits fall with increases in S: $\frac{\mathrm{d}E\left[\Pi_{i}^{T^{*}}(q^{*},B^{*})\right]}{\mathrm{d}S}$ equals $-\alpha\theta L(\widetilde{m}^{*}) < 0$ too (see proposition 3.4). Notice that the two latter effects would be non-existent if θ were zero. Therefore, with a zero detection policy S wouldn't affect the traffickers' expected profits neither increase deterrence.

Furthermore, one increase in S will not affect the expected profits of incorruptible officers (see Proposition 3.5); Instead, the expected profits of corrupted officers will diminish, since they depend positively on $\widetilde{m}^*$: $\dfrac{\mathrm{d}E\left[\Pi_j^{SL*}(e^*,q^*,B^*)\right]}{\mathrm{d}S} = (1-\alpha)\theta\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}S} = -(1-\alpha)\theta$ (see Proposition 3.6), which again would disappear if θ were zero; the explanation is that in this particular case officers wouldn't have to charge a risk premium (Bowles and Garoupa, 1997), neither B^* wouldn't increase with S.

In addition, increases in this parameter strengthen law enforcement as they provoke raises in the seizure probability (and drops in traffickers' success probability) (see Proposition 3.1).

Increases in the corrupt officers' probability of detection

The impact of this parameter on the equilibrium level of bribes, B^*, depends on the weight of traffickers in the bargaining process: if their weight is large, it will increase; on the contrary if it is small, then $\dfrac{\mathrm{d}B^*}{\mathrm{d}\theta} < 0$.

In addition, it can be checked that one increase in θ will induce a downward trend in the critical value of m, $\widetilde{m}^*$[21], discouraging corruption, and lowering the probability of successful bribery. Furthermore, it will cause a decrease in $\widetilde{\mu}^*$ too (see Long-run Equilibrium Theorem), because it will generate a decrease in the traffickers' expected profits (see Proposition 3.4). Consequently, increases in the corrupt officers' probability of detection induce more drug-trafficking deterrence, lowering the proportion of illicit agents actually selling drugs at the wholesale markets (see Eq. (3.39)).

In contrast, changes in this parameter do not alter the expected profits of incorruptible officers (see Eq. (3.42)). Nonetheless, expected profits of corruptible officers decrease as a result of a change in it (see Proposition 3.6); this effect is originated in the fact that for this type of LEAs, expected

[21] I proved this at the end of section 3.31, when examining the third-stage's results. Also see Proposition 3.3

profits partly hinge on the bribery revenues, which depend on θ (see the second term on the right side of Eq. (3.43), $(1-\alpha)\theta(\widetilde{m}^*-m)$).

Moreover, the higher is θ, the lower is the traffickers' success probability and the higher is the seizure probability, due to its impact on $\widetilde{m}^*$. As a result, more resources and better strategies used to discover, detect and capture corrupt officers strengthen law enforcement.

The effects of traditional criminal policy instruments (F, S, and θ) are as expected; they go in the same direction of Becker (1968) and Bowles and Garoupa (1997)'s main findings: all of them are effective to deter the entry of more traffickers to illicit markets in spite of the presence of corrupt agents. However, fines on traffickers are less effective as they encourage more corruption and corrupted officers; More effective alternatives are fines imposed to corruptible LEAs, S, as well as better police technologies and strategies to detect and capture this type of officers, which lead to increases in θ. But another effective policy instrument is the premium rate given to the officers in retribution to their achievements in interdiction tasks. In what follows, I will explain the reasons behind this statement.

Another proposed instrument: Increases in the premium rate

One increase in the premium rate will provoke a fall in the critical value $\widetilde{m}^*$. It can be checked that it is a linear-decreasing function of this parameter (see Proposition 3.3). Therefore, higher premium rates strengthen corruption deterrence and induce a lowering in the probability of successful bribery (see Eqs. (3.17) and (3.18)); Figure 3.2 shows this result. That's a reason why the premium rate constitutes a more effective instrument than F and θ: Unlike the first one, it potentiates corruption deterrence when it rises, and in contrast to the second one (θ)—whose marginal effects on $\widetilde{m}^*$ are decreasing—, marginal increases in it result in constant falls in $\widetilde{m}^*$ (due to its linearity in this parameter). A similar effect occurs on $\widetilde{m}^*$ when S increases.

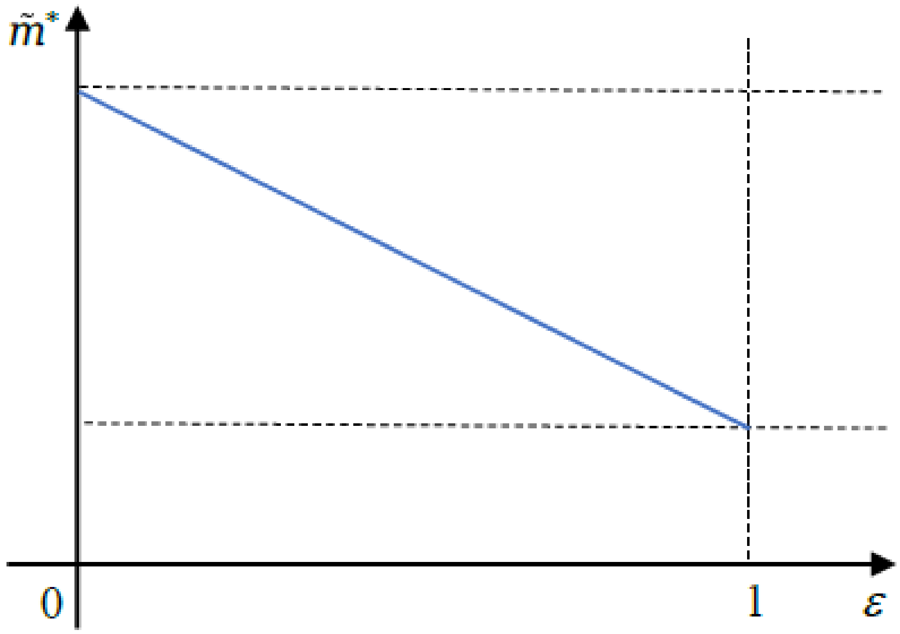


Figure 3.2: Critical value of moral costs as a function of the premium rate.

Furthermore, one increase in the premium rate will induce a fall in the critical value of fixed costs, $\widetilde{\mu}^*$, too; being this variable a convex-decreasing function of it (see Long-run Equilibrium Theorem and Figure 3.3). That's the reason why, for low levels of the premium rate, one increase in it causes a significant lowering in $\widetilde{\mu}^*$, as occurs with the effects of traditional policy instruments (F, S, and θ) on this variable. As a result, increases in the premium rate, deter the entry of more traffickers to illegal business and, consequently, lowers the proportion of them actually selling drugs at the wholesale market (see Eq. (3.39)). The explanation lies in the negative impact ε's increases have on expected traffickers' profits: they are a convex-decreasing function of ε too (see Proposition 3.4 and Figure 3.4).

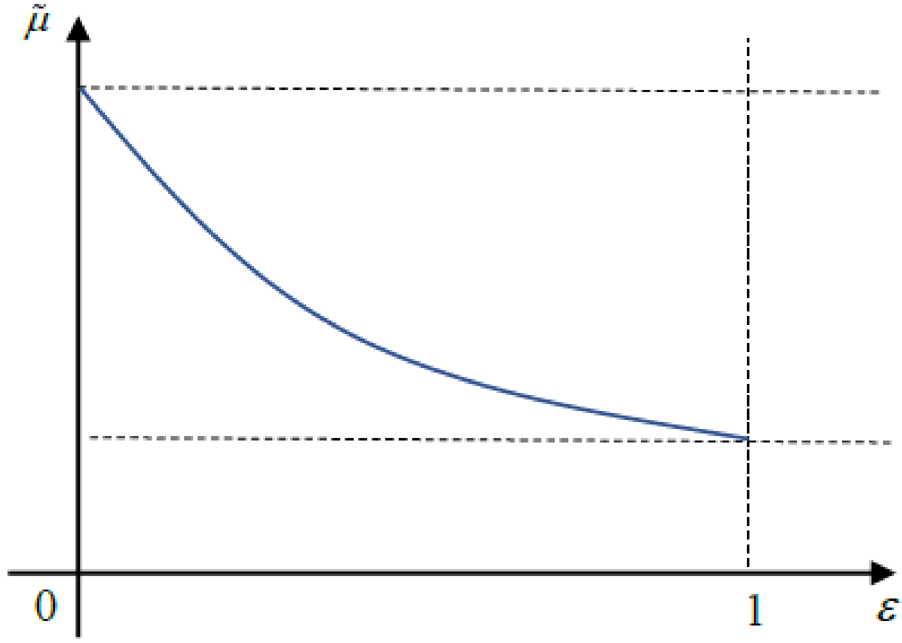


Figure 3.3: Critical value of fixed costs as a function of the premium rate.

What about the impact of ε's changes on the LEAs expected profits? First, it can be proved that for incorruptible officers they increase linearly with the premium rate (see Proposition 3.5 and Figure 3.5) due to the positive impact of larger rewards over interdiction achievements, given by the term $\varepsilon(a^2/4)$ (see Eq. (3.42)).

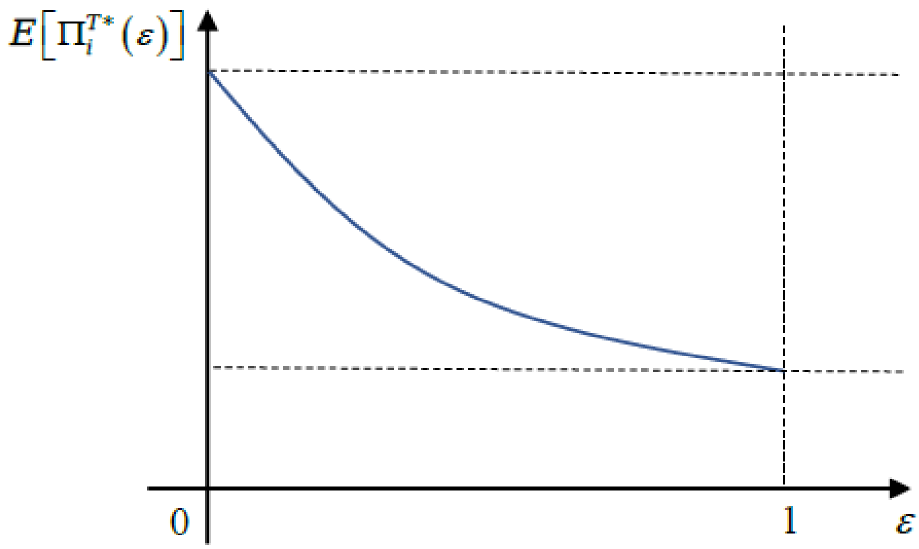


Figure 3.4: Traffickers' expected profits as a function of the premium rate.

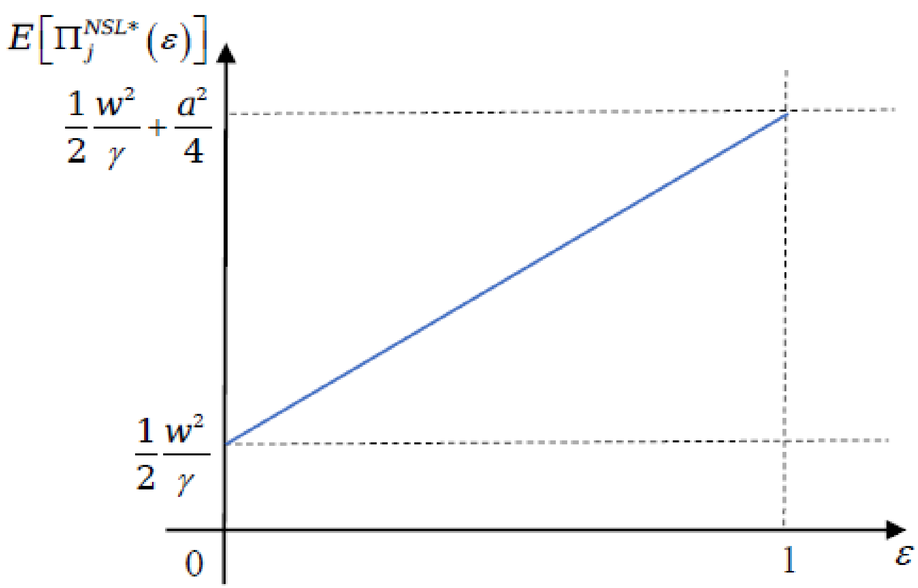


Figure 3.5: Incorruptible LEAs' expected profits as a function of the premium rate.

For corruptible LEAs, expected profits are a linear function of the premium rate too (see Eq. (3.43) and Proposition 3.6). However, profits are less steep for them than for incorruptible officers (See Figure 3.6), because in this case two different kinds of effect occur when there ins an increase in ε (see Proposition 3.6 and its proof): First, a direct positive marginal impact on rewards giving by ${p_d}^* q^*$ (see Eq. 3.43), which also arises for incorruptible officers. Second, a negative effect on $\widetilde{m}^*$, which —as I already explained— is a convex-decreasing function of ε. This second effect attenuates the first one. Nonetheless, the net effect remains positive as $\dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\varepsilon} = (1-(1-\alpha)\psi)(a^2/4)$, and $0 < (1-(1-\alpha)\psi) < 1$ (see Proposition 6).

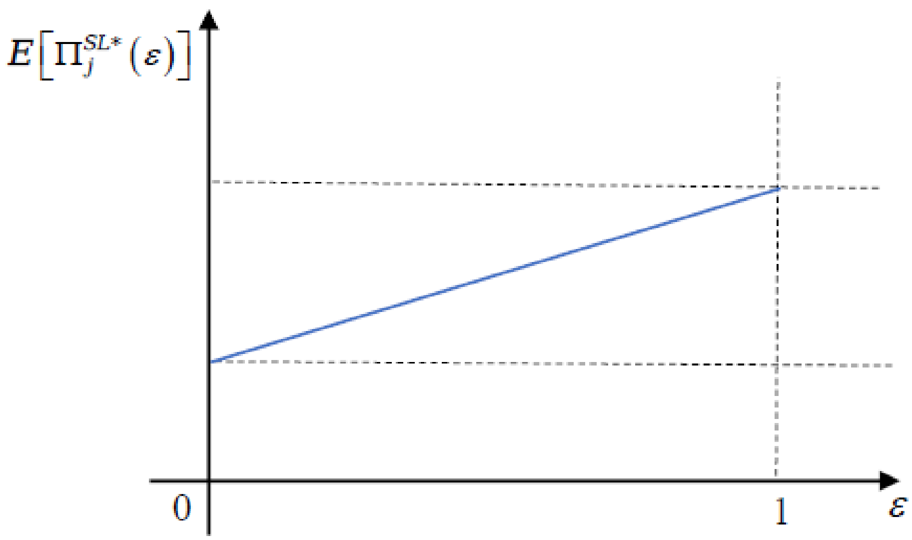


Figure 3.6: Corruptible LEAs' expected profits as a function of the premium rate (case a).

The impact on the LEA's expected profits of this achievements-oriented rewards policy is another interesting result supporting its implementation, since it creates incentives to improve interdiction. Although an enhanced rewards policy (with higher ε levels) leads to increases in expected profits both for incorruptible and corruptible officers but at different rates, it strengthens corruption deterrence, lowering the probability of successful bribery. In contrast, traditional criminal-policy instruments, F, S, and θ do not alter the expected profits for incorruptible officers.

Furthermore, due to their negative impact trough $\widetilde{m}^*$ on the equilibrium probability of successful bribery ($L(\widetilde{m}^*)$), increases in the premium rate result in rises in the probability of interdiction, $z^* = 1 - L(\widetilde{m}^*)\psi$ (see Proposition 3.1), while at the same time they lower the traffickers' success probability.

In a nutshell, a rewards policy based on the interdiction achievements of the officers constitutes an alternative and effective kind of policy, specially for relatively low levels of the premium rate, for which its deterrence effects on drug-trafficking are stronger. This result contrasts with a reward policy focused on salaries, which affects the equilibrium levels of efforts both for incorruptible and corruptible officers, and through them their expected profits, strengthening their incentives to improve their law enforcement activities, but don't alter traffickers decisions nor corruption deterrence.

Demand-side anti-drug policies

Even though the model is not focused on the demand-side —not analyzing drug-consumers choices nor preferences—, examination of the consequences of a market-size expansion points out the relevance of designing and implementing public policies to prevent and control drug consumption: if drug-market size is the most powerful force encouraging the performance of illicit organizations, then demand-side policies play a central role as they may inhibit market-size expansions. Indeed, drug consumption around the globe is the primary force bolstering illicit drugs business, so that public campaigns to prevent and control consumption must be a primary concern for governments.

In terms of the model, these policies would prevent additional increases or eventually provoke reductions in parameter a [22].

3.5 Conclusions

This paper analyzes theoretically the influence of corruption in drug trafficking at the wholesale scale, wherein drugs are trafficked (i.e. transported, distributed

[22] A natural extension of the model would be to develop the demand-side, analyzing consumer choices and endogenizing parameter a.

and sold) at a medium or large scale. It is useful to understand the recent boom in cocaine trafficking from Latin America to Europe, for which container shipping has been consolidated as the main form of transnational transport (Ramírez, 2021). The analytical model proposed disentangles the main forces fueling drug trafficking in this context, identifying the key mechanisms encouraging corruption and the performance of criminal organizations controlling drug trafficking. It also sheds light on the different anti-drug policy alternatives that can be designed and implemented, some of them with more effectiveness than the others, to deter corruption and drug trafficking.

Regarding the main forces fueling drug trafficking, the model finds that the drug-market size is the most powerful force encouraging the performance of illicit organizations, as it has a powerful direct impact on the value of drugs sold, and hence, weakens corruption deterrence and encourages drug trafficking. This implies that demand-side anti-drug policies constitute determinant and necessary strategies to fight against drug trafficking. The consumption of illicit drugs around the world is the primary force fostering drug trafficking, reason why public campaigns to prevent and control drugs consumption are of enormous importance. Investments in those kinds of public programs certainly require governments to accept that drug trafficking entails a problem of public health, and consequently, design policies and interventions accordingly. Recent informs (EMCDDA (2019, 2020, 2021)) highlight the chronic and severe health problems related with drug consumption and how it is a significant contributor to the burden of disease all around the world (EMCDDA, 2021).

Although the model does not analyze explicitly consumer choices — i.e., it assumes that market-size, as a component of the demand function, constitutes an exogenous parameter—, it implies all these policy considerations.

The model also shows that technological progress in drug transportation and trafficking is a key factor fueling illegal activities, because it encourages corruption and the participation of more agents in illegal business at the wholesale level, weakening also the interdiction effectiveness.

More trafficker's weight in the bargaining process does not affect corruption deterrence but encourage the entry of more traffickers to the market. Its impact is explained by the positive effect it has on traffickers' expected profits. This finding reveals that even when successful bargaining on bribes with officers, the economic and violent powers of traffickers matter, since they influence negotiation conditions and the resulting amount of bribes to trade.

Regarding anti-drug policy, the model finds many interesting results: First, although increases in salaries may not have a direct impact on corruption deterrence nor on trafficking discouragement, they are useful to encourage officers interdiction-tasks, since they represent higher expected profits for them. This finding goes in the same direction of Becker and Stigler (1974) analysis of law enforcement.

Second, according to some seminal papers in the field (Becker, 1968; Bowles and Garoupa, 1997), this paper finds that traditional criminal policy instruments, as fines imposed to traffickers, to officers, or the probability of detection of corrupted officers, are in each case effective to deter the entry of more traffickers to illicit markets in the presence of corrupt agents. Nevertheless, the model demonstrates that fines on traffickers are less effective as they trigger perverse incentives for more corruption and corrupted agents, being more effective alternatives fines to officers as well as the development of better police technologies and strategies to detect and capture corrupt officers.

Third and more important, the model shows that a premium rate given to the officers in retribution to their achievements in interdiction, is an alternative effective instrument to fight against drug trafficking at the wholesale level for at least three reasons: 1) In contrast to increases in the fine imposed to traffickers, higher premium rates strengthen corruption deterrence and provoke reductions in the probability of successful bribery. 2) Increases in the premium rate deter the entry of more traffickers to illegal business, being this effect more powerful for low levels of it. 3) Moreover, rises in the premium rate cause an upward trend in the expected profits for incorruptible officers steeper than for corruptible agents. This result contrast with the effects of traditional criminal-policy instruments, which do not alter the expected profits for incorruptible agents.

Summing up, a rewards policy based on the interdiction achievements of the officers represents a powerful alternative, in particular for low levels of the premium rate, for which its deterrence effects on drug trafficking are more potent.

Consequently, the analysis finds theoretical evidence supporting the starting hypothesis: although traditional criminal policy instruments in general tend to be effective to deter corruption and drug trafficking, a premium rate given to LEAs in retribution to their achievements in interdiction activities constitutes an alternative and effective policy instrument.

Though the model constitutes an useful framework to explain drug trafficking on the midstream links of the illegal productive chain, and to understand the relevance of corruption for its success and development, it is important to mention it has some shortcomings: Firstly, it makes abstraction of the demand-side, not incorporating the drug-consumers choice analysis, but departing from an inverse-demand function, which is assumed as given. Due to this limitation, the model does not allow us to analyze properly demand-side anti-drug policies.

Secondly, in contrast to models analyzing other stages of the illegal productive chain, for which the analysis of violent strategies and actions of traffickers is more significant (see, for instance, Raffo and Segura (2018, 2015) and Raffo (2015) for an analysis of the upper stages of the productive chain, or Grossman and Mejía (2008) and Serrano-López (2020) for studies of its bottom stages). However, the focus on corruption ("the plata"), making abstraction of violent actions ("the plomo") enables us to concentrate the analysis in what has been called the "cancer of corruption"(den Held, 2021).

Thirdly, the model does not consider the processes of drugs diversification that has been evolving during last decades, due to the design and elaboration of new drugs, specially synthetic ones (EMCDDA, 2019, 2020, 2021): For instance, only in 2019 "over 400 new psychoactive substances were detected on Europe's drug market" (EMCDDA, 2021, p. 26). As the model assumes an atomistic-monopolistic competition market structure, the analytical framework is not useful to explain the entry of new producers and sellers offering new drugs[23].

Last but not least, it is important to remark promising avenues for future research: Analyzing drug-consumers choice within the model's framework would enable us to endogeneize the demand function and market size. This extension —as I already mentioned— would be relevant to analyze demand-side policies.

Moreover, another version of the model to analyze the process of drug diversification that has been advancing during last decades would be relevant to understand the recent evolution of drug markets. This would imply to develop the new version of the model using a monopolistic competition market structure with horizontal and/or vertical differentiation.

Besides that, examining statistically the impact of the different anti-drug-policy alternatives on seizures and drug sales in the biggest drug-collection centers (i.e., for the main drug-collection centers in Europe) would be a contribution to the empirical literature on the matter.

[23]A recently published article analyzes this process for the drugs cryptomarket using a Dixit-Stiglitz monopolistic competition framework (see Raffo et al. (2021), Dixit and Stiglitz (1977)).

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Appendices

Appendix A

Chapter 1

A.1 Additional analysis for the baseline models

Table A.1: Difference in means Test for the treated municipalities before and after the ban of praying.

	Mean Control	SD Control	Mean Treat	SD Treat	Diff	p-value
Coca crops (ha)	250.635	911.780	922.295	2042.082	-671.660	0.000
Share of coca	1.705	5.360	6.227	11.980	-4.522	0.000

Notes: The difference in means Test compares the outcome variable for the treated municipalities before and after the ban of praying. the First Row presents the difference in means test for the outcome variable measured in absolute terms (in hectares of coca crops), while the second one presents it measuring the outcome variable as a share of municipal area with coca plantation per 1,000 hectares.

Table A.2: Dynamic baseline model and parallel trends.

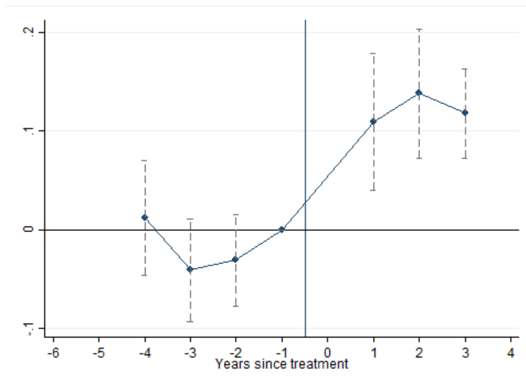
Dependent variable: Share of coca cultivation over 1,000 hectares.		
	(1)	(2)
VARIABLES		
D2011*Treatment	0.014	0.023
	(0.029)	(0.029)
D2012*Treatment	-0.039	-0.032
	(0.026)	(0.024)
D2013*Treatment	-0.029	-0.022
	(0.023)	(0.023)
D2016*Treatment	0.102***	0.087***
	(0.035)	(0.033)
D2017*Treatment	0.126***	0.106***
	(0.032)	(0.033)
D2018*Treatment	0.105***	0.089***
	(0.022)	(0.024)
Observations	1,736	1,736
R-squared	0.185	0.313
Municipalities	248	248
Municipality FE	YES	YES
Dept-Year FE	YES	YES
Controls	NO	YES
Years	2011-2018(2015)	2011-2018(2015)

Notes: The models use the baseline sample omitting the year 2015 with a total of 248 municipalities. Entries represent the estimated coefficients from dynamic panel regressions including municipality fixed effects and department-year fixed effects. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns present robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

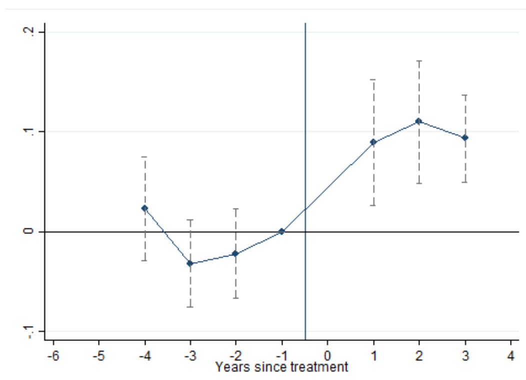
A.2 Additional analysis for larger samples

Additional figures

Figure A.1: Event study larger-sample model



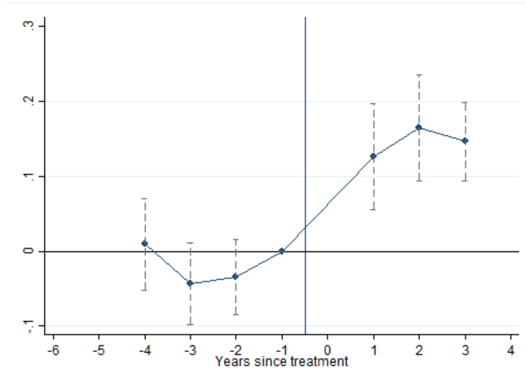
(a) Regression without controls.



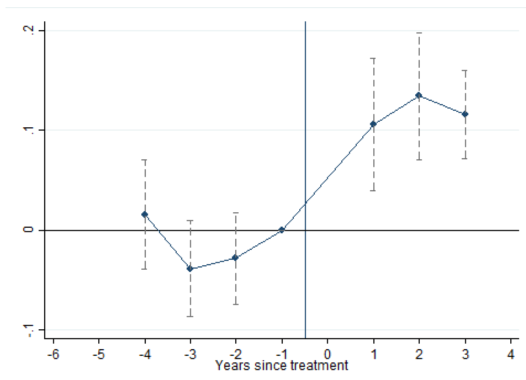
(b) Regression with controls.

Notes: These figures present the point estimates of the regressions and the confidence interval at the 95%

Figure A.2: Event study largest-sample model



(a) Regression without controls.



(b) Regression with controls.

Notes: These figures present the point estimates of the regressions and the confidence interval at the 95%

Additional tables

Table A.3: Dynamic larger-sample model and parallel trends.

Dependent variable: Share of coca cultivation over 1,000 hectares.

VARIABLES	(1)	(2)
D2011*Treatment3	0.012	0.020
	(0.030)	(0.029)
D2012*Treatment3	-0.041	-0.035
	(0.026)	(0.024)
D2013*Treatment3	-0.031	-0.024
	(0.024)	(0.023)
D2016*Treatment3	0.109***	0.096***
	(0.035)	(0.033)
D2017*Treatment3	0.138***	0.119***
	(0.033)	(0.033)
D2018*Treatment3	0.118***	0.102***
	(0.023)	(0.024)
Observations	2,289	2,289
R-squared	0.168	0.273
Municipalities	327	327
Municipality FE	YES	YES
Dept-Year FE	YES	YES
Controls	No	YES
Years	2011-2018(2015)	2011-2018(2015)

Notes: These models use the larger sample with municipalities producing coca at least for a year during the period 1999-2018, which includes 327 municipalities. The treatment variable does not require sampled municipalities to have planted coca at least for a year during the pre-treatment period, but to have historically planted it. Entries represent the estimated coefficients from non-parametric panel regressions including municipality fixed effects and department-year fixed effects. In both columns the year 2015 is omitted from the sample, reason why the relevant treatment variable is $Treatment3$. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns present robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.4: Dynamic largest-sample model and parallel trends.

Dependent variable: Share of coca cultivation over 1,000 hectares.

	(1)	(2)
VARIABLES		
D2011*Treatment3	0.009	0.009
	(0.031)	(0.031)
D2012*Treatment3	-0.043	-0.043
	(0.028)	(0.028)
D2013*Treatment3	-0.034	-0.034
	(0.026)	(0.026)
D2016*Treatment3	0.126***	0.126***
	(0.036)	(0.036)
D2017*Treatment3	0.164***	0.164***
	(0.036)	(0.036)
D2018*Treatment3	0.146***	0.146***
	(0.027)	(0.027)
Observations	7,770	7,770
R-squared	0.133	0.133
Municipalities	1,110	1,110
Municipality FE	YES	YES
Dept-Year FE	YES	YES
Controls	No	YES
Years	2011-2018(2015)	2011-2018(2015)

Notes: These models use the largest sample with the majority of municipalities and the corresponding treatment variables. Entries represent the estimated coefficients from dynamic panel regressions including municipality fixed effects and department-year fixed effects. In both three columns the year 2015 is omitted from the sample. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns present robust standard errors in parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.3 A negative binomial model

The negative binomial data approach constitutes a modeling alternative since coca-crops data tend to exhibit overdispersion and a large number of zero values. These models can be stated as follows:

$$ln(Y_{it}) = \alpha_i + \lambda_{dt} + \theta(lnTreatmentk_i * Post_t) + \sum_{c \in \mathbf{X}, j \in J} \gamma(c \times \delta_j) + \epsilon_{idt} \quad \text{(A.1)}$$

In this regression Y_{it} corresponds to the number of hectares planted in each municipality (in absolute terms); The rest of the variables remain as before. It is assumed that

$$Y_{it}|x_{it} \sim NB(\mu, \mu(1+\eta)), \quad \text{(A.2)}$$

where x_{it} represent all the regressors in Eq. (A.1). μ is the expected value of of $Y_{it}|x_{it}$, $E(Y_{it}|x_{it}) = exp(\alpha_i + \lambda_{dt} + \theta(lnTreatment * Post_t) + \sum_{c \in \mathbf{X}, j \in J} \gamma(c \times \delta_j))$[1].

Negative binomial regressions

All the negative binomial regressions estimating the models of Eq. (A.1) result as expected: the corresponding treatment variables of the four regressions are statistically significant (at the 1% level) and the coefficient of interest, θ, is always positive and relatively close to the estimated values of the precedent models. Moreover, it can be checked that in all the cases the models are robust as established by the Wald Chi-2 Test of variables' joint significance. The estimation of the models without robust errors give exactly the same coefficients. In that case, it can be checked that regressions are robust according to the LR Chi-2 Test of variables' joint significance. In addition, for the four regressions, according to the LR significance test for the parameter alpha of the negative binomial distribution —denoted as η in

[1] Strictly speaking, this distribution corresponds to a quadratic variance function, the negative binomial 2 (NB2) model (Cameron and Trivedi, 2005, 2013). Also, it is worth noting that $E(Y_{it}|x_{it}) < VAR(Y_{it}|x_{it})$.

Eq.(A.2)— there is enough statistical evidence to reject the null hypothesis of it being zero. This gives support to the negative-binomial distribution as an appropriate framework, and a better modeling choice than the standard Poisson distribution.

Column (1) of Table A5 exhibits the estimation of the binomial version of the baseline model; the variable of interest is the same of the original model, but measured as the natural logarithm of the sum of the hectares sprayed (plus one) during the pre-treatment period (2011-2014). The estimated average treatment effect equals 0.14, a little larger value than the baseline estimation. Owing to the logarithmic form of the outcome variable under this regression's calculation algorithm and the logarithmic form of the treatment, its value can be interpreted directly in percentage changes. This means that a decrease of 1% in aerial spraying linked to its ban causes an increase of 0.14% in coca crops between the post-treatment period.

Column (2) shows the estimation for the binomial version of the model including the year 2015. The coefficient showing the marginal impact of the spraying banning now gives 0.122, a little larger value than the estimated coefficient for the original model including that year (see Table 1.4).

Furthermore, columns (3) and (4) present the estimations for the larger-sample models of Table 1.6 using the negative binomial setting. The relevant coefficients are closer to the original ones: for the model excluding the year 2015, it gives 0.093, while for the model including that year it gives 0.107 [2].

These estimations indicate that similar results are found using this alternative setting, so that the baseline estimations tend to be stable under different modeling hypothesis and sampling choices. In addition, they reveal that the negative binomial setting constitutes another interesting approach that may be used in more depth to examine other aspects of the evolution of coca crops.

[2] In the original model with $Treatment3 * Post$ and $Treatment4 * Post$ including controls, the respective coefficients are 0.115 and 0.109.

Table A.5: Alternative negative binomial model.

	Dependent variable: Coca plantations in hectares			
	(1)	(2)	(3)	(4)
VARIABLES				
lnTreatment*Post	0.140***			
	(0.023)			
lnTreatment2*Post		0.122***		
		(0.019)		
lnTreatment3*Post			0.093***	
			(0.022)	
lnTreatment4*Post				0.107***
				(0.019)
Observations	1,736	2,032	2,289	2,616
Pseudo R2	0.182	0.186	0.224	0.229
Municipalities	248	254	327	327
Municipality FE	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES
Years	2011-2018(2015)	2011-2018	2011-2018(2015)	2011-2018

Notes: Notes: Entries represent the estimated coefficients from a negative binomial regression (NB2 model) including municipality fixed effects and year fixed effects. These models use three different types of samples: the baseline sample with 248 municipalities (Column (1)), the extended baseline sample with 254 municipalities when the year 2015 in included (column (2)), and the larger sample with municipalities producing coca at least for a year during the period 1999-2018, which includes 327 municipalities (Column (3) when omitting year 2015 and Column (4) when including it). The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the natural logarithm of the linear distance to the main wholesale food market (in kilometers) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. All the columns present robust standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.4 Additional analysis of mechanisms

Additional Figures

Figure A.3: Natural regions of Colombia.

Source:Poveda Sánchez et al. (2020).

Additional Tables

Table A.6: The influence of the distance to the main wholesale food market for the larger sample of municipalities.

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MarketDist*Treatment3*Post	0.911**	0.595*	0.595**			
	(0.355)	(0.352)	(0.260)			
Treatment3*Post	-0.180	-0.092	-0.092			
	(0.115)	(0.117)	(0.085)			
MarketDist*Post	-0.767	-4.705	-4.705**	-1.221	-5.275	-5.275***
	(2.166)	(4.189)	(2.047)	(1.725)	(3.770)	(1.482)
MarketDist*Treatment4*Post				0.740**	0.502*	0.502**
				(0.302)	(0.282)	(0.213)
Treatment4*Post				-0.134	-0.067	-0.067
				(0.104)	(0.102)	(0.066)
Observations	2,289	2,289	2,289	2,616	2,616	2,616
R-squared	0.691	0.726	0.726	0.713	0.745	0.745
Municipalities	327	327	327	327	327	327
Municipality FE	YES	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018	2011-2018

Notes: These models use the larger sample with municipalities producing coca for at least a year during the period 1999-2018, which includes 327 municipalities. The treatment variable does not require sampled municipalities to have planted coca at least for a year during the pre-treatment period, but to have historically planted it. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. In Columns (1)-(3) the year 2015 is omitted from the sample, while in Columns (4)-(6) it is included. The potential mechanism is an index of the linear distance to the principal wholesale food market, calculated dividing the original variable by its maximum value, so that it becomes normalized (between zero and one). The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1)-(2) and (4)-(5) present robust standard errors in parenthesis, while Columns (3) and (6) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.7: The influence of the distance to the main wholesale food market for the largest sample of municipalities.

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MarketDist*Treatment3*Post	1.011*	0.999**	0.999***			
	(0.518)	(0.478)	(0.272)			
Treatment3*Post	-0.097	-0.120	-0.120*			
	(0.120)	(0.115)	(0.068)			
MarketDist*Post	1.983	-2.279	-2.279**	1.447	-2.210*	-2.210***
	(1.419)	(1.404)	(1.028)	(1.083)	(1.300)	(0.643)
MarketDist*Treatment4*Post				0.813*	0.820**	0.820***
				(0.431)	(0.400)	(0.298)
Treatment4*Post				-0.063	-0.085	-0.085
				(0.106)	(0.103)	(0.073)
Observations	7,770	7,770	7,770	8,880	8,880	8,880
R-squared	0.697	0.715	0.715	0.719	0.735	0.735
Municipalities	1,110	1,110	1,110	1,110	1,110	1,110
Municipality FE	YES	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018	2011-2018

Notes: These models use the largest sample with the majority of municipalities and the corresponding treatment variables. Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. In Columns (1)-(3) the year 2015 is omitted from the sample, while in Columns (4)-(6) it is included. The potential mechanism is an index of the linear distance to the principal wholesale food market, calculated dividing the original variable by its maximum value, so that it becomes normalized (between zero and one). The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1)-(2) and (4)-(5) present robust standard errors in parenthesis, while Columns (3) and (6) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.8: Departmental models with statistically significant treatment effects

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment3*Post	0.641***	0.277***	0.208***	0.316***	0.081**	0.062**	0.277**
	(0.205)	(0.084)	(0.035)	(0.057)	(0.034)	(0.028)	(0.110)
Observations	511	154	112	84	392	105	91
R-squared	0.411	0.325	0.689	0.524	0.300	0.248	0.380
Municipalities	73	22	16	12	56	15	13
Department	Antioquia	Bolivar	Caquetá	Cordoba	Nariño	Valle	Putumayo
Municipality FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO	NO	NO
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)

Notes: Entries represent the estimated coefficients from departmental small-panel regressions including municipality fixed effects and department-year fixed effects. The departmental regressions with statistically insignificant treatments or with a number of municipalities smaller than the number of years were omitted. In all the regressions the year 2015 is omitted and controls are excluded due to the small size of the departmental sub-samples. All the columns present robust standard errors (clustered by municipalities) in parenthesis. *** p¡0.01, ** p¡0.05, * p¡0.1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.5 Other potential mechanisms and factors explaining the upsurge of coca crops

What about other factors explaining the coca crops evolution during 2014-2018? Could they constitute other potential mechanisms? As I pointed out in the introduction in reference to the literature explaining the increase of coca crops during the period 2014-2018, at least seven different hypotheses can be identified. In this section, I analyze the influence of three of these factors: the gold price, the exchange rate, and the armed conflict.

The trend of the gold price:

Let's consider first the influence of the gold price. Remember that the causal relationship between the price of gold and coca crops is based on the possibility of substituting gold mining with cocoa plating and vice versa. Some researchers have argued that the rebound of coca crops since 2014 may be partly explained by a reverse of the migration from coca cultivation to illegal gold mining (Rico-Valencia, 2017; Bargent, 2015; Sáenz, 2018), which had occurred between 2008 and 2013, especially in the north of Colombia — i.e., in the sub-region of Bajo Cauca, in the north of Antioquia department— (Bargent, 2015). Figure A4 depicts the trends of the international gold price of gold and coca crops.

Table A9 presents a set of models examining the impact of the gold price trend on the coca crops. They use Dube and Vargas' strategy to estimate the effect of commodity shocks (Dube and Vargas, 2013). The treatment variable interacts the trend of the international gold price with $Treatment$. The table shows that the impact of the gold price has the expected negative sign and is statistically significant at the 1% or 5% level. For the baseline sample, a marginal increase in the price of gold when interacted with the mean value of the treatment (i.e., the intensity of spraying during the period 2011-2014) causes a decrease of around 0.3 hectares of coca as a fraction of the municipal area per 1,000 hectares (see Columns (1)-(3)). This result holds with the baseline sample as well as with the larger sample of 254 municipalities.

Although this effect does not constitute a mechanism explaining the impact of the fumigation ban, it confirms the relevance of the price of gold, as an alternative factor explaining the evolution of coca plantations.

Table A.9: The influence of the international gold price.

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PriceGold*Treatment1	-0.289**	-0.229**	-0.229***			
	(0.121)	(0.115)	(0.068)			
PriceGold*Treatment2				-0.264**	-0.223**	-0.223***
				(0.106)	(0.099)	(0.057)
Observations	1,736	1,736	1,736	2,032	2,032	2,032
R-squared	0.671	0.725	0.725	0.696	0.742	0.742
Municipalities	248	248	248	254	254	254
Municipality FE	YES	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018	2011-2018

Notes: Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. These models use the baseline sample with 248 municipalities (Columns (1)-(2)) or the baseline extended sample of 254 municipalities when the year 2015 in included (columns (3)-(4)). The treatment corresponds to the interaction of the international gold price trend and the treatment (the spraying intensity during the pre-treatment period). The gold price is measured in U.S. dollars per thousandth of troy once. The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1)-(2) and (4)-(5) present robust standard errors (clustered by municipalities) in parenthesis, while Columns (3) and (6) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

***The depreciation of the exchange rate**:*

Table A10 presents the estimations of regressions examining the impact of the nominal exchange rate on coca crops. They also use Dube and Vargas' strategy to estimate the effect of commodity shocks. The variable of interest corresponds to the interaction of the nominal exchange rate (of Colombian Pesos to U.S. dollars) trend with the treatment (the spraying intensity during the pre-treatment period). The estimated coefficients associated with the treatment have the expected positive signs and the correspondent variables are statistically significant at the 1% or 5% level in all cases. The models for the baseline sample, show that one increase in the exchange rate when interacted with the mean value of the treatment causes an increase of around

0.22 ha of coca as a fraction of the municipal area per 1,000 hectares (see Columns (1)-(3)).

Again, this effect does not constitute a mechanism of the impact of the fumigation ban. However, it gives evidence supporting the hypothesis that the exchange rate may have affected the evolution of coca crops during the study period.

Table A.10: The impact of the nominal exchange rate.

Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
erate*Treatment	0.267***	0.216**	0.216***			
	(0.101)	(0.098)	(0.054)			
erate*Treatment2				0.269***	0.231**	0.231***
				(0.095)	(0.092)	(0.052)
Constant	-8.396***	-8.031**	-8.031***	-9.204***	-7.528**	-7.528***
	(3.110)	(3.124)	(2.414)	(3.430)	(3.335)	(1.815)
Observations	1,736	1,736	1,736	2,032	2,032	2,032
R-squared	0.680	0.730	0.730	0.707	0.749	0.749
Municipalities	248	248	248	254	254	254
Municipality FE	YES	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018	2011-2018

Notes: Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. These models use the baseline sample with 248 municipalities (Columns (1)-(2)) or the baseline extended sample of 254 municipalities when the year 2015 in included (columns (3)-(4)). The treatment corresponds to the interaction of the nominal exchange rate (of Colombian Pesos to U.S. dollars) trend with the treatment (the spraying intensity during the pre-treatment period). The controls are interacted with yearly dummies and include a dummy variable that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1)-(2) and (4)-(5) present robust standard errors (clustered by municipalities) in parenthesis, while Columns (3) and (6) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The pressure of illegal armed groups:

Last but not least. Consider the impact of conflict. As already explained, many authors have argued that the possible pressure of illegal armed groups such as the FARC or other criminal bands may be a factor explaining the considerable increase of coca crops during 2014-2018 (Prem et al., 2021;

Santos, 2019; Rocha-García, 2019). Mejía et al. (2019) (see also Prem et al. (2021)) show that the surge in coca growing is differentially higher in territories with the incidence of illegal armed groups different to FARC attempting to gain control of crops to get resources derived from the drug trade.

Table A11 presents the estimations of a triple differences model where the treatment variable $Treatment * Post$ interacts with a dummy of conflict, $conflict$, taking the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period. The regressions show that the coefficient of interest in all cases is low, around 0,03, and statistically insignificant. Hence, there is no statistical evidence of the differential impact of the treatment ($Treatment * Post$) for municipalities with at least one attack by an armed group or any clash between a pair or triad of them.

However, the impact of the interaction of the dummy of conflict, $conflict$, with the temporal dummy, $Post$, is statistically significant at the 1 % or 5 % level in all cases. The coefficients associated with $conflict * Post$ are around 3.1 for the baseline regressions (see columns (1) and (2)), which means that the increase of one standard deviation in the proportion of municipalities with at least one attack by an armed group or any clash between a pair or triad of them (during the pre-treatment) produces one increase in the proportion of municipal area with coca crops around 3 hectares per1,000 hectares after the ban of spraying.

This implies that the impact of conflict is relevant as a variable affecting the outcome for the post-treatment but probably affects the evolution of crops through a different channel.

Table A.11: The impact of conflict.

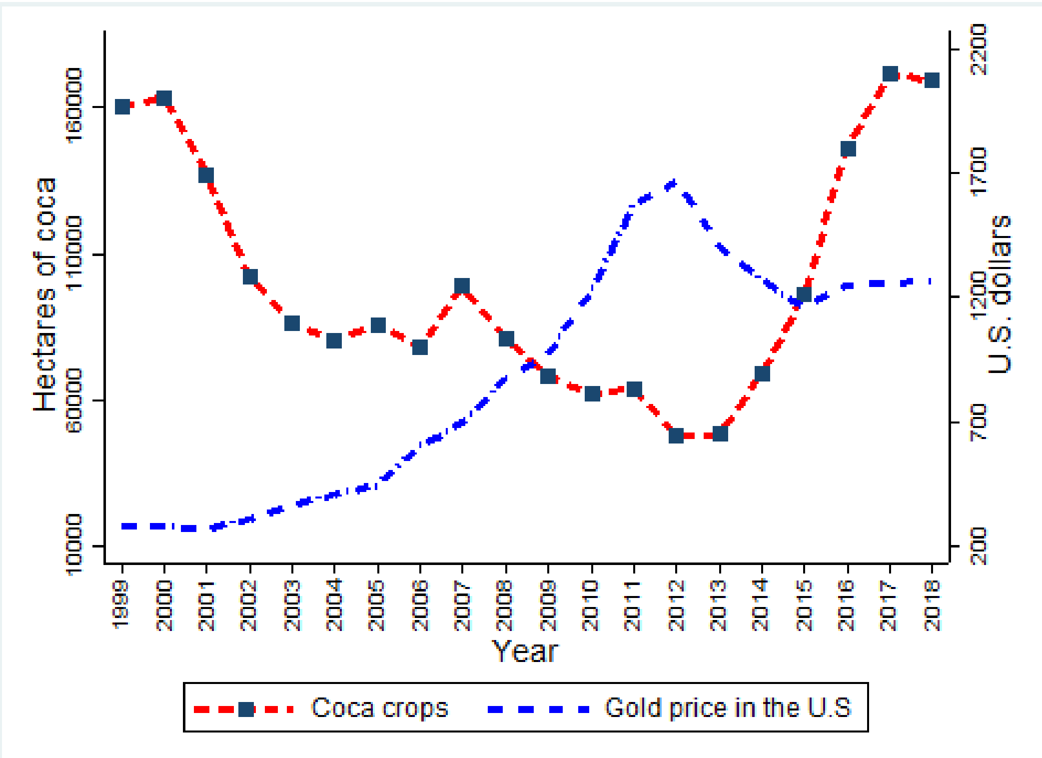
Dependent variable: Share of coca cultivation over 1,000 hectares

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
conflict*Treatment*Post	0.083	0.029	0.029			
	(0.059)	(0.060)	(0.035)			
Treatment*Post	0.037	0.076**	0.076***			
	(0.027)	(0.036)	(0.022)			
conflict*Post	3.547***	3.140**	3.140***	3.054***	2.832**	2.832***
	(0.935)	(1.301)	(0.689)	(0.797)	(1.122)	(0.586)
conflict*Treatment2*Post				0.083*	0.033	0.033
				(0.049)	(0.049)	(0.028)
Treatment2*Post				0.033	0.071**	0.071***
				(0.021)	(0.030)	(0.016)
Observations	1,736	1,736	1,736	2,032	2,032	2,032
R-squared	0.695	0.730	0.730	0.716	0.749	0.749
Municipalities	248	248	248	256	256	256
Municipality FE	YES	YES	YES	YES	YES	YES
Dept-Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	YES	YES	NO	YES	YES
Years	2011-2018(2015)	2011-2018(2015)	2011-2018(2015)	2011-2018	2011-2018	2011-2018

Notes: Entries represent the estimated coefficients from OLS regressions including municipality fixed effects and year fixed effects. These models use the baseline sample with 248 municipalities (Columns (1)-(2)) or the baseline extended sample of 254 municipalities when the year 2015 in included (columns (3)-(4)). The potential mechanism is a dummy variable ($conflict$) that takes the value of one for municipalities with at least one attack by an armed group or any clash between a pair or triad of them during the pre-treatment period interacted with the treatment (Post*Treatment). The controls are interacted with yearly dummies and include, the natural logarithm of the height of the municipal (meters above sea level) plus one, the linear distance to Bogotá (in kilometers) plus one, regional dummies, an UBN (Unsatisfied Basic need index) for the year 2011 (divided by hundred), the natural logarithm of the urban population in 2011 plus one, and the natural logarithm of the rural population in 2011 plus one. Columns (1)-(2) and (4)-(5) present robust standard errors (clustered by municipalities) in parenthesis, while Columns (3) and (6) present bootstrap standard errors. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Additional Figures

Figure A.4: Trends of the gold price and coca crops.



Notes: The international price of gold (measured in U.S. dollars per thousandth of troy once) is taken from the World Gold Council.

Appendix B

Chapter 2

Proofs of Propositions

Proposition 2.2. *$\forall P \in [0, \varepsilon p_d q]$, $F(P)$ and $f(P)$ are parabolic functions of P, convex-decreasing for $P < \frac{\varepsilon p_d q}{4}$ but increasing for $P > \frac{\varepsilon p_d q}{4}$.*

Proof. It can be checked that $f'(P) \gtreqless 0 \Leftrightarrow P \gtreqless \frac{\varepsilon p_d q}{4}$. Also, $f''(P) = \frac{1}{4}\gamma\sqrt{\varepsilon p_d q}P^{-\frac{3}{2}} > 0$. Furthermore, $b \leq 1 \Rightarrow 0 \leq P \leq \varepsilon p_d q$. In addition, $F'(P) \gtreqless 0 \Leftrightarrow P \gtreqless \frac{\varepsilon p_d q}{4}$; $F''(P) = \frac{1}{4}\sqrt{\varepsilon p_d q}P^{-\frac{3}{2}} > 0$, and $\lim\limits_{P \to 0} B = \lim\limits_{P \to \varepsilon p_d q} B = \frac{1}{\gamma}$.

∎

Proposition 2.3. *In the perfect-subgame Nash equilibrium, i) P is a convex-increasing function in α, ii) and a convex-decreasing function in ρ. iii) $\forall \varepsilon \in \left[\frac{1}{\beta+2\rho}, 1\right]$, it is a parabolic function of ε, convex-decreasing for $\varepsilon < \dfrac{1}{\beta}$ but convex-increasing for $\varepsilon > \dfrac{1}{\beta}$. iv) It increases (decreases) when there is a rise in β for $\varepsilon > \frac{1}{\rho}$ $\left(\varepsilon < \frac{1}{\rho}\right)$.*

Proof. i) $\dfrac{\mathrm{d}P^*}{\mathrm{d}\alpha} = \dfrac{\alpha\left(\frac{1}{\varepsilon} + 2\beta + \beta^2\varepsilon\right)}{8(\beta+\rho)^2} > 0$, so that P^* in increasing in α; $\dfrac{\mathrm{d}^2P^*}{\mathrm{d}\alpha^2} = \dfrac{\left(\frac{1}{\varepsilon} + 2\beta + \beta^2\varepsilon\right)}{8(\beta+\rho)^2} > 0$, reason why P^* is convex in this parameter. ii) $\dfrac{\mathrm{d}P^*}{\mathrm{d}\rho} = \dfrac{-\alpha^2\left(\frac{1}{\varepsilon} + 2\beta + \beta^2\varepsilon\right)}{8(\beta+\rho)^2} < 0, \dfrac{\mathrm{d}^2P^*}{\mathrm{d}\rho^2} = \dfrac{3\alpha^2\left(\frac{1}{\varepsilon} + 2\beta + \beta^2\varepsilon\right)}{8(\beta+\rho)^2} > 0$. Also,

$\lim_{\rho \to 1} P^* = \frac{\alpha^2\left(\frac{1}{\varepsilon} + 2\beta + \beta^2\varepsilon\right)}{16(\beta+1)^2}$, and $\lim_{\rho\to\infty} P^* = 0$. This shows that P^* is a convex-decreasing function in ρ. iii) It can be checked that $\frac{\mathrm{d}P^*}{\mathrm{d}\varepsilon} = \frac{\alpha^2\left(-\frac{1}{\varepsilon^2} + \beta^2\right)}{16(\beta+\rho)^2} \gtreqless 0 \Leftrightarrow \varepsilon \gtreqless \frac{1}{\beta}$. In addition, $\frac{\mathrm{d}^2P^*}{\mathrm{d}\varepsilon^2} = \frac{\alpha^2}{16(\beta+\rho)^2\varepsilon^3} > 0$. As a result, P^* is a parabolic function of ε. Furthermore, as it will be showed in the proof of Proposition 2.5 that $\frac{1}{\beta+2\rho} \leq \varepsilon \leq 1$, the limits of P^* with respect to ε are: $\lim_{\varepsilon\to\frac{1}{\beta+2\rho}} P^* = \frac{\alpha^2}{4(\beta+2\rho)}$, and $\lim_{\varepsilon\to 1} P^* = \frac{\alpha^2(1+\beta)^2}{16(\beta+\rho)^2}$. iv) Finally, it can be checked that $\frac{\mathrm{d}P^*}{\mathrm{d}\beta} = \frac{\alpha^2\left(\rho + 2\rho\varepsilon\beta - \beta - \frac{1}{\varepsilon}\right)}{8(\beta+\rho)^3} \gtreqless 0 \Leftrightarrow \varepsilon \gtreqless \frac{1}{\rho}$.

■

Proposition 2.4. *In the perfect-subgame Nash equilibrium, i) b is a concave-decreasing function in α, ii) and a linear-decreasing function in γ. iii) $\forall\varepsilon \in \left[\frac{1}{\beta+2\rho}, 1\right]$, it is a convex decreasing function of ε. iv) It increases (decreases) when there is a rise in β for $\varepsilon < \frac{1}{\rho}$ $\left(\varepsilon > \frac{1}{\rho}\right)$. v) it is a parabolic function of ρ.*

Proof. i) $\frac{\mathrm{d}b^*}{\mathrm{d}\alpha} = \frac{-2\alpha\gamma}{16(\beta+\rho)^2}\left(2\rho - \frac{1}{\varepsilon} + \beta^2\varepsilon + 2\rho\beta\varepsilon\right) < 0$, so that b^* is decreasing in α; $\frac{\mathrm{d}^2b^*}{\mathrm{d}\alpha^2} = \frac{-2\gamma}{16(\beta+\rho)^2}\left(2\rho - \frac{1}{\varepsilon} + \beta^2\varepsilon + 2\rho\beta\varepsilon\right) < 0$, reason why b^* is concave in this parameter. In addition, $\lim_{\alpha\to 0} b^* = 1$, and $\lim_{\alpha\to 1} b^* = 1 - \frac{\gamma}{16(\beta+\rho)^2}\left(2\rho - \frac{1}{\varepsilon} + \beta^2\varepsilon + 2\rho\beta\varepsilon\right)$, which lies between 1 and 0; This warranties that b^* is well bounded. ii) It can checked that $\frac{\mathrm{d}b^*}{\mathrm{d}\gamma} = \frac{-\alpha^2}{4(\beta+\rho)^2}\left(2\rho - \frac{1}{\varepsilon} + \beta^2\varepsilon + 2\rho\beta\varepsilon\right) < 0$, and $\frac{\mathrm{d}^2b^*}{\mathrm{d}\gamma^2} = 0$. Hence b^* decreases linearly with γ. iii) $\frac{\mathrm{d}b^*}{\mathrm{d}\varepsilon} = \frac{-\alpha^2\gamma}{16(\beta+\rho)^2}\left(\frac{1}{\varepsilon^2} + \beta^2 + 2\rho\beta\right) < 0$, and $\frac{\mathrm{d}^2b^*}{\mathrm{d}\varepsilon^2} = \frac{\alpha^2\gamma(\frac{1}{\varepsilon})^2}{8(\beta+\rho)^2} > 0$. Hence b^* is convex and decreasing in ε. In addition, $\lim_{\varepsilon\to\frac{1}{2\rho+\beta}} b^* = 1$, and $\lim_{\varepsilon\to 1} b^* = 1 - \frac{\alpha^2\gamma}{16(\beta+\rho)^2}\left(\beta(2\rho+\beta) + 2\rho - 1\right)$, which proves that b^* is well bounded between 0 and 1 in terms of ε's domain. iv) It can be checked that $\frac{\mathrm{d}b^*}{\mathrm{d}\beta} = \frac{\alpha^2\gamma}{8(\beta+\rho)^2}\left(\varepsilon\rho - 1\right)^2 \lesseqgtr 0 \Leftrightarrow \varepsilon \lesseqgtr \frac{1}{\rho}$. Furthermore, $\frac{\mathrm{d}^2b^*}{\mathrm{d}\beta^2} = \frac{3\alpha^2\gamma}{8(\beta+\rho)^4} > 0$, which shows that b^* is a convex function in β, that can increase or decrease in this parameter depending on its relative value with respect to $\frac{1}{\rho}$. v) It can be checked that $\frac{\mathrm{d}b^*}{\mathrm{d}\rho} = \frac{-\alpha^2\gamma}{8(\beta+\rho)^3}\left(\beta + \frac{1}{\varepsilon} - \rho(1+\beta)\varepsilon\right) \gtreqless 0 \Leftrightarrow \rho \gtreqless \frac{\beta+\frac{1}{\varepsilon}}{(\beta+1)\varepsilon}$. Moreover, $\frac{\mathrm{d}^2b^*}{\mathrm{d}\rho^2} = \frac{\alpha^2\gamma(1+\beta)\varepsilon}{8(\beta+\rho)} > 0$, which proves that b^* is a parabolic function of ρ. Also, $\lim_{\rho\to 1} b^* = 1 - \frac{\alpha^2\gamma}{16\beta^2}\left(2 - \frac{1}{\varepsilon} + \beta^2\varepsilon + 2\beta^{\varepsilon}\right)$, and $\lim_{\rho\to\infty} b^* = 1$, which proves that b^* is bounded between 0 and 1 in terms of ρ's domain.

■

Contest Equilibrium Theorem. *In the perfect-subgame Nash equilibrium: i) z^* is a concave-increasing function of ρ, ii) and a convex-decreasing (convex-increasing) function of β for $\varepsilon > \frac{1}{\beta}$ ($\varepsilon < \frac{1}{\beta}$). iii) Also, $\forall\varepsilon \in \left[\frac{1}{\beta+2\rho}, 1\right]$ it is an increasing function of ε. The analogous opposite effects occur for $(1-z^*)$.*

Proof. i) $\frac{\mathrm{d}z^*}{\mathrm{d}\rho} = \frac{2(\beta+\frac{1}{\varepsilon})}{(\beta+\rho)^2} > 0$, and $\frac{\mathrm{d}^2z^*}{\mathrm{d}\rho^2} = \frac{-4(\beta+\frac{1}{\varepsilon})}{(\beta+\rho)^3} < 0$, so that z^* is concave and increasing in ρ. Furthermore, while $\lim_{\rho\to 1} z^* = \frac{(\beta+2-\frac{1}{\varepsilon})}{2(\beta+1)}$, which lies between 0 and 1, as expected. Also, $\lim_{\rho\to\infty} z^* = 1$. ii) It can be checked that $\frac{\mathrm{d}z^*}{\mathrm{d}\beta} = \frac{\frac{1}{\varepsilon}-\rho}{2(\beta+\rho)^2} \gtreqless 0 \Leftrightarrow \varepsilon \lesseqgtr \frac{1}{\rho}$, and $\frac{\mathrm{d}^2z^*}{\mathrm{d}\beta^2} = \frac{\rho-\frac{1}{\varepsilon}}{2(\beta+\rho)^3} \gtreqless 0 \Leftrightarrow \varepsilon \gtreqless \frac{1}{\rho}$. Therefore z^* can increase or decrease with respect to β depending on the relative value of ε in relation to $\frac{1}{\rho}$. The concavity or convexity of this relationship depends on the relative values of ε and $\frac{1}{\rho}$ too. Also, $\lim_{\beta\to 1} z^* = \frac{(1+2\rho-\frac{1}{\varepsilon})^2}{2(\rho+1)}$, and $\lim_{\beta\to\infty} z^* = \frac{1}{2}$, which lies between 0 and 1, as expected. iii) $\frac{\mathrm{d}z^*}{\mathrm{d}\varepsilon} = \frac{1/\varepsilon^2}{2(\beta+\rho)} > 0$, and $\frac{\mathrm{d}^2z^*}{\mathrm{d}\varepsilon^2} = \frac{-1/\varepsilon^2}{2(\beta+\rho)^2} < 0$. This proves that z^* is a concave-increasing function of ε. On the other hand, it can be checked that $z^* \geq 0 \Leftrightarrow \varepsilon \geq \frac{1}{\beta+2\rho}$. As a result, $\lim_{\varepsilon\to\frac{1}{\beta+2\rho}} z^* = 0$. But, as this minimum level of ε must also be lower than one, $\beta+2\rho > 1$. Furthermore, $\lim_{\varepsilon\to 1} z^* = \frac{\beta+2\rho-1}{2(\beta+\rho)}$. This upper limit of z^* must be lower than one, which implies $\beta+2\rho > 1$ again. An analogous analysis can be done for $(1-z^*)$; Let's consider the implications of ε's domain on $(1-z^*)$: $\lim_{\varepsilon\to\frac{1}{\beta+2\rho}} (1-z^*) = 1$, and $\lim_{\varepsilon\to 1}(1-z^*) = \dfrac{1+\beta}{2(\beta+\rho)}$. The lowest limit of $(1-z^*)$ implies $\beta+2\rho>1$ once again.

■

Proposition 2.5. *In the perfect-subgame Nash equilibrium, i) $E\left[\Pi_L{}^*\right]$ is a concave-increasing function of ρ, ii) and a convex-increasing function of α. iii) It is also a convex-decreasing function of γ, iv) and a convex-decreasing function of β. iv) Furthermore, $\forall\varepsilon\in\left[\frac{1}{\beta+2\rho},1\right]$, it increases linearly in ε.*

Proof. i) It can be checked that $\dfrac{\mathrm{d}E\left[\Pi_L{}^*\right]}{\mathrm{d}\rho} = \dfrac{\alpha^2(\varepsilon\beta+1)}{4(\beta+\rho)^2} > 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_L{}^*\right]}{\mathrm{d}\rho^2} = \dfrac{-\alpha^2(\varepsilon\beta+1)}{2(\beta+\rho)^3} < 0$, so that the LEA's expected profits are a concave-increasing function of ρ. In addition, it can be proved that $\lim_{\rho\to 1}E\left[\Pi_L{}^*\right] = w+\dfrac{1}{2\gamma}+\dfrac{\alpha^2(\varepsilon-1)}{4(\beta+1)}-\theta(m+S) < \lim_{\rho\to\infty}E\left[\Pi_L{}^*\right] = w+\frac{1}{2\gamma}+\dfrac{\alpha^2\varepsilon}{4}-\theta(m+S)$. ii) $\dfrac{\mathrm{d}E\left[\Pi_L{}^*\right]}{\mathrm{d}\alpha} = \dfrac{\alpha(\varepsilon\rho-1)}{2(\beta+\rho)} \gtreqqless 0 \Leftrightarrow \varepsilon \gtreqqless \frac{1}{\rho}$, and $\dfrac{\mathrm{d}^2E\left[\Pi_L{}^*\right]}{\mathrm{d}\alpha^2} = \dfrac{(\varepsilon\rho-1)}{2(\beta+\rho)} \gtreqqless 0 \Leftrightarrow \varepsilon \gtreqqless \frac{1}{\rho}$, so that $E\left[\Pi_L{}^*\right]$ is a convex-increasing (concave-decreasing) function of α when $\varepsilon > \frac{1}{\rho}$ $\quad(\varepsilon\leq\frac{1}{\rho})$. Also, $\lim_{\alpha\to 0}E\left[\Pi_L{}^*\right] = w+\dfrac{1}{2\gamma}-\theta(m+S)$, while $\lim_{\alpha\to\infty}E\left[\Pi_L{}^*\right]=\infty$. iii) $\dfrac{\mathrm{d}E\left[\Pi_L{}^*\right]}{\mathrm{d}\gamma} = -\dfrac{1}{2\gamma^2} < 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_L{}^*\right]}{\mathrm{d}\gamma^2} = \dfrac{1}{2\gamma^3} > 0$, so that $E\left[\Pi_L{}^*\right]$ is a convex-decreasing function of γ, for which $\lim_{\gamma\to 0}E\left[\Pi_L{}^*\right]=\infty$, and $\lim_{\gamma\to\infty}E\left[\Pi_L{}^*\right] = w+\dfrac{\alpha^2}{4(\beta+\rho)}\left[\rho\varepsilon-1\right]-\theta(m+S)$. iv) It can be easily checked that $\dfrac{\mathrm{d}E\left[\Pi_L{}^*\right]}{\mathrm{d}\varepsilon} = \dfrac{\rho\alpha^2}{4(\beta+\rho)} > 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_L{}^*\right]}{\mathrm{d}\varepsilon^2} = 0$. ■

Proposition 2.6. *In the perfect-subgame Nash equilibrium, i) $E\left[\Pi_T{}^*\right]$ is a convex-decreasing function of ρ, ii) and a convex-increasing function of α. iii) It is also a concave-increasing function of γ, iv) and $\forall\varepsilon\in\left[\frac{1}{\beta+2\rho},1\right]$, it is a parabolic function of ε, decreasing for $\varepsilon<\dfrac{1}{\beta}$ but increasing for $\varepsilon>\dfrac{1}{\beta}$.*

Proof. i) It can be checked that $\dfrac{\mathrm{d}E\left[\Pi_T{}^*\right]}{\mathrm{d}\rho} = \dfrac{-\alpha^2}{16(\beta+\rho)^2}\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right] < 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_T{}^*\right]}{\mathrm{d}\rho^2} = \dfrac{\alpha^2}{16(\beta+\rho)^3}\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right] > 0$, reason why $E\left[\Pi_T{}^*\right]$ is a convex-decreasing function of ρ. It is worth noting that $\lim_{\rho\to 1} E\left[\Pi_T{}^*\right] = \frac{\alpha^2}{16(\beta+1)}\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right]-\frac{\beta}{\gamma} > \lim_{\rho\to\infty} E\left[\Pi_T{}^*\right] = -\frac{\beta}{\gamma}$. ii) $\frac{\mathrm{d}E\left[\Pi_T{}^*\right]}{\mathrm{d}\alpha} = \frac{\alpha}{8(\beta+\rho)}\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right] > 0$, and $\frac{\mathrm{d}^2E\left[\Pi_T{}^*\right]}{\mathrm{d}\alpha^2} = \frac{\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right]}{8(\beta+\rho)} > 0$, so that traffickers' profits are convex and increasing in α. In addition, $\lim_{\alpha\to 0} E\left[\Pi_T{}^*\right] = 0$, and $\lim_{\alpha\to\infty} E\left[\Pi_T{}^*\right] = \infty$. iii) $\frac{\mathrm{d}E\left[\Pi_T{}^*\right]}{\mathrm{d}\gamma} = \frac{\beta}{\gamma^2} > 0$, and $\frac{\mathrm{d}^2E\left[\Pi_T{}^*\right]}{\mathrm{d}\gamma^2} = -\frac{\beta}{\gamma^3} < 0$. Therefore, $E\left[\Pi_T{}^*\right]$ are increasing and convex in γ. In addition, $\lim_{\gamma\to 0} E\left[\Pi_T{}^*\right] = -\infty$, and $\lim_{\gamma\to\infty} E\left[\Pi_T{}^*\right] = \frac{\alpha^2}{16(\beta+\rho)}\left[\varepsilon\beta^2+2\beta+\frac{1}{\varepsilon}\right]$. iv) Finally, $\frac{\mathrm{d}E\left[\Pi_T{}^*\right]}{\mathrm{d}\varepsilon} = \frac{\alpha^2\left(-\frac{1}{\varepsilon^2}+\beta^2\right)}{16(\beta+\rho)} \gtreqqless 0 \Leftrightarrow \varepsilon \gtreqqless \frac{1}{\beta}$. In addition, $\frac{\mathrm{d}^2E\left[\Pi_T{}^*\right]}{\mathrm{d}\varepsilon^2} = \frac{\alpha^2}{16(\beta+\rho)\varepsilon^3} > 0$. As a result, $E\left[\Pi_T{}^*\right]$ is a parabolic function of ε. Furthermore, $\lim_{\varepsilon\to\frac{1}{\beta+2\rho}} E\left[\Pi_T{}^*\right] = \frac{\alpha^2(\beta+\rho)}{4(\beta+2\rho)} - \frac{\beta}{\gamma}$, and $\lim_{\varepsilon\to 1} E\left[\Pi_T{}^*\right] = \frac{\alpha^2}{16(\beta+\rho)}\left[\beta^2+2\beta+1\right] - \frac{\beta}{\gamma}$.

■

Appendix C

Chapter 3

Appendix: Proofs of Propositions

Long-run Equilibrium Theorem. *In the perfect-subgame Nash equilibrium,* $(\forall \alpha \in [\hat{\alpha}, 1])(\forall \psi \in [\hat{\psi}, 1])(\forall \theta \in [0, \hat{\theta}])(\exists \widetilde{\mu}(\widetilde{m}^*) \geq 0)$*, such that* $\widetilde{\mu}(\widetilde{m}^*)$*: i) is a strict convex-increasing function of* a*, ii) increases linearly with* α*, iii) is a strict convex-increasing function of* ψ*, iv) a strict convex-decreasing function of* F*, v) a strict convex-decreasing function of* S*, vi) a strict convex-decreasing function of* θ*, and vii) and a strict convex-decreasing function of* ε*.*

Proof. i) $\forall a \in \mathbb{R}_{++}, \dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}a} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}a} = \alpha L(\widetilde{m}^*)\dfrac{a(1-\varepsilon)\psi}{2} > 0$, and $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}a^2} = \dfrac{\alpha(1-\varepsilon)\psi}{2}\left[\dfrac{l(\widetilde{m}^*)a^2(1-\varepsilon)\psi}{2\theta} + L(\widetilde{m}^*)\right] > 0$, so that $\widetilde{\mu}$ is a strict convex-increasing function of a. ii) First notice that $\widetilde{\mu} \geq 0 \implies \alpha \geq \hat{\alpha}$. It can be checked that $\forall \alpha \in [\hat{\alpha}, 1], \dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}\alpha} = \theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\, dm\right] > 0$, which ensures that $\widetilde{\mu}$ increases linearly with α, since $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}\alpha^2} = 0$. iii) First, it can be proved that $\widetilde{\mu} \geq 0 \implies \psi \geq \hat{\psi}$. Since, $\forall \psi \in [\hat{\psi}, 1], \dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}\psi} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\psi} = \alpha L(\widetilde{m}^*)\left[F(1-\theta) + (1-\varepsilon)(a^2/4)\right] > 0$, $\widetilde{\mu}$ is a monotonic increasing function of ψ; In addition as, $\forall \psi \in [\hat{\psi}, 1], \dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}\psi^2} = \dfrac{\alpha l(\widetilde{m}^*)}{\theta}\left[F(1-\theta) + (1-\varepsilon)(a^2/4)\right]^2 > 0$, $\widetilde{\mu}$ is also a strict convex function of ψ. iv) It can be checked that $\forall F \in \mathbb{R}_{++}, \dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}F} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}F} - 1 = \alpha L(\widetilde{m}^*)\dfrac{(1-\theta)}{\theta}\psi - 1 < 0$, and $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}F^2} =$

$\dfrac{\alpha l(\widetilde{m}^*)(1-\theta)^2\psi^2}{\theta} > 0$, results which ensure that $\widetilde{\mu}$ is a strict convex-decreasing function of F. v) Also, it can be proved that $\forall S \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}S} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}S} = -\alpha\theta L(\widetilde{m}^*) < 0$, and $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}S^2} = \alpha\theta l(\widetilde{m}^*) > 0$, reason why $\widetilde{\mu}$ is a strict convex-decreasing function of S. vi) First, note that $\widetilde{\mu} \geq 0 \implies \theta \leq \hat{\theta}$, which is lower than $\widetilde{\theta}$. $\forall\theta \in [0, \hat{\theta}]$, $\dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}\theta} = -\alpha L(\widetilde{m}^*)\left[F + S - \int_0^{\widetilde{m}^*} ml(m)\, dm\ \right] < 0$, and $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}\theta^2} = \alpha l(\widetilde{m}^*)\psi\left[\dfrac{F(1-\theta)}{\theta^2} + \dfrac{(1-\varepsilon)(a^2/4)}{\theta^2}\right]$ $\cdot\left[F + S + \int_0^{\widetilde{m}^*} ml(m)\, dm\ + L(\widetilde{m}^*)\widetilde{m}^*\right] > 0$, results ensuring that $\widetilde{\mu}$ is a strict convex-decreasing function of θ. vii) Lastly, it can be proved that $\forall\varepsilon \in [0,1]$, $\dfrac{\mathrm{d}\widetilde{\mu}}{\mathrm{d}\varepsilon} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\varepsilon} = -\alpha\psi L(\widetilde{m}^*)(a^2/4) < 0$, and $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}\varepsilon^2} = \dfrac{\alpha\psi^2 a^4 l(\widetilde{m}^*)}{16\theta} > 0$, assuring that $\widetilde{\mu}$ is a strict convex-decreasing function of ε.

■

Proposition 3.3. *In the perfect-subgame Nash equilibrium,* $\forall\alpha \in [\hat{\alpha}, 1]$, $\forall\psi \in [\hat{\psi}, 1]$, *and* $\forall\theta \in [0, \hat{\theta}]$, *i)* $\widetilde{m}$ *is a strict convex-increasing function of* a, *ii) a linear increasing function of* ψ. *iii) It increases linearly with* F, *iv) but decreases linearly with* S; *v) It is also a strict convex-decreasing function of* θ, *and vi) a linear decreasing function of* ε.

Proof. i) It can be checked that $\forall a \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}a} = \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}(p_d^* q^*)} \cdot \dfrac{\mathrm{d}(p_d^* q^*)}{\mathrm{d}a} = \dfrac{\psi(1-\varepsilon)a}{2\theta} > 0$, reason why $\widetilde{m}^*$ is a monotonic increasing function of a, and also $\forall a \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}^2\widetilde{m}^*}{\mathrm{d}a^2} = \dfrac{\psi(1-\varepsilon)}{2\theta} > 0$, which proves that $\widetilde{m}^*$ corresponds to a strict convex function of a. ii) It can be verified that $\forall\psi \in [\hat{\psi}, 1]$, $\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\psi} = \left[\dfrac{F(1-\theta)}{\theta} + \dfrac{(1-\varepsilon)(a^2/4)}{\theta}\right] > 0$, and $\dfrac{\mathrm{d}^2\widetilde{m}^*}{\mathrm{d}\psi^2} = 0$, which means that $\widetilde{m}^*$ is a linear increasing function of ψ. iii) It can be proved that $\forall F \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}F} = \dfrac{(1-\theta)\psi}{\theta} > 0$, and $\dfrac{\mathrm{d}^2\widetilde{m}^*}{\mathrm{d}F^2} = 0$. Therefore, $\widetilde{m}^*$ increases linearly with F. iv) It is easy to check that $\forall S \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}S} = -1 < 0$, and $\dfrac{\mathrm{d}^2\widetilde{m}^*}{\mathrm{d}S^2} = 0$, which assures that $\widetilde{m}^*$ decreases linearly with S. iv) It can be proved that $\forall\theta \in [0, \hat{\theta}]$,

$\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\theta} = -\dfrac{F\psi}{\theta^2} - \dfrac{(1-\varepsilon)(a^2/4)\psi}{\theta^2} < 0$, and $\dfrac{\mathrm{d}^2\widetilde{m}^*}{\mathrm{d}\theta^2} = \dfrac{2F\psi}{\theta^3} + \dfrac{(1-\varepsilon)(a^2/2)\psi}{\theta^3} > 0$, which ensures that $\widetilde{m}^*$ is a strict convex function of θ. v) Lastly, $\widetilde{m}^*$ decreases linearly with ε, since $\forall\varepsilon \in [0,1]$, $\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\varepsilon} = -\dfrac{\psi(a^2/4)}{\theta} > 0$, and $\dfrac{\mathrm{d}^2\widetilde{m}^*}{\mathrm{d}\varepsilon^2} = 0$. ■

Proposition 3.4. *In the perfect-subgame Nash equilibrium,* $\forall\alpha \in [\hat{\alpha}, 1]$*,* $\forall\psi \in [\hat{\psi}, 1]$*, and* $\forall\theta \in [0, \hat{\theta}]$*, i)* $E\left[\Pi_i^{T^*}(q^*, B^*)\right]$ *is a strict convex-increasing function of* a*, ii) increases linearly with* α*, and iii) is a strict convex-increasing function of* ψ*. iv) It is also a convex-decreasing function of* F*, v) a strict convex-decreasing function of* S*, vi) a strict convex-decreasing function of* θ*, and vii) a strict convex-decreasing function of* ε*.*

Proof. i) $\forall a \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}E\left[\Pi_i^{T^*}\right]}{\mathrm{d}a} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}a} = \alpha L(\widetilde{m}^*)\dfrac{a(1-\varepsilon)\psi}{2} > 0$, assuring that $E\left[\Pi_i^{T^*}\right]$ is a monotonic increasing function of a. Also, $\forall a \in \mathbb{R}^+$, $\dfrac{\mathrm{d}^2E\left[\Pi_i^{T^*}\right]}{\mathrm{d}a^2} = \dfrac{\alpha(1-\varepsilon)\psi}{2}\left[\dfrac{l(\widetilde{m}^*)a^2(1-\varepsilon)\psi}{2\theta} + L(\widetilde{m}^*)\right] > 0$, so that $E\left[\Pi_i^{T^*}\right]$ is a strict convex function of a.

ii) $\forall\alpha \in [\hat{\alpha}, 1]$, $\dfrac{\mathrm{d}E\left[\Pi_i^{T^*}\right]}{\mathrm{d}\alpha} = \theta\left[L(\widetilde{m}^*)\widetilde{m}^* - \int_0^{\widetilde{m}^*} ml(m)\,dm\right] > 0$, which ensures that $E\left[\Pi_i^{T^*}\right]$ increases linearly with α, as $\dfrac{\mathrm{d}^2E\left[\Pi_i^{T^*}\right]}{\mathrm{d}\alpha^2} = 0$.

iii) $\forall\psi \in [\hat{\psi}, 1]$, $\dfrac{\mathrm{d}E\left[\Pi_i^{T^*}\right]}{\mathrm{d}\psi} = \alpha\theta L(\widetilde{m}^*)\cdot\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\psi} = \alpha L(\widetilde{m}^*)\left[F(1-\theta) + (1-\varepsilon)(a^2/4)\right] > 0$, so that $E\left[\Pi_i^{T^*}\right]$ is a monotonic increasing function of ψ; In addition, since $\forall\psi \in [\hat{\psi}, 1]$, $\dfrac{\mathrm{d}^2E\left[\Pi_i^{T^*}\right]}{\mathrm{d}\psi^2} = \dfrac{\alpha l(\widetilde{m}^*)}{\theta}\left[F(1-\theta) + (1-\varepsilon)(a^2/4)\right]^2 > 0$, $E\left[\Pi_i^{T^*}\right]$ is also a strict convex function of ψ.

iv) $\forall F \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}E\left[\Pi_i^{T^*}\right]}{\mathrm{d}F} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}F} - 1 = \alpha L(\widetilde{m}^*)\dfrac{(1-\theta)}{\theta}\psi - 1 < 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_i^{T^*}\right]}{\mathrm{d}F^2} = \dfrac{\alpha l(\widetilde{m}^*)(1-\theta)^2\psi^2}{\theta} > 0$, which ensure that $E\left[\Pi_i^{T^*}\right]$ is a strict convex-decreasing function of F.

v) Since $\forall S \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}E\left[\Pi_i^{T^*}\right]}{\mathrm{d}S} = \alpha\theta L(\widetilde{m}^*) \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}S} = -\alpha\theta L(\widetilde{m}^*) < 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_i^{T^*}\right]}{\mathrm{d}S^2} = \alpha\theta l(\widetilde{m}^*) > 0$, $E\left[\Pi_i^{T^*}\right]$ is a strict convex-decreasing function of S.

vi) It can be proved that $\forall\theta \in [0, \hat{\theta}]$,

$\dfrac{\mathrm{d}E\left[\Pi_i^{T*}\right]}{\mathrm{d}\theta} = -\alpha L(\widetilde{m}^*)\left[F + S - \int_0^{\widetilde{m}^*} ml(m)\,dm\;\right] < 0$, and in addition $\dfrac{\mathrm{d}^2\widetilde{\mu}}{\mathrm{d}\theta^2} = \alpha l(\widetilde{m}^*)\psi\left[\dfrac{F(1-\theta)}{\theta^2} + \dfrac{(1-\varepsilon)(a^2/4)}{\theta^2}\right]\left[F + S + \int_0^{\widetilde{m}^*} ml(m)\,dm\; + L(\widetilde{m}^*)\widetilde{m}^*\right] > 0$, reason why $E\left[\Pi_i^{T*}\right]$ is a strict convex-decreasing function of θ.

vii) Lastly, it can be checked that $\forall\varepsilon \in [0,1]$, $\dfrac{\mathrm{d}E\left[\Pi_i^{T*}\right]}{\mathrm{d}\varepsilon} = \alpha\theta L(\widetilde{m}^*)\cdot\dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\varepsilon} = -\alpha\psi L(\widetilde{m}^*)(a^2/4) < 0$, and $\dfrac{\mathrm{d}^2E\left[\Pi_i^{T*}\right]}{\mathrm{d}\varepsilon^2} = \dfrac{\alpha\psi^2a^4l(\widetilde{m}^*)}{16\theta} > 0$, which ensures that $E\left[\Pi_i^{T*}\right]$ is a strict convex-decreasing function of ε.

■

Proposition 3.5. *In the perfect-subgame Nash equilibrium,* $\forall\alpha \in [\hat{\alpha}, 1]$, $\forall\psi \in [\hat{\psi}, 1]$, *and* $\forall\theta \in [0, \hat{\theta}]$, *i)* $E\left[\Pi_j^{NSL*}(e^*, q^*)\right]$ *is a strict convex-increasing function of* a*, ii) it does not depend on* α*, neither on* ψ*. iii) Also, it does not depend on* F*, neither on* S *nor* θ*. iv) Furthermore, it is a convex-increasing function of the salaries,* w*, and a convex-decreasing function of* γ*. v) Lastly, it increases linearly with* ε*.*

Proof. i) $\forall a \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}a} = \varepsilon(a/2) > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}a^2} = \varepsilon/2 > 0$, reason why $E\left[\Pi_j^{NSL*}\right]$ is a strict convex-increasing function of a. ii)-iii) Straightforwardly from Eq. (42). iv) It is easy to check that $\forall w \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}w} = \frac{w}{\gamma} > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}w^2} = \frac{1}{\gamma} > 0$, so that $E\left[\Pi_j^{NSL*}\right]$ is a strict convex-increasing function of w; Also, $\forall\gamma \in \mathbb{R}_{++}$, $\dfrac{\mathrm{d}E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}\gamma} = -\frac{w}{\gamma^2} > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}\gamma^2} = \frac{w}{\gamma^3} > 0$, reason why $E\left[\Pi_j^{NSL*}\right]$ is a strict convex-decreasing function of γ. v) Moreover, since $\forall\varepsilon \in [0,1]$, $\dfrac{\mathrm{d}^2E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}\varepsilon} = a^2/4 > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}\varepsilon^2} = 0$, $E\left[\Pi_j^{NSL*}\right]$ increases linearly with ε. ■

Proposition 3.6. *In the perfect-subgame Nash equilibrium,* $\forall\alpha \in [\hat{\alpha}, 1]$, $\forall\psi \in [\hat{\psi}, 1]$, *and* $\forall\theta \in [0, \hat{\theta}]$, *i)* $E\left[\Pi_j^{SL*}(e^*, q^*, B^*)\right]$ *is a convex-increasing function of* a*, ii) decreases linearly with* α *iii) but increases linearly with* ψ *and with* F*. iv) It also decreases linearly with* S *and with* θ*. v) Furthermore, it is a convex-increasing function of their salaries,* w*, and a convex-decreasing* *function of γ. vi) Lastly, it increases linearly with ε but at a lesser rate than for $E\left[\Pi_j^{NSL*}(e^*, q^*)\right]$.*

Proof. i) $\forall a \in \mathbb{R}_{++}, \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}a} = \varepsilon(a/2) + (1-\alpha)\theta \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}a} = (a/2)(\varepsilon(1-\psi) + \psi(1-\alpha(1-\varepsilon))) > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}a^2} = (1/2)(\varepsilon(1-\psi) + \psi(1-\alpha(1-\varepsilon))) > 0$, so that $E\left[\Pi_j^{SL*}\right]$ is a strict convex-increasing function of a. ii) $\forall\alpha \in [\hat{\alpha}, 1], \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\alpha} = -\theta(\widetilde{m}^* - m) < 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\alpha^2} = 0$, proving that $E\left[\Pi_j^{SL*}\right]$ decreases linearly with α. iii) It can be checked that $\forall\psi \in [\hat{\psi}, 1]$, $\dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\psi} = (1-\alpha)\theta \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\psi} = (1-\alpha)\theta\left[F(1-\theta) + (1-\varepsilon)(a^2/4)\right] > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\psi^2} = 0$, which ensures that $E\left[\Pi_j^{SL*}\right]$ increases linearly with ψ. Moreover, $\forall F \in \mathbb{R}_{++}, \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}F} = (1-\alpha)\theta \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}F} = (1-\alpha)(1-\theta)\psi > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}F^2} = 0$, which assures that $E\left[\Pi_j^{SL*}\right]$ increases linearly with F too. iv) Since $\forall S \in \mathbb{R}_{++}, \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}S} = (1-\alpha)\theta \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}S} = -(1-\alpha)\theta < 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}S^2} = 0$, $E\left[\Pi_j^{SL*}\right]$ decreases linearly with S. Also, $\forall\theta \in [0, \hat{\theta}]$, $\dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\theta} = (1-\alpha)(\widetilde{m}^* - m) + (1-\alpha)\theta \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\theta} = -(1-\alpha)(F+S+m) < 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\theta^2} = 0$, reason why $E\left[\Pi_j^{SL*}\right]$ decreases linearly with θ too. v) It is easy to check that $\forall w \in \mathbb{R}_{++}, \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}w} = \frac{w}{\gamma} > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}w^2} = \frac{1}{\gamma} > 0$, which ensures that $E\left[\Pi_j^{SL*}\right]$ is a strict convex-increasing function of w; In addition, $\forall\gamma \in \mathbb{R}_{++}, \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\gamma} = -\frac{w}{\gamma^2} > 0$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\gamma^2} = \frac{w}{\gamma^3} > 0$, assuring that $E\left[\Pi_j^{SL*}\right]$ is a strict convex-decreasing function of γ. vi) Lastly, it can be proved that $\forall\varepsilon \in [0, 1], \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\varepsilon} = a^2/4 + (1-\alpha)\theta \cdot \dfrac{\mathrm{d}\widetilde{m}^*}{\mathrm{d}\varepsilon} > 0 = (1-(1-\alpha)\psi)(a^2/4)$ and $\dfrac{\mathrm{d}^2E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\varepsilon^2} = 0$, ensuring that $E\left[\Pi_j^{SL*}\right]$ increases linearly with ε. Moreover, as long as $0 < (1-(1-\alpha)\psi) < 1$, $0 < \dfrac{\mathrm{d}E\left[\Pi_j^{SL*}\right]}{\mathrm{d}\varepsilon} < \dfrac{\mathrm{d}E\left[\Pi_j^{NSL*}\right]}{\mathrm{d}\varepsilon}, \forall\varepsilon \in [0, 1]$. ■